IE423
QUALITY ENGINEERING

PROJECT PART 3 -QUALITY CONTROL ON IMAGES

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1. Introduction

Linen is a flax-based natural fiber and textile that is predominantly used for homeware applications. Linen is famous because of its strength and durability hence it is known as versatile fabric. It is highly absorbent and can absorb up to 20% of its own weight. Linen is 100% natural and oldest fabric used by ancient Mesopotamia, ancient Egypt, ancient Greece. While linen is similar to cotton, it is made from fibers derived from the stems of the flax plant instead of the bolls that grow around cotton seeds (AanyaLinen, webpage).

To prepare for linen production, manufacturers of this fiber start by separating flax fibers from the woody interior of flax stems. The first step after the separation is combing, where inner fibers are combed into thin strands. In the next step, spinning, combed fibers are connected with devices called spreaders, and the resulting strings, called rovings, are then ready to be spun. After being spun on a spinning frame, the resulting yarn is reeled onto a bobbin in the reeling step. Finally, in the drying step, flax manufacturers dry the finished yarn and reel it onto bobbins. The yarn is then ready to be dyed, treated, and made into apparel, homewares, or other types of textile products (Sewport, webpage).

In the garment industry, quality control is practiced right from the initial stage of sourcing raw materials to the stage of the final finished garment. It is highly important to monitor the processing of linen for detecting any deviation from quality level since defects rate causes a direct effect on the profit margin of the product and decreases the quality cost during the manufacturing of the product. For the linen manufacturing industry, (which is a sub-branch of textile) quality control is conducted by checking for various failures such as fabric defects, color defects, and manufacturing defects. To achieve this aim, automated visual inspection including a refined image acquisition system and an effective texture analysis procedure is necessary to replace the human workforce since performances of human inspectors are highly influenced by emotional, physical and environmental distractions. Thus, a robust visual defect monitoring system can be achieved by implementing the right quality control algorithm.

2. Background Information

There are many studies conducted that discuss multivariate image analysis, the focus point of the automated process and product monitoring, and its uses in textile process industries including also linen. The most commonly used and widely beneficial methods used for automated vision today are Multivariate Image Analysis (MIA), Wavelet Texture Analysis (WTA) and the Gray Level Co-occurrence Matrix (GLCM). MIA method proposed in the late 80s includes applying PCA to a multivariate unfolded image of the textile, linen in our case, and storing the spectral signature data of the pixels in a new score space. Later, the masking step takes place and spectral properties are discovered by iteratively segmenting the score state. Since there is a sequence of products and manufacturing processes in linen processing, computing the number of pixels having a specific signature in each image on the sequence after masking, gives the chance to monitor defects and outlier occurring rates.

In addition to spectral signature-based methods such as MIA, there is a popular texture-based statistical method such as GLCM for quality monitoring of the linen process. Haralick et al used 14 textural features represented by stochastic properties to characterize distribution and relationships between the gray levels of an image, which are calculated from gray-level co-occurrence matrix (GLCM) related to second-order statistics of pixel intensity. GLCM monitors process by utilizing simultaneous occurrence probability of two pixels. As a statistical method, GCLM is much easy to use and computationally affordable. Another popular method is WTA since it shows a better performance than most of the other transform-based methods. The wavelet transform has been widely used in signaling de-noising due to its extraordinary time-frequency representation capability, thus PCA based on wavelet illustrates the better fault detection performance than the classical approach. However, the type and length of wavelet filters and structure of the wavelet packet tree must be carefully decided, and this may require good knowledge in advanced signal processing and wavelet theory.

In addition to these most popular models, there are also some different methods in the literature that are model-based, structural, geometrical besides other statistical and transform-based methods mentioned above (Duchesne et.al, 122). *The background information described in this part mainly obtained from the article by Duchesne et al [see references].*

3. Approach

In this part of the project, we are expected to build a control procedure that detects the regions that display unexpected and abnormal appearance in given images of the linen. In order to achieve this, we started the study by examining the existing literature about visual monitoring methods suggested and implemented throughout history. After comparing them in terms of the difficulty and the compatibility to our knowledge levels, we decided to proceed using the Grey Level Co-occurrence Matrix (GLCM) approach. The reason for us to choose this approach is that it is easier for us to apply and interpret the calculations, steps, and results since it uses the logic of simultaneous occurrence probability of two pixels, something we are familiar from our prior probability and statistics courses. Also, the defective regions are clearly displayed on the image at the end of the algorithm execution thus the monitoring is fairly easy for everyone.

After deciding the GLCM method and turned our 20 images into a grayscale version, we decided on our window size after a few trials, which is an odd number big enough to cover the variability of our images. Later, we defined the spatial relations we are searching between the reference and the neighbor pixel in each window in our R code which are up-next, down-next, and diagonal-nexts. The last step required for finishing the GLCM method is to decide on the texture measures we wanted to calculate in our model. We selected 6 measures (mean, variance, contrast, correlation, dissimilarity, and homogeneity) that we think are important and enough to display out of control situations in the images.

However, all are calculated using the entries in the GLCM, not the original pixel values. At the end of the execution of the same R algorithm for each image given, we obtained 6 different images for 6 measures calculated for each image. By looking at these images, we succeeded to detect the defective regions on the linen surface easily and automate the visual monitoring of linen processing, which is the aim of the study.

As we mentioned above our method uses normalized occurrence probabilities to specify the defect in linen. However, using the full image with this algorithm is not a vice choice generally. Since all linen pictures have a trend on the different parts of the picture, the best way for applying our method is by creating a window around a cell and calculating the texture measures with the pixels inside of the related window. Let's explain how our method works in a clear way. Firstly, for each pixel, it creates a window around according to our window size choices. Then it is creating a GLCM matrix for this window by using the number of occurrences for each grey level combinations. However, as we can see the pixels on the outer rows and columns cannot be covered with our selected window size. So, that the usual way of handling this is to fill in these edge pixels with the nearest texture calculation, thus having a repeated uniform border and our computer algorithm also works in that way. By doing that we had a normalized GLCM for each pixel except outer pixels in the picture. The normalized GLCM and each value of the matrices can be written as:

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$$

After that, there is a part named texture measure calculation. For this part, our method has 14 different texture measure calculations and each one has a special way of calculating the texture measure by considering and applying different methods. We chose some of the texture measure types and we will mention them detailly in the forward section. After finding texture measures for each pixel and each type, our method fills the pixels with the texture measure values of each pixel.

Consequently, we have a picture matrix with texture measures for each pixel. This matrix represents our statistics values to differentiate defects from the linen. Now we can create any control charts by using these statistics values and also draw a manual version of the pictures that glcm function already creates itself. However, since we have 250000 data points, we chose to plot GLCM texture measure plots instead of control charts. This way, we achieved a more compact and understandable visual representation for quality control. In the next step in our quality control process for linen samples, we use these statistics obtained to build our own statistical quality control procedure and control charts. In order to build our out-of-control checking condition, we targeted a detailed procedure so included the explanatory power of every measure we used in GCLM method by giving each of them equal weights in the formula. In the end, the out-of-control checking formula used in our quality control procedure is obtained as:

$$Mean\ ooc\ cond. + Variance\ ooc\ cond. + Homogeneity\ ooc\ cond. + Dissimilarity\ ooc\ cond. + Contrast\ ooc\ cond. + Correlation\ ooc\ cond. >= 3$$

The out-of-control condition for a measure is either 1 (outside the acceptable bounds calculated using 0.002 two-sided significance level which is European convention value) or 0 (in control situation) by the nature of our algorithm. If the condition above holds, that points to an out-of-control situation for that region in the texture image with 3 out of the 6 measures has a value outside the boundaries and the corresponding pixel value is turned to 0. That results in a black point indicating the out-of-control pixel and defective texture there. The same control procedure is applied to each and every 20 images in order to achieve compatibility in controlling.

"Descriptive Group" texture measures such as mean, variance, contrast use equations similar to those for common descriptive statistics. "Contrast Group" measures (correlation, dissimilarity, and homogeneity) contrast use weights related to the distance from the GLCM diagonal.

A.Descriptive Group

A.1. GLCM Mean

GLCM Mean shows how it differs from the mean of the pixel values in the window. The GLCM Mean is not simply the average of all the original pixel values in the image window. The pixel value is weighted not by its frequency of occurrence by itself but by the frequency of its occurrence in combination with a certain neighbor pixel value. Mean Equation:

$$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right) \quad \mu_j = \sum_{i,j=0}^{N-1} j\left(P_{i,j}\right)$$

A.2. GLCM Variance

Variance is calculated with the mean and the dispersion around the mean of pixel values within the GLCM. Due to the fact that it has to use the GLCM, it deals specifically with the combinations of reference and neighbor pixels, so it is not the same as the variance of grey levels in the original image. Variance Equation:

$$\sigma_i^{2} = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2 \quad \sigma_j^{2} = \sum_{i,j=0}^{N-1} P_{i,j}\left(j-\mu_j\right)^2$$

A.3. GLCM Correlation

The GLCM Correlation calculates the linear dependency of grey levels with their neighboring pixels. Correlation Equation:

$$\sum_{i,j=0}^{N-1} P_{i,j}\left[\frac{\left(i-\mu_i\right)\left(j-\mu_j\right)}{\sqrt{\left(\sigma_i^{2}\right)\left(\sigma_j^{2}\right)}}\right]$$

B. Contrast group

B.1. Contrast

Contrast can be also called "sum of squares variance". The weights continue to increase exponentially as (i-j) increases. For example, when their difference is 1, then the weight is 1 and can be classified as a small contrast value. However, when they differ by 2, then the weight is increased to 4. Contrast equation:

$$\sum_{i,j=0}^{N-1} P_{i,j}\left(i-j\right)^2$$

B.2. Dissimilarity

Instead of weights increasing exponentially as one moves away from the diagonal as contrast did, the dissimilarity weights increase linearly. Dissimilarity equation:

$$\sum_{i,j=0}^{N-1} P_{i,j}\left|i-j\right|$$

B.3. Homogeneity

Homogeneity weights values are calculated by the inverse of the Contrast weight, with weights decreasing exponentially away from the diagonal. Homogeneity Equation:

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+\left(i-j\right)^2}$$

The information about the GLCM application on textures in the "Approach" part is obtained from the paper by Hall-Beyer [see references].

4. Results

Our results can be seen from the HTML file on the "Project Part 3" on the webpage.

5. Conclusion and Future Work

Since our GLCM method takes different statistical texture measure types into consideration, the method can be applied to different types of image processing problems. In our situation, we chose the 6 different algorithms, and, in our opinion, our defect detection process seems to be successful. As we share in the result part the GLCM plot can identify the defects by giving colors to our texture measure values by creating a chart. But we don’t have to use it, so we gave a method by creating a chart with the texture measure values of the matrices for all images. We can create an upper and lower bound by calculating the mean and standard deviation for each texture measure type and created an equation to detect the outliers by using 6 texture measures. Then the outliers will be the out of control pixels according to GLCM method and their number will be zero so we can detect them by plotting the matrices. If we checked this method, it also gives a clear result and extra room for choosing the significance level by ourselves. However, GLCM is not perfect like every method and there are some drawbacks that GLCM can’t reach. Firstly, we are using window size to use the trend more properly because there can be a different trend in the different parts of the picture. In some linen pictures, we have to increase the window size to identify the defect according to possible defect sizes and trends. However, when window size increases the uncovered row and column numbers are also increasing. Then, if there is a defect on the edges of the image, our method has some hardships with increased window size. So, it creates a trade-off between identifying possible defects in a clearer way or considering the probability of happening a defect on the edges of the image. If we think about the grey level that we choose in the function, it is clear that we are eliminating and losing some data to reach a better conclusion. We are using 32 grey levels by approximating the 256 grey levels to the near ones. So, it is possible to skip or distort some statistics of our system while eliminating and generalizing the data. However, it is necessary because our main tool is occurrences and with such a huge grey level numbers the closest colors cannot be identified as an occurrence and consequently, our method means nothing in this manner.

Also, since we have 6 texture measure types and 6 different measure matrices at the end, the success of the texture measure types are different for various images. Mainly, mean generates some successful and clear result but in some images with a thin defect, dissimilarity also gives a clear result.

At the end of the study, we can conclude that our method was successful in detecting defective regions of the linen texture. Thus, we can recommend this approach for further use in the linen process visual quality monitoring aims. Naturally, it has few accurate classifications, but they can be classified as insignificant. Since there is always room for improvement in all methods, some recommendations can be done such as GLCM with an improved and more complex texture measure statistics. Also, there are some applications of neural network applications for defect detection. They use the parameters of the GLCM matrix as the features and train the neural network. Based on the error residuals the control chart is implemented, and out of control points are identified. This method can be used for the more advanced application of defect detection (Ngan, 451).

6. References

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