International Journal of Modern Trends in Engineering and Research
www.ijmter.com
e-ISSN No.:2349-9745, Date: 2-4 July, 2015

Application of Contourlet Transform for Fabric Defect Detection

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Abstract - In this paper Contourlet based statistical modeling is used for Fabric Defect Detection. The Contourlet transform is a recently proposed two dimensional method used for image analysis. It is very efficient for representing images with fine geometrical structure. In the proposed method for defect detection Contourlet based feature extraction is used. Contourlet Transform is capable of capturing the smooth edges information. A new filter bank structure is the Contourlet filter bank that can provide a flexible multiscale and directional decomposition for images. Specifically, a discrete-domain multiresolution and multi direction expansion using non-separable filter banks, in much the same way those wavelets were derived from filter banks. This construction results in a flexible multiresolution, local, and directional image expansion using contour segments, and thus it is named the Contourlet Transform. Edges are image points with discontinuity, whereas contours are edges that are localized and regular. So Contourlet can be defined as a multi-scale, local and directional contour segment which can be constructed using filter banks. Contourlet transform can be used for the detection of defect in fabric. If there is defect in fabric its price reduces so it is very important to detect defect in fabric.
Keywords - Contourlet Transform, Fabric Defect detection, Laplacian Pyramid, Gaussian Pyramid, Double Filter Bank

I. INTRODUCTION

Fabric, being a widely used material in daily life, is manufactured with textile fibers. Textile fibers can be made of natural element such as cotton or wool; or a composite of different elements such as wool and nylon or polyester. In particular, defects results from machine faults, yarn problems, poor finishing, and excessive stretching etc. Examples of some of the defects are netting multiple, warp float, the hole, dropped stitches and stains serious defect can render the fabric product unsalable and a loss in revenues. Traditionally, human inspection was the only means to assure quality. It helps instant correction of small defects, but human errors while detecting the defect occurs due to fatigueness, accuracy is also less and fine defects are often undetected. Hence, automated inspection becomes a natural way forward to improve fabric quality, increased accuracy and efficiency and reduce labor costs. Automated fabric defect detection is therefore beneficial.

II. PROPOSED METHOD

In this paper we are using Contourlet transform for fabric defect detection. First the preprocessing is done on acquired image (image with defect). In preprocessing the image is converted from RGB to gray & histogram equalization is done. Then Contourlet transform is used to extract the features in the image. After extracting the edge of the defect, thresholding is applied to detect the defect in the image. The detection of the defect is explained in following section stepwise with example.

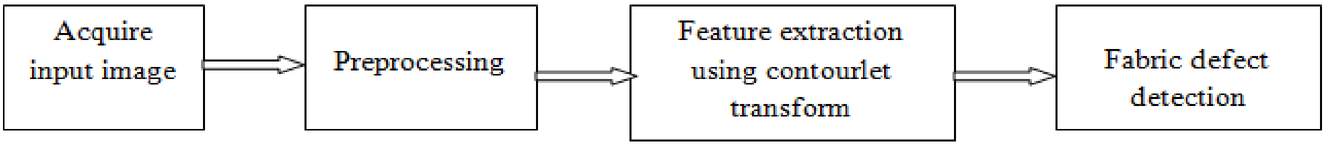


Fig. 1 Block Diagram of Proposed System

(a)Input image with defect *(b) Preprocessed image* *(c) Feature extraction using Contourlet transform* *(d) Defect detection*

Fig. 2 Fabric defect detection of the acquired input image

2.1 Contourlet Transform

The Contourlet transform is a 2-D transform technique for image representation and analysis. It is also referred as Pyramidal Directional Filter Bank. The transform uses a double filter bank structure for obtaining sparse expansions for typical images having smooth contours. It consists of two filter bank known as Laplacian Pyramid (LP) and second known as Directional Filter Bank (DFB). In particular, the Contourlets have elongated supports at various scales, directions and aspect ratios. This allows Contourlets to efficiently approximate a smooth contour at multiple resolutions. In the frequency domain, the Contourlet transform provides a multiscale and directional decomposition. The Contourlet transform uses a double filter bank structure to get the smooth contours of images. In this double filter bank, the Laplacian Pyramid (LP) is first used to capture the point discontinuities, and then a Directional Filter Bank (DFB) is used to form those point discontinuities into linear structures as shown in Fig.3.

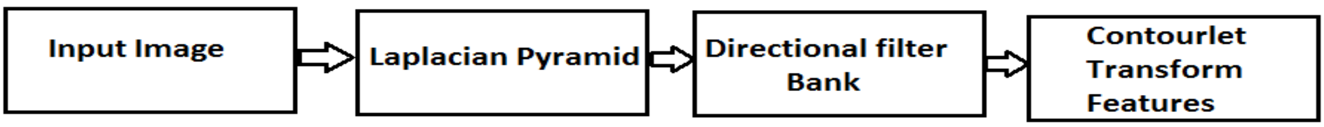


Fig. 3 Contourlet Transform Procedure

The Laplacian Pyramid (LP) decomposition only produces one band pass image in a multi dimensional signal processing, which can avoid frequency scrambling. And DFB is only fit for high frequency since it will leak the low frequency of signals in its directional subbands. This is the reason to combine DFB with LP, which is multiscale decomposition and remove the low frequency. Therefore, image signals pass through LP subbands to get band pass signals and pass those signals through DFB to capture the directional information of image. This double filter bank structure of combination of LP and DFB is also called as Pyramid Directional Filter Bank (PDFB) [9].

2.2 Gaussian Pyramid

The first step in Laplacian pyramid coding is to low-pass filter the original image g_0 to obtain image g_1. We say that g_1 is a "reduced" version of g_0 in that both resolution and sample density are decreased. In a similar way we form g_2 as a reduced version of g_1, and so on. Filtering is performed by a procedure equivalent to convolution with one of a family of local, symmetric weighting functions. An important member of this family resembles the Gaussian probability distribution, so the sequence of images g_0, g_1, g_2, ------- g_n, is called the Gaussian pyramid. [3]

2.3 Gaussian Pyramid Generation

Suppose the image is represented initially by the arrays g_0 which contains C columns and R rows of pixels. Each pixel represents the light intensity at the corresponding image point by an integer I between 0 and K - 1. This image becomes the bottom or zero level of the Gaussian pyramid. Pyramid level 1 contains image g_1, which is a reduced or low-pass filtered version of g_0. Each value within level 1 is computed as a weighted average of values in level 0 within a 5-by-5 window. Each value within level 2, representing g_2, is then obtained, from values within level l by applying the same pattern of weights. The size of the weighting function is not critical. The level-to-level averaging process is performed by the function REDUCE. [3]

$$g_k = REDUCE(g_{k-l}) \tag{1}$$

Which means, for levels $0 < l < N$ and nodes i, j, $0 \leq i < C_l$, $0 \leq j < R_l$.

$$g_l(i,j) = \sum_{m=-1}^{1} \sum_{n=-1}^{1} w(m,n) * g_{l-1} * (2i+m, 2j+n) \tag{2}$$

Here N refers to the number of levels in the pyramid, while C_l, and R_l are the dimensions of the l^{th} level.

2.4 Laplacian Pyramid

One way to obtain a multiscale decomposition can be obtained by using the Laplacian Pyramid. The LP decomposition at each level generates a down sampled low pass version of the original image and the difference between the original image and the 1st Gaussian level which results in a band pass image. [3]

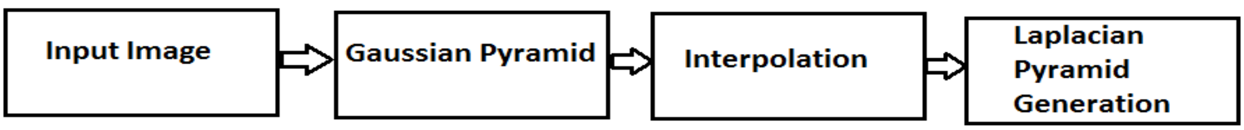


Fig.4 Basic Steps in Laplacian Pyramid Generation

1st level Laplacian *2nd level Laplacian* *3rd level Laplacian* *4th level Laplacian*

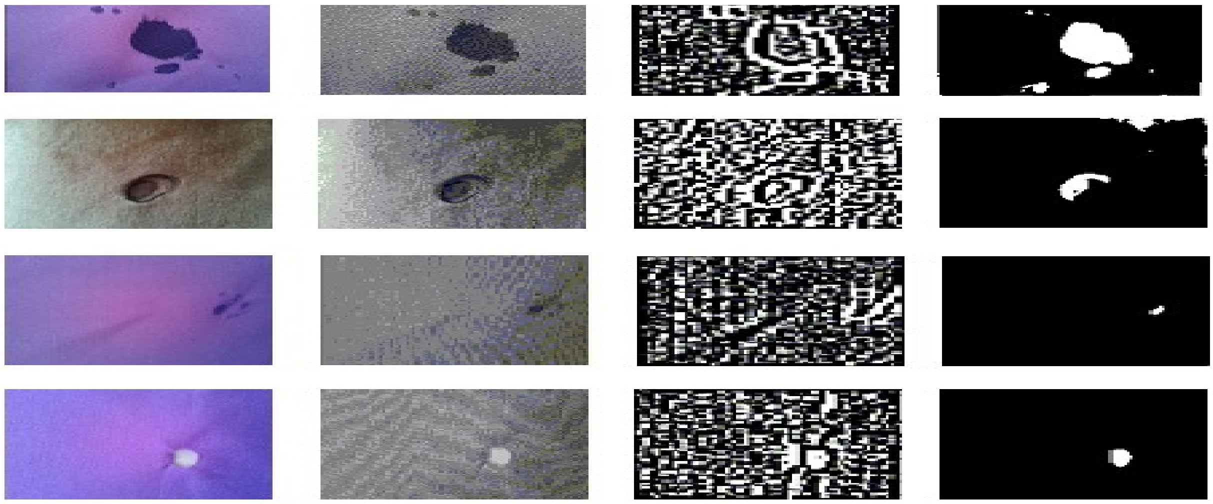
Fig. 5 Laplacian pyramid generation of defected image

2.5 Directional Filter Bank (DFB)

DFB is designed to capture the high frequency content like smooth contours and directional edges. This DFB is implemented by using a k-level binary tree decomposition that leads to 2k directional sub-bands with wedge shaped frequency partitioning [7]. The DFB divides a 2-D spectrum into two directions, horizontal and vertical. The second one is a shearing operator, which amounts to the reordering of image pixels. Due to these two operations, directional information is preserved. The scheme is flexible since it allows for a different number of directions at each scale. [14]

2.6 Defect Detection

In first step we found the Gaussian pyramids of the defected image up to 4th level. The 1st Gaussian pyramid is obtained by taking the convolution of the original defected image with low pass filter kernel. The 2nd level Gaussian pyramid is obtained by taking convolution of the 1st level Gaussian pyramid with the low pass filter kernel. Similar way we found the next level Gaussian pyramids. The Laplacian is then computed as the difference between the original image and the low pass filtered image. This process is continued to obtain a set of band-pass filtered images. Thus the Laplacian Pyramid is a set of band pass filters. The 1st level Gaussian pyramid is half the size of original image, 2nd level Gaussian is half the size of 1st level Gaussian and so on… therefore we have applied interpolation to find Laplacian pyramid as it is difference between the Gaussian pyramids and we cannot subtract the two different size Gaussians from each other. By passing the Laplacian pyramid from directional filter bank we obtained the smooth contours of the defect as shown in Fig.7 (c). Then we have done binarization using threshold method to get the defect as shown in Fig.7 (d). Thus defect detection is done by using contourlet transform.



(a) Defected image (b) Preprocessed image c) Feature extraction (d) Defect detected

Fig.6 Results obtained

CONCLUSION

The drawbacks associated with the 2-D wavelet transform such as multiresolution, localization, directionality and anisotropy are overcame by Contourlet transform. Contourlet transform is capable of capturing the smooth edges information. A new filter bank structure is the Contourlet filter bank that can provide a flexible multiscale and directional decomposition for images.
Contourlet transform is good at detecting texture directions. Accuracy of defect detection is higher than wavelet related methods. Only simple norm-based metric is required for defect detection. It is easily adjustable for detecting fine details in any orientation at various scale levels.

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