Independent Component Analysis for Texture Defect Detection

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ABSTRACT

In this paper, a novel method for texture defect detection is presented. The method makes use of Independent Component Analysis (ICA) for feature extraction from the non-overlapping subwindows of texture images and classifies a subwindow as defective or non-defective according to Euclidean distance between the feature obtained from average value of the features of a defect free sample and the feature obtained from one subwindow of a test image. The experimental results demonstrating the use of this method for visual inspection of textile products obtained from a real factory environment are also presented.

I- INTRODUCTION

Defect detection from images plays significant role in quality of manufactured products and its application areas continue to increase. Numerous methods have been proposed for performing this task. Amet et.al. [1] have used sub-band domain co-occurrence matrices for texture defect detection, Karras et.al. [11] have suggested focusing on detecting defects from images' wavelet transformation and vector quantization related properties of the associated wavelet coefficients, Chetverikov et.al. [4] have approached the texture defect detection problem in a more theoretical way, based on regularity and orientation criteria. Chen and Jain used a structural approach to defect detection in textured images. Dewaele et.al. used signal processing methods to detect point defects and line defects in texture images. Cohen et.al. [5] used MRF models for defect inspection of textile surfaces while Erçil et.al. [6] used similar techniques for inspection of painted metallic surfaces. Atalay has implemented MRF model-based method on a TMS320C40 parallel processing system for real-time defect inspection of textile fabrics [2]. For surveys of texture analysis, see Van Gool et.al., Reed et.al., Rao, Tuceryan and Jain [12,-14].

In the work of Hurri [7], different types of texture images are used to examine general characteristics of independent components (ICs) of texture images and results are found inadequate to draw any conclusion about the ICs of texture images. The reason for this comes from the fact that every texture image in the set of texture images brings about its own ICs that describe its environment. Since every texture defines its own environment, finding ICs of a set of texture images of the same type will help us to comprehend the weave structure of the texture by its ICs.

This paper addresses a new application that uses ICA for locating and also partially identifying defects in textile fabric images.

II- ICA FUNDAMENTALS

1- Overview

ICA is a generative model which means that it describes how the observed data $\boldsymbol{x}$ can be represented as a superposition of independent components s_j's.

$$\boldsymbol{x}=\boldsymbol{A}\boldsymbol{s} \qquad (1)$$

where $\boldsymbol{x}$ *is* the observed vector that consists of the observations x_j's, $\mathbf{s}$ is the source vector that consists of the independent components s_i's and $\boldsymbol{A}$ is the mixing matrix. In ICA, vector $\boldsymbol{x}$ is the only a priori known quantity and both $\boldsymbol{A}$ and $\boldsymbol{s}$ are assumed to be unknown. Therefore $\boldsymbol{A}$ and $\boldsymbol{s}$ should be somehow estimated with the information that $\boldsymbol{s}$ is non-gaussian and entries of the $\boldsymbol{s}$ vector are statistically independent. Fortunately, ICA enables us to make use of the given assumptions in the model to estimate both $\boldsymbol{A}$ and $\boldsymbol{s}$. Once $\mathbf{A}$ is estimated**,** the sources can be computed as;

$$\boldsymbol{s}=\boldsymbol{W}\boldsymbol{x} \qquad (2)$$

where $\boldsymbol{W}$ is the (pseudo)inverse of the mixing matrix $\boldsymbol{A}$ and is called the demixing matrix.[8, 9].

2- ICA Model and Sparse Coding for Image Feature Extraction

Sparse coding is closely related to ICA and it represents data by having just a few active units out of larger collection of model vectors. Therefore in sparse coding data is represented by each of the components that is rarely active (i.e., zero most of the time) [10].

Using sparse coding to represent image data in lower dimensions will be a practical feature extraction tool in pattern recognition problems as the sparse coding aims to reduce the redundancy in representing the data.

Sparse coding can be denoted by a linear representation by;

$$\boldsymbol{s}=\boldsymbol{M}\boldsymbol{x} \qquad (3)$$

where $\boldsymbol{x}$ is a n-D observed (random) vector, $\boldsymbol{s}$ is m-D linearly transformed vector and $\boldsymbol{M}$ is m x n matrix that linearly transforms $\boldsymbol{x}$ into $\boldsymbol{s}$.

The relation that exists between sparse coding and ICA is that their data models are related closely as can be seen from Eqs.(2) and (3).

In this paper, ICA or equivalently sparse coding is used for feature extraction from the texture images. Hence columns of $\boldsymbol{A}$ in ICA model represents the features (basis vectors or ICs), and s_i component of $\boldsymbol{s}$ vector becomes a coefficient of the i-th feature in the observed data $\boldsymbol{x}$ (see equation (1)).

III- METHODOLOGY & SYSTEM DESCRIPTION

A machine vision system generally contains two important parts; (i) feature extraction and (ii) decision making.

In this work, the defect detection system composes of two blocks: first one is the offline block, in which ICs for a set of texture images are extracted and using these basis vectors, feature vectors from defect free images are calculated and are fed into the defect detection part of the online phase. The second phase is the online block where test images with a wide range of texture defects are handled and their features are extracted by sparse coding method.

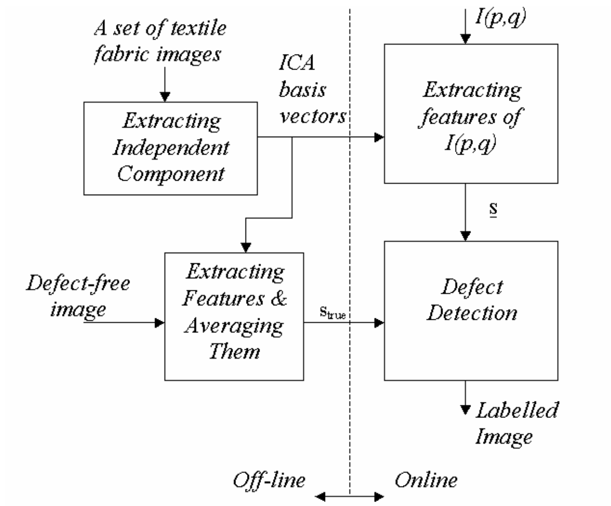

Fig. 3.1: Defect detection system block diagram used in this project

In this project, the data set contains one defect free image and 19 defective textile fabric images where each corresponds to a different defect type and one defect free image. In the first stage of the feature extraction, ICs were obtained from this set.

Test images *I(n,m)* of size 256x256 are assumed to be acquired by a CCD camera in real time and this image is fed through the feature extractor as seen in Figure 3.1. Feature vectors are calculated within local non-overlapping subwindows of size *NxN*. The choice of subwindow size depends on two factors: 1) how localized the defects are (i.e., size of the defects); and 2) for a non-defective sample how representative of the texture is the data in a window of such size [1]. Second factor is important since the size of the window determines how well the texture is represented. Too small window size will result in ICs, which do not represent texture appropriately. In this project, best results are achieved by using subwindow size of 16x16 so in the rest of the paper we will use this subwindow size. Thus, features extracted from every subwindow which represents a distinct region in image *I(n,m)* and corresponds to the columns of the S_I matrix obtained at the output of the feature extraction part (see Fig. 3.1)

The steps can be summarized as follows:

Off-line (Learning) Phase:

1) Obtain ICA basis vectors from a set of non-defective and defective images
2) Construct the matrix **A** using the ICA basis vectors as the columns of **A**
3) Partition a defect-free textile fabric image into sub-windows of *NxN*.
4) For each sub-window calculate the coefficient vector (the feature vector) using the sparse coding method (Eq.(5))
5) Compute $\mathbf{s_{true}}$ vector by averaging the feature vectors computed for each sub-window.

On-line Feature Extraction Phase:

1) Partition a test image *I(p,q)*, into sub-windows of *NxN*.
2) For each sub-window calculate the coefficient vector (the feature vector) using the sparse coding method (Eq. (5)).
3) Construct the matrix $\mathbf{S_I}$ using the feature vector $\mathbf{s_i}$ of each sub-window as the columns of $\mathbf{S_I}$

On-line Detection Part:

1) Compute Euclidean distance between each column of matrix $\mathbf{S_I}$ corresponding to the feature vector of each sub-window and vector $\mathbf{s_{true}}$.

$$\text{distance}_i = \left[(\mathbf{s_{true}} - \mathbf{s_i})^T (\mathbf{s_{true}} - \mathbf{s_i})\right]^{1/2} \qquad (6)$$

where s_i is the i-th column of matrix S_I.

2) Classify a sub-window as defective if distance exceeds some threshold value α.

$$\text{sub-windows}_i = \begin{cases} \text{defective} & \text{if} \quad distance_i > \alpha \\ \text{nondefective} & \text{otherwise} \end{cases} \qquad (1)$$

The threshold value is determined by the following formula;

$$\alpha = D_m + \eta IQR \qquad (5)$$

where D_m is the median value of the feature vector of a subwindow (i.e., a column of S_I matrix), *IQR is the inter quartile range* and η is a constant determined experimentally. (For Gaussian distribution η = 1.67 corresponds to 95% confidence interval.)

IV- IMPLEMENTATION & RESULTS

In this paper, symmetric fixed-point ICA algorithm with *tanh(x)* nonlinearity is used [15]. By means of ICA hidden factors underlying the fabric images data set are obtained. 16 ICs are used for the analysis. This value is obtained by trial and error.

In the first place, ICA is directly applied to the original images which have many vertical and horizontal stripes representing the weave structure. In this case it is observed that some of the ICs (or equivalently basis vectors) have high frequency characteristics which affects our Euclidean distances (cf. Fig. 4.1 basis vectors 5, 7, 8, 9, 11, 13, and 15), hence the resulting defect detection performance was low.

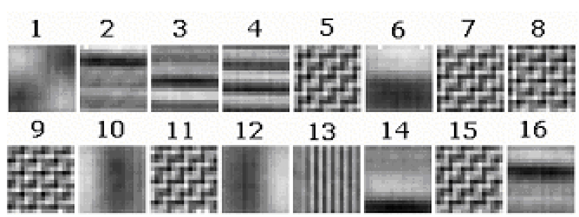

Fig. 4.1. Independent components of original set

In order to eliminate this problem, IC's with high frequency characteristics are neglected and distances are calculated for the remaining set of IC's. These new results are promising and defect detection performance increased but some defects are still missed and there are false alarms as well (Fig. 4.2).

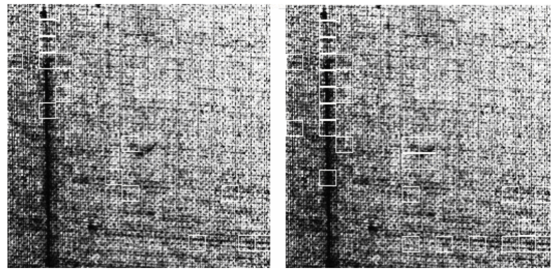

Fig. 4.2: Image on the right side and image on the left side with and without neglecting high freq. ICs respectively (white boxes correspond to subwindows that are detected as defective).

Changing the threshold values did not effectively improve the results. From this experience, we came up with the idea that weave structure of textile fabric image should, somehow, be eliminated while preserving the essential characteristics of the defects. Thereby, median filtering and some histogram modification operations are performed consecutively (see Fig. 4.3). For median filtering, a *3X3* mask is used where as histogram modification includes intensity level slicing, setting all pixels with gray level values bigger than 200 as 200 and then increasing the brightness, thus removing the underlying texture.

This pre-processing operation is carried out for all images and new set of images, from which IC's without high frequency characteristics are extracted, are obtained (Fig.4.4).

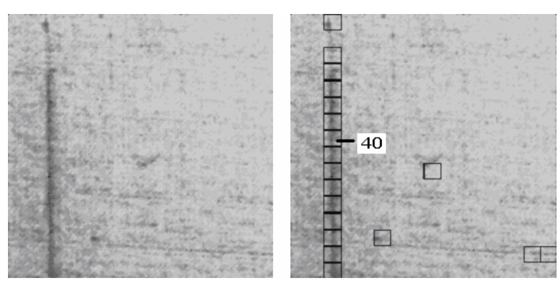

Fig. 4.3. Image on the left side is obtained after pre-processing and image on the right side is the result of our algorithm (black boxes correspond to subwindows that are detected as defective).

These ICs, in fact, correspond to various structures present in the texture of fabric. In the resulting set of ICs vertical bars in basis vectors 1, 9, and 11 can be though as the consequence of vertical defects and vertical stripes in the textile fabric structure, whereas horizontal bar in basis vectors 2, 3, 7, 8, 13, and 16 can be though as the consequence of horizontal defects and horizontal stripes in the textile fabric structure. Also there are spot-like structures in the basis vectors 10, 12, 14, and 15, which can be resulted because of partially captured defects, or small holes in the texture. There are also some other basis vectors, which represent the typical weave characteristics such as basis vectors 4, 5 and 6.

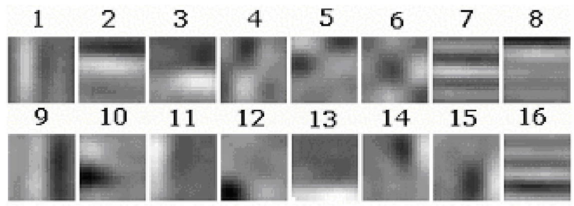

Fig 4.4: Independent components of pre-processed set

In the light of this kind of cause and effect relation between structure of texture and ICs, a defected region in an image is expected to have one or more dominant basis vectors that describe the defect (refer to Fig. 4.5).

Figure 4.5 illustrates the basis vector coefficients from a defective sub-image, window 40 in Figure 4.3b. In Fig. 4.5, it is observed that coefficient of the 11th basis vector is dominant among the other basis vectors. This basis vector has a vertical-bar shape as can be seen in Fig. 4.4. Thus, vertical defect in a fabric image activated vertical-bar-shaped IC's in the set of basis vectors. Hence, defect type identification can also be achieved with this method.

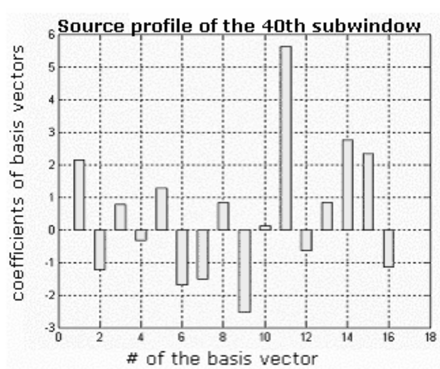

Fig. 4.5 Bar graph showing the coefficients of the corresponding basis vectors (or equivalently ICs).

In Fig. 4.6 source profile of a defect free subwindow (subwindow 49) of the same image is given. Observe that there is no dominant basis vector in the 49th subwindow and coefficient values are close to zero. Compare the coefficients of 49th and 40th subwindows. (Note that the scales of Figures 4.5 and 4.6 are different.)

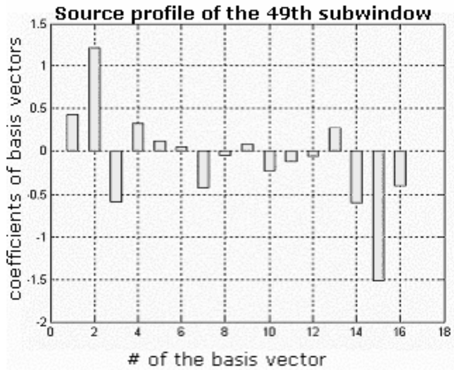

Fig. 4.6 Bar graph showing the coefficients of the corresponding basis vectors (or equivalently ICs).

Detection Rates:

Defect detection rates are calculated by the following formula,

$$CR = 100x(N_{CC} + N_{DD}) / N_{Total} \qquad (6)$$

where N_{CC} is the number of correctly classified nondefective subwindows, N_{DD} is the number of correctly classified defective subwindows and N_{Total} is the total number of subwindows being tested.

i- First Method: 88.59 % (ICA applied directly to original set without neglecting ICs with high frequency characteristics, and η=1.0)

ii- Second Method: 89.41 % (ICA applied directly to original set with neglecting ICs with high frequency characteristics, and η=1.0)

iii- Third Method: 96.74 % (ICA applied to pre-processed image set, and η=1.5)

V- CONCLUSION

A new methodology for defect detection is developed which can also be applied to defect detection. Compared to previous detection rates in [1] that are varying between 85 and 92 per cent, ICA enables better detection with 4-5 per cent overall increase. Besides that this new method has very low real time computational requirements, since the online part of the computations involves just a simple matrix multiplication.

In conclusion, we could say that the proposed defect detection by ICA method is a promising approach suitable for a real time inspection system in textile industry.

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