The objective of this work is to propose and investigate a texture analysis technique based on wavelet transforms for fault detection in the textile industry.

The approach proposed in this work involves the gathering of texture patterns using wavelet transform, as in [3], followed by a statistical analysis of normality to detect outliers\(^1\). Regions of the cloth image whose texture values behave as outliers will be considered faulty.

This text is organized as follows. The next section presents the methodology with emphasis on the texture measurement technique and on the statistical analysis to detect areas on a cloth containing imperfections. Section 3 describes the experiments performed to evaluate the proposed techniques. Experiment results are presented and discussed in section 4 followed by a sum-

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\(^1\) Points that lie outside a set of characteristics
mary of the work along with the main conclusion obtained from it.

The input to a column low-pass filter and to a column high-pass filter. The output of each filter is applied to two further row filters generating four outputs: a) the approximation, b) the horizontal detail, c) vertical detail and d) diagonal detail. Each time a wavelet filter is applied, a down sample of the output images is performed so that the total amount of data points keeps constant. This pyramidal algorithm can be applied recursively on the image approximation (a). The output of each new run of the algorithm is called a level. Texture attributes are obtained by computing variance, standard deviation, entropy or any other similar measurement over the outputs b) to d) of each level, resulting in a vector containing the texture attributes.

In this work three levels of analysis were used, each of them producing three variance measurements for horizontal, vertical and diagonal texture characteristics. A final measurement, corresponding to the variance of the final image approximation is performed. Therefore the texture of a block from the input image is represented by a ten dimensional texture vector.

In this work, Daubechies orthogonal wavelets [6] are used. Their construction is based on orthogonalization and factorization conditions. They have compact support and are non-symmetric although work fine with a wide range of tensorial moments.

2.1 Wavelet Based Texture Measurement

The second step of the system presented in this work consists of measuring texture characteristics of blocks cropped from the input image. Textures are measured using a wavelet-based approach, described in full detail in [3] [5].

Wavelets are short duration waves with zero mean value. They can be scaled and translated, breaking bidimensional images in different scales to obtain greater or lower information of some image detail. When global image information is required, larger scales are used while lower scales are used for detail information.

Different from continuous transform, the discrete wavelet transform is computed using scales and positions given by powers of two.

Thinking in terms of images, low frequencies correspond, in general, to global information associated to the image identification. High frequencies on the other hand, are responsible for the details inside the image.

In the present work, texture is measured here by using a pyramidal algorithm that applies low-pass and high-pass filters to the original image, generating four sub-images as shown in Figure 2. The original image is divided in equal size square blocks. Using a wavelet based technique the texture of each block is measured, producing a set of patterns that describes the texture over a cloth sample.

In the third step, a statistical procedure is applied to identify patterns that do not follow the variability inferred from the other patterns.

The following sections explain the algorithms used in steps 2 and 3.

2.2 Detecting Faulty Blocks

The procedure to detect faulty blocks bases on the assumption that the texture patterns obtained from a single cloth sample come from a multivariate normal distribution. This assumption may be assessed by a visual inspection of chi-square plots [4] built with the texture values obtained from the available data. These tests have indicated that the assumption of normality was quite plausible in all cases.

The procedure to identify faulty blocks explores the following property of Gaussian populations:

If \( \mathbf{x} \) denotes a pattern from a Gaussian population then the generalized squared distances

\[
(\mathbf{x} - \bar{\mathbf{x}}) \Sigma^{-1} (\mathbf{x} - \bar{\mathbf{x}})
\]
Behave like a chi-square random variable with the degree of freedom equal to the dimension of \( x \), where \( \bar{x} \) and \( S \) denote respectively the sample mean and the sample covariance matrix, estimated on the available patterns.

A large value for the generalized squared distance, indicates that the corresponding block does not behave like the other blocks from the same cloth sample. This is taken as evidence that this block contains a imperfection.

So the detection procedure consists in determining the patterns whose generalized squared distance falls inside a given limit upper percentile of the chi-square distribution. This is the conventional outlier detection procedure applied to a normal population.

A critical issue in this procedure is the choice of the limit upper percentile. Small values will imply in a large number of faulty blocks being accepted as faultless (false positives). A large upper percentile will instead lead the system to reject a large number of faultless blocks (false negatives). The effect of the limit upper percentile over the system performance is revisited in section 4.1.

3 Experiments

A fault detection system using the techniques described in the previous sections, was built and evaluated on images of pieces of cloth obtained from [1]. This data set consists of sixteen 256×256 gray scale images, eight of them containing distinct types of imperfections. Eight images contain faultless cloth samples. Figure 3 and Figure 4 show examples from each data set.

Each 256×256 gray scale input image is segmented in 64 non-overlapping blocks with size of 32×32 pixels. The texture is measured by applying the wavelet approach described in section 2.1, producing for each block a vector of 10 texture attributes. This corresponds to step 2 in Figure 1.

![Figure 3: Example of a faultless sample](image)

![Figure 4: Example of faulty sample with a bright stripe; the division of the image in square blocks is also shown.](image)

4 Results

4.1 Assessing the Assumption of Normality

The assumption of normality was checked for all cloth samples used in the experiments according to the procedure outlined in section 2.2.

Figure 5 shows the chi-square plot for each cloth samples used in the experiments. The plots are organized row wise: the first row corresponds to samples 1 to 4, second row to samples 5 to 8, and so on. Straight-line segments to improve the visualization connect adjacent points in the plot. Only faultless blocks were considered in this analysis. For normal populations this plot (in solid line) should resemble a straight line through the origin having slope 1 (dashed line).

A visual inspection on Figure 5 indicates that the normality assumption is quite plausible in all cases. An S shaped curve generally indicates a departure from the normality assumption. Although this can be observed in some curves, such as sample 5 (row 2: column 2), 12 (row 3: column 4) and 14 (row 4: column 2), even in such cases the curves are quite close to the straight line, and normality can be assumed.
4.2 System Performance

Table 1 shows the upper percentile corresponding to the block with the largest Mahalanobis Distance for each faultless sample (samples 1 to 8). This means that the proposed fault detection system would be able to accept all blocks from the faultless samples by setting the threshold upper percentile to a value not greater than what is given in the right column of Table 1.

![Image of ROC plots](image)

Figure 5: Chi-square plots of the sixteen cloth samples. First 2 rows correspond to the faultless samples, last 2 rows to faulty samples.

According to the normality assumption it is expected that the more distant block in Mahalanobis sense will fall in an upper percentile in the chi-square distribution below 100%/64=1.6%. This is consistent with the data presented in Table 1.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Faultless Images</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Maximal upper percentile for 100% performance (%)</td>
</tr>
<tr>
<td>1</td>
<td>1.4</td>
</tr>
<tr>
<td>2</td>
<td>0.3</td>
</tr>
<tr>
<td>3</td>
<td>0.6</td>
</tr>
<tr>
<td>4</td>
<td>0.2</td>
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<tr>
<td>5</td>
<td>1.6</td>
</tr>
<tr>
<td>6</td>
<td>1.0</td>
</tr>
<tr>
<td>7</td>
<td>0.5</td>
</tr>
<tr>
<td>8</td>
<td>0.4</td>
</tr>
</tbody>
</table>

Table 1: Percentile for 100% performance on faultless samples.

Samples 9 to 16 contain faulty blocks. Once a limit upper percentile is selected the system will potentially reject some faultless block (false negatives) and also accept some faulty blocks (false positives). By varying the value of the limit upper percentile a plot relating the number of false positives and false negatives can be drawn, the so-called Receiver Operating Characteristic or ROC plot.

![Image of ROC plots](image)

Figure 6 shows the ROC plots for the samples 9 to 16. Again in this Figure adjacent points are connected to improve the visualization. System performance is related to the closeness of the ROC curve to the axes. The closer the curve is to the axes, the higher is the performance. The plots show, therefore, that the system performed very well for most faulty samples. One exception was for sample 12 (1st row: 4th column of Figure 6).

This result was obtained using the cloth sample shown in Figure 4, which has a imperfection in the form of a horizontal bright stripe in the lower half of the image. An unfortunate coincidence made the stripe to lay along the border of adjacent blocks in which the input image was segmented, as can be seen from Figure 4. This reduced the influence of the imperfection over the texture of such blocks and the system was not able to capture them appropriately.

Table 2 summarizes the performance results for samples 9 to 16. The second column contains the number of faulty blocks in each sample. The last column on the right presents the limit upper percentile for the point closest to the origin in each ROC plot. This is generally taken as the condition for maximal system performance. The two columns in the middle of Table 2 have the number of false positives and false negatives for the maximal performance.

![Image of ROC plots](image)

Figure 6: ROC plots for the samples containing faulty blocks (samples 9 to 16).

The Table indicates that the limit upper percentile for maximal performance changes from sample to sample. Therefore in a real system the selection of this value must be done for each particular cloth type, what would require some experimental work before the system is put into operation.

As already indicated in Figure 6, the poorest performance was obtained for sample 12. In all other cases the system attained a very good performance.

Better results may be expected by improving the image acquisition process. It can be clearly seen from Figure 3 that the cloth sample in this case looks a little
wrinkled on the image. This may have negatively influenced the results. A more careful sample preparation and image acquisition would probably allow better performance figures. Image enhancement techniques may also help to compensate imperfections of the image sensor or in the acquisition procedure.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Number of Faulty Blocks</th>
<th>Images with Faulty Blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Number of False Positives</td>
</tr>
<tr>
<td>9</td>
<td></td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td></td>
<td>1</td>
</tr>
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<tr>
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<td>11</td>
</tr>
<tr>
<td>16</td>
<td></td>
<td>2</td>
</tr>
</tbody>
</table>

Table 2: Performance data of the samples containing faulty blocks (samples 9 to 16).

A performance improvement may also be achieved by introducing some refinements into the proposed algorithm. The use of overlapping blocks instead of distinct blocks may enable the system to capture imperfections placed in a neighborhood of block borders, as in the sample 12 depicted in Figure 6.

A further refinement could be tested by using an appropriate transformation to make non-normal data more “normal looking” alike. Since the proposed method is based on the normality assumption, that may bring an important performance improvement. Procedures to select such transformations are presented in [4].

5 Conclusions

A new procedure to detect imperfections on cloth samples is proposed. The image of a cloth sample is initially segmented in equal size blocks. Using a wavelet based approach, the texture of each individual block is measured. An imperfection is detected by identifying blocks whose associated texture characteristics strongly depart from the Gaussian behavior.

Encouraging results were obtained in experiments performed on sixteen cloth samples. Higher system performance may be further achieved, by improving the image acquisition procedure, by enhancing the image before the analysis and by splitting the input image in overlapping blocks.

6 References