# DEFECT DETECTION IN TEXTILE FABRIC IMAGES USING WAVELET TRANSFORMS AND INDEPENDENT COMPONENT ANALYSIS

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In this paper, a new method based on the use of wavelet transformation prior to independent component analysis for solving the problem of defect detection in textile fabric images is presented. Different sub-bands of the wavelet packet tree scheme of the defect-free sub-windows are obtained and independent components of these subbands are calculated as the basis vectors. The true feature vectors corresponding to these basis vectors are computed. The test sub-window is labeled as defective or not according to the Euclidean distance between the true feature vector representing the non-defective regions and the feature vector of the sub-window under test. The advantage of adding wavelet analysis prior to independent component analysis is presented.

## 1. Introduction

Automated industrial inspection systems based on hardware and/or software tools are increasingly being installed in factories in order to increase the quality of products, and to speed up the production procedure. One of the industry fields where automated visual inspection systems are most needed is the textile industry. In this work, a new method, which combines the concepts of wavelet transformation and Independent Component Analysis (ICA) for defect detection problem in textile images, is presented. Both of the above concepts are proved to possess good performance capacities in various fields such as biomedical engineering, signal and speech processing. The aim of this study is to find the independent components of the wavelet transform of textile fabric images for the purpose of defect detection. It is intended to be a continuum of studies done on detect defection in textile fabric images by Atalay [1], Meylani [2] who used adaptive two-dimensional lattice filters, Latif-Amet *et. al.* [3] who used subband domain co-occurence matrices and Sezer *et. al.*[4] who used ICA based methods.

## 2. Independent Component Analysis

ICA aims to find a linear transformation of original data such that the new representation is the one that minimizes the statistical dependence of the components present in the representation. ICA tries to find the hidden components that capture the essential structure of the data. The representation achieved by ICA facilitates the analysis of the data encountered in such fields like, data compression, pattern recognition, de-noising [5]. The basic ICA model is shown as

$$\boldsymbol{x} = \boldsymbol{A}\boldsymbol{s} \tag{2.1}$$

where $\boldsymbol{x}$ is the random vector containing the mixtures, $\boldsymbol{s}$ is the random vector containing the sources, and $\boldsymbol{A}$ is the mixing matrix. No *a priori* information about the mixing matrix and the sources are known. In order to make the problem of estimating the independent components by observing only the mixtures $\boldsymbol{x}$ solvable, the sources $\boldsymbol{s}$ must be assumed to be independent from each other with each having a nongaussian probability distribution. The sources $\boldsymbol{s}$ can be estimated after finding the de-mixing matrix $\boldsymbol{B}$ given in equation (2.2):

$$\boldsymbol{s} = \boldsymbol{B}\boldsymbol{x} \tag{2.2}$$

The demixing matrix can be estimated by maximization of the nongaussianity of the sources. As the nongausianity of the mixtures is increased, they become statistically more independent from each other [6].

Hurri et. al.[7] have presented some results in applying ICA to image data. The aim of ICA is to make the image pixels as mutually independent as possible.

An image sub-window $I(x,y)$ can be represented as a linear sum of its basis functions (i.e. independent components) which can be extracted by ICA.

$$I(x,y)=\sum_{i=1}^{n}a_i(x,y)s_i \qquad (2.4)$$

Here, $a_i(x,y)$ are called as *basis functions*, and the $s_i$ constitute the feature vector that will be used in the proposed defect detection system.

## 3. Wavelet Packets

The decomposition of a signal can be done via the conventional method of wavelet transform and is called as *pyramid structured wavelet transform* [8]. Each time the low frequency band is split, the other bands are not used. This is suitable for signals with most of their energy concentrated in the low frequency regions. However, for some signals, energy is concentrated at the middle frequencies. In this case, we have to split all the bands. This is called as *wavelet packet decomposition*. A two-dimensional wavelet packet tree decomposition and the terminology used in this paper are shown in Fig.3.1.

| | | | |
|---|---|---|---|
| *AA* | *AH* | *HA* | *HH* |
| *AV* | *AD* | *HV* | *HD* |
| *VA* | *VH* | *DA* | *DH* |
| *VV* | *VD* | *DV* | *DD* |

Fig. 3.1: 2-D wavelet packet tree decomposition

## 4. Methodology

Our defect detection system consists mainly of two parts: feature extraction and detection. In feature extraction part, a true feature vector is aimed to be extracted by training the system with clean regions of the fabric images. The feature vector of a test sub-window is compared with the true feature vector in the detection part. The general methodology is as follows:

As a first preprocessing step, the mean of every image is subtracted from itself, and then every image is divided by its variance in order to make the ICA estimation better conditioned [5-6]. The aim of this project is to apply sub-band analysis prior to ICA. The procedure is as follows: 10000 sub-windows of size $N\times N$ are taken from random points of the defect free images, and these sub-windows are converted into column vectors each of size $N^2\times 1$. After the sub-windows of the defect-free image(s) are extracted, the subbands of these image sub-windows are decomposed. These subbands are extracted by 2-level wavelet transformation. According to the application, one or more subbands can be taken from the possible 16 subbands of the 2-level wavelet packet tree scheme. Writing those column vectors as the columns of a matrix forms a data matrix $\boldsymbol{X}$ of size $N^2\times 10000$. Let $k$ represent the number of subbands taken during the algorithm. There will be $k$ $\boldsymbol{X}$ matrices each composed by a different subband of the image sub-windows. Since 2-level wavelet transformation is used, this means that the resulting size of the subband will be $(N/4)\times(N/4)$. This makes the size of each $\boldsymbol{X}$ matrix $(N^2/16)\times 10000$.

After the data acquisition part, the dimension of the data may be reduced to a number that is equal to the number of desired independent components. Dimension reduction decreases the computation time. Dimension reduction is performed by Principal Component Analysis (PCA). Let $m$ represent the number of desired independent components. In PCA, $m$ eigenvectors with the $m$ highest eigenvalues of the covariance matrix of $\boldsymbol{X}$ are chosen. By that way, the size of $\boldsymbol{X}$ is reduced to $m\times 10000$.

As mentioned previously, feature vectors used are nothing but the coefficients of the independent components; namely, the $s_i$'s in Eq. (2.4) constitute the feature vectors. By the way of multiplying each 10000 sub-window by the $k$ de-mixing matrices, which are found by the ICA algorithm, 10000 feature vectors, $\mathbf{s}$, are extracted for each sub-band. This makes a total of $k$ feature vectors for a sub-window. The size of $\mathbf{s}$ is $m\times 1$. In order to find the $\boldsymbol{s_{true}}$ vector, which is the true feature vector representing the clean regions, mean of those 10000 feature vectors (coefficients of the independent components) are taken for each sub-band. This makes a total of $k$ $\boldsymbol{s_{true}}$ vectors.

In the detection part, the de-mixing matrix found in the feature extraction part is used. The image to be tested is divided into $N\times N$ non-overlapping sub-windows making a total of $256^2/N^2$ sub-windows, since the size of each fabric image is $256\times 256$. Each sub-window is multiplied by $k$ de-mixing matrices, and the corresponding $\boldsymbol{s}$ vectors (feature vectors) are obtained. The Euclidian distances between these vectors and the $k$ $\boldsymbol{s}_{true}$ vectors are found. If the mean of these $k$ distances is above the threshold value determined by the equation (4.1), the corresponding sub-window is said to be defective, otherwise it is said to be non-defective. This procedure is done for all the test windows.

$$\alpha = D_m + \eta(D_u - D_l) \qquad (4.1)$$

where $D_m$ is the median value of distances, $(D_u - D_l)$ is the *inter-quartile range* and $\eta$ is a constant determined experimentally. Mahalanobis distance measure is also tried, and it is observed that both distance measures lead to similar detection rates.

Performance rate of defect detection is calculated by the following formula:

$$\text{Detection Rate (\%)} = 100 \times (N_{CC} + N_{DD})/N_{Total} \qquad (4.2)$$

Here, $N_{CC}$ is the number of sub-windows classified as being non-defective when they are actually non-defective; $N_{DD}$ is the number of sub-windows classified as being defective when they are indeed defective, and $N_{total}$ is the total number of sub-windows.

## 5. Implementation and Results

In all the experiments, 16 non-defective and 18 defective images are used.

*Experiment 1:* First the defects are detected by using only ICA. 16 independent components are extracted with a window size of 16×16. The extracted independent components are shown (Fig.5.1).

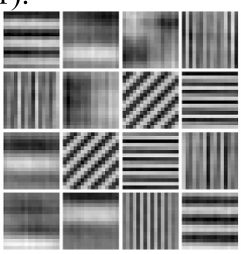

Fig. 5.1: Independent components of defect free textile fabric images

*Experiment 2:* Sub-band analysis prior to ICA is performed. The data matrix $\boldsymbol{X}$ is formed by the AA subbands of the sub-windows. The wavelet transformation is performed by 16-tap Daubachies wavelet filters. Battle-Lémarie wavelet filters, symlets, coiflets, Haar, discrete Meyer, and biorthogonal wavelets are also tried. However, the best performance is provided by 16-tap Daubachies wavelet filters. 16 independent components are extracted, and the sub-window size is taken as 16×16. In order to prevent overlearning and increase the defect detection rate, the number of independent components is reduced to 8 by PCA.

*Experiment 3:* Many reasonable combinations of sub-bands from the 2-level wavelet packet tree scheme are used. The best results are obtained by taking the AA sub-band. This is due to the fact that most of the energy is stored in this band. Taking all of the four sub-bands in the left quarter of the wavelet packet tree (i.e. the AA, AH, AV, and AD subbands) gave a satisfactory detection rate yet not as much as that of the case where only the AA sub-band was taken. There are mainly two types of defects: intensity defects where the gray level values of the defective parts are different from those of the overall image and geometrical defects where not the gray level value but the textural characteristics are different from those of the general fabric image. It is found that while the method where only the AA sub-band is used leads to better detection rates for intensity defects, in order to obtain a satisfactory defect detection rate for geometrical defects, the aforementioned 4 sub-bands must be used. This phenomenon can be observed in Figs.5.2 and 5.3 where defect detection is performed for intensity defects and for geometrical defects, respectively. So, the best parts of both methods are taken by *decision fusion*. Decision fusion of the two methods are performed by combining the detected defects of the two methods by the logical OR operator. By that way we obtained the best results among all the other methods.

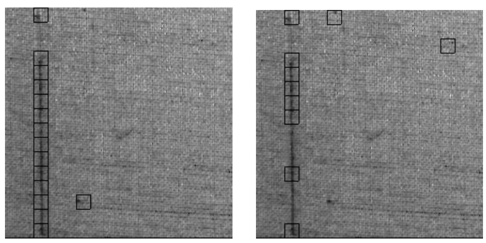

Fig. 5.2: Intensity defects obtained by using 1 sub-band (left), and 4 subbands (right) with 16 ICs

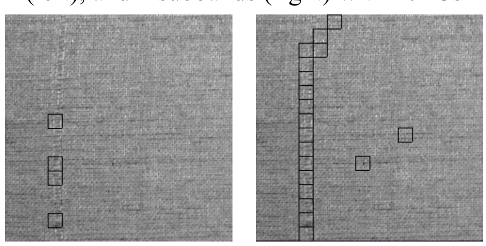

Fig. 5.3: Geometrical defects obtained by using 1 sub-band (left), and 4 sub-bands (right) with 16 ICs

Below is the summary of the experiments that give thorough information about what sub-band analysis adds upon ICA. The following abbreviations are used in order to name the applications in short hand:

<u>WS</u>: Window Size; <u>SB</u>: Number of Subbands used; <u>IC</u>: Number of Independent Components; <u>ICA</u>: Independent Component Analysis; <u>W</u>: Wavelet Transform; <u>WICA</u>: Wavelet applied prior to ICA; <u>DecFus</u>: Decision Fusion of two methods where in one method only the AA sub-band is used, and in the other method all the AA, AH, AV, and AD subbands are used.

The applications are as follows:

Application 1: ICA_16IC_WS16
Application 2: WICA_1SB_16IC_WS16
Application 3: WICA_4SB_16IC_WS16
Application 4: W_1SB_WS16
Application 5: W_4SB_WS16
Application 6: WICA_1SB_8IC_WS16
Application 7: WICA_4SB_8IC_WS16
Application 8: WICA_1SB_5IC_WS16
Application 9: WICA_4SB_5IC_WS16
Application 10: DecFus_16IC_WS16
Application 11: DecFus_8IC_WS16
Application 12: WICA_1SB_8IC_WS32
Application 13: WICA_4SB_8IC_WS32

In applications 4 and 5 only wavelet transformation is used. This is accomplished by building the feature vector of a sub-window by the energies of the chosen sub-bands. In the last two applications, the window size is chosen as 32×32. A comparison of the defect detection rates of all the methods is shown in Fig. 5.4a. The Receiver Operating Curves (ROCs) are plotted (Fig.5.4b) for the sake of comparison.

For practical purposes, the η value used in determining the decision threshold given by equation (4.1) is optimized per method. That is to say, the optimum value for η is found for a method. By that way, the user of this system can simply substitute this optimum η value for the method he uses no matter what the fabric images are.

## 6. Conclusions

A new method, which combines concepts of wavelet transformation and ICA for defect detection, is presented. It can be concluded that applying wavelet analysis prior to ICA increases the defect detection rate compared to the use of wavelet transformation or ICA alone.

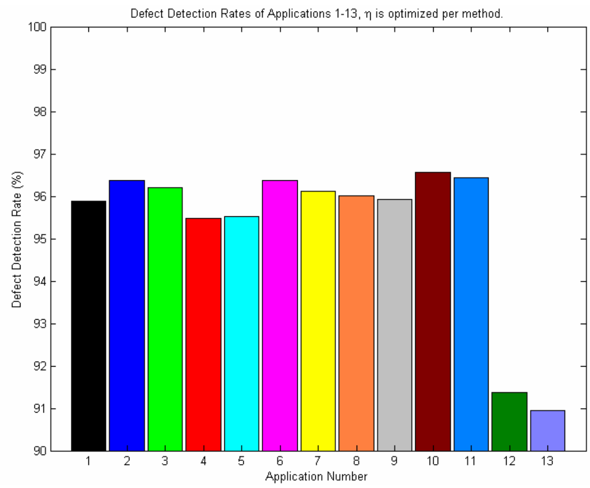


Fig. 5.4a: Defect Detection Rates of applications

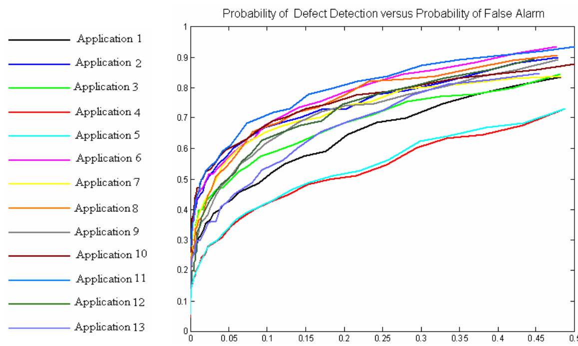


Fig. 5.4b: Receiver Operating Curves

## 7. References

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