CONTOURLET TRANSFORM FOR FABRIC DEFECT DETECTION

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ABSTRACT

Contourlet Transform is the advanced method for the detection of fabric defects. Smooth edge information can be obtained from Contourlet Transform. It has many advantages such as multi directionality, anisotropy, multi resolution over Wavelet Transform. A new filter bank structure is the contourlet filter bank that can provide a flexible multi scale and directional decomposition for images. A new filter bank structure is there which consist of Laplacian Pyramid and Directional Filter Bank. 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.

Keywords: Contourlet Transform, Defect Detection, Directional Filter Bank, Gaussian Pyramid, Laplacian Pyramid

1 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 result from machine faults, yarn problems, poor finishing, and excessive stretching, among others. Examples of some of the defects are netting multiple, warp float, hole, dropped stitches and press-off. A serious defect can render the fabric product unsalable and a loss in revenues. Traditionally, human inspection, carried out in wooden board, is the only means to assure quality. It helps instant correction of small defects, but human error occurs due to fatigue, 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.

Minh N. Do and Martin Vetterli in the paper "Wavelet Based Texture Retrieval Using Generalized Gaussian Density and Kullback- Leibler Distance," have proposed statistical view of texture retrieval by combining Feature Extraction and Similarity Measurement. Wavelet based texture retrieval is based on accurate modeling of marginal distribution of wavelet coefficients using Generalized Gaussian Density.

Minh N. Do and Martin Vetterli in the paper "The Contourlet Transform: An Efficient Directional Multi resolution Image Representation," have proposed double filter bank structure, named the pyramidal directional filter bank, by combining the Laplacian Pyramid with a directional filter bank The result is called the Contourlet Transform, which provides a flexible multi resolution, local and directional expansion for images.

Mohand Said Allili in the paper "Wavelet Modeling Using Finite Mixtures of Generalized Gaussian Distributions: Application to Texture Discrimination and Retrieval" have addressed statistical based texture modeling using wavelets. He proposed that the new method for representing the marginal distribution of wavelet coefficients is finite mixture of generalized Gaussian distributions which captures wide range of histogram shapes which provide better description and discrimination of texture.

Wavelet Transforms can be used as a means of feature detection. After the wavelet decomposition at each level, the image will be divided into four sub-images which are the approximate, horizontal, vertical, and diagonal coefficients. In order to obtain the approximate coefficients, the rows and columns are passed through the low-pass filter which resembles the original image, albeit at a sub sampled resolution. Next the horizontal coefficients are obtained by passing the rows through the low-pass filter and the columns through the high-pass filter, which will emphasize the horizontal edges. The vertical coefficients are obtained by passing the columns through the low-pass filter and the rows through the high-pass filter that will stress the vertical edges. Lastly, when both the columns and rows are passed through the high-pass filter, this will produce the diagonal coefficients which accent the diagonal edges. Some of the benefits of using wavelet decomposition are that multiscale analysis; salient features of original image are preserved in the approximate coefficients, real-time implementation, and can be developed for a parallel computer. One disadvantage with wavelet decomposition is that wavelets are not shift invariant; therefore, wavelets are not able to change with the translation operator. Also the wavelet transform is incapable of providing directionality and anisotropy. These disadvantages of wavelet transform are overcome by contourlet transform.

The Contourlet Transform is a 2-D transform technique recently developed for image representation and analysis. Also referred to as the pyramidal directional filter bank, it consists of two filter banks. The first filter bank, known as the Laplacian pyramid, is utilized to generate a multiscale representation of an image of interest. Subsequently, the subband images from the multiscale decomposition are processed by a directional filter bank to reveal the directional details at each specific scale level. The output values from the second filter bank are called "contourlet coefficients."

II PROPOSED METHOD

In this paper we are going to use contourlet transform and MoGG for fabric defect detection. First the preprocessing is done on original image (image with defect). In preprocessing there can be color to gray conversion or noise removal in the image is done.

Then contourlet transform is used to extract the features in the image. Then using MoGG modeling of contourlet coefficients the fabric defect detection is done.

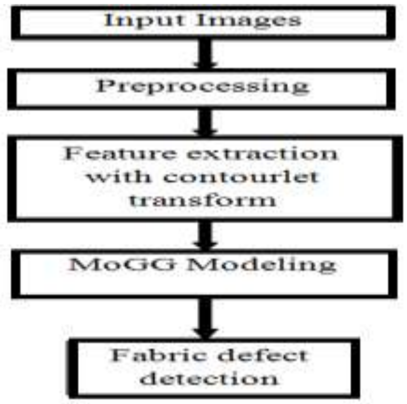


Fig: 2.1: Block Diagram of Proposed System

2.1 Contourlet Transform

The transform uses a double filter bank structure for obtaining sparse expansions for typical images having smooth contours. In the double filter bank structure: Laplacian Pyramid (LP) and 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.2.2.

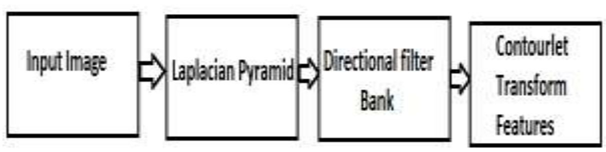


Fig. 2.2: Contourlet transform procedure

The Laplacian Pyramid (LP) decomposition only produces one band pass image in a multidimensional 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), and this transform is approximate the original image by using basic contour, so it is also called discrete contourlet transform.

2.2 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 and the difference between the original and the prediction, resulting in a band pass image.

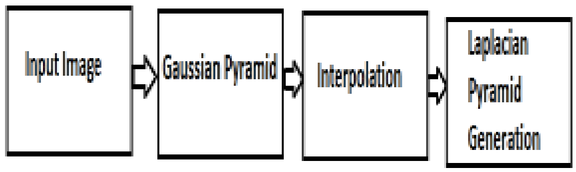


Fig. 2.3: Basic steps in Laplacian pyramid generation

The original image is convolved with a Gaussian kernel. The resulting image is a low pass filtered version of the original image. 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 (since each one is the difference between two levels of the Gaussian pyramid). Thus the Laplacian Pyramid is a set of band pass filters. By repeating these steps several times a sequence of images, are obtained. If these images are stacked one above another, the result is a tapering pyramid data structure as shown in Fig. 2.4

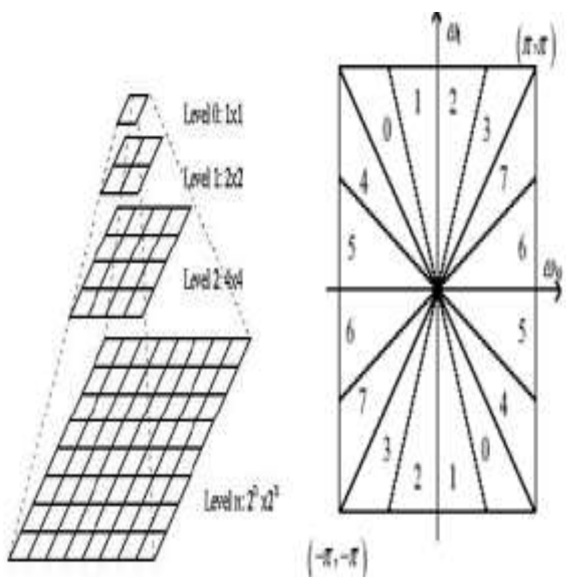


Fig. 2.4: Laplacian Pyramid structure & DFB Frequency Partitioning [9]

2.3 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 as shown in Fig.2.4 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.

2.4 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.

2.4.1 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 1 by applying the same pattern of weights. A graphical representation of this process in one dimension is given in Fig.2.5. The size of the weighting function is not critical. We have selected the 5-by-5 pattern because it provides adequate filtering at low computational cost. The level-to-level averaging process is performed by the function REDUCE.

g_k = REDUCE (g_k- 1)

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

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

Here N refers to the number of levels in the pyramid, while C and R, is the dimensions of the l^{th} level.

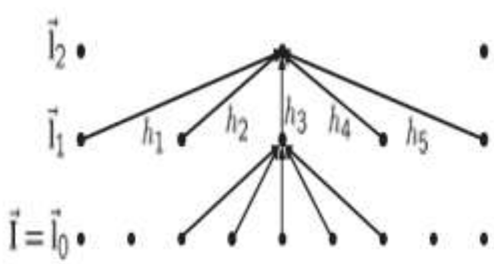
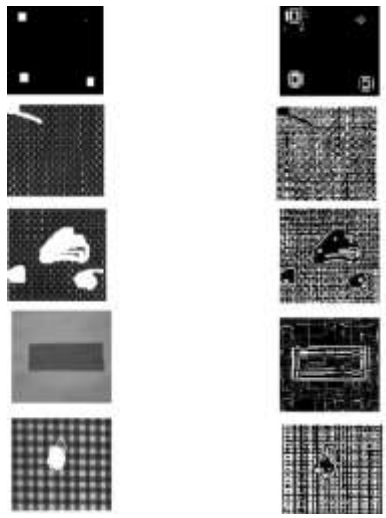


Fig.2.5: One-dimensional graphic representation of the process which generates a Gaussian Pyramid [9]

III EXPERIMENTAL RESULTS



(a) (b)

Fig.3.1: (a) Original images with defects (b) Detected defect in images

IV 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 classification is higher than wavelet related methods. Only simple norm-based metric is required for texture classification.

REFERENCES

[1] M. S. Allili and N. Baaziz, "Contourlet-based texture retrieval using a mixture of generalized Gaussian distributions," in Proc. Int. Conf. Computer Analysis of Images and Patterns, 2011, no. 2, pp. 446–454.

[2] N. Baaziz, "Adaptive watermarking schemes based on a redundant contourlet transform," in Proc. IEEE Int. Conf. on Image Processing, 2005, pp. I-221–I-224.

[3] P. J. Burt and E. H. Adelson, "The Laplacian pyramid as a compact image code," IEEE Trans. Commun., vol. 31, no. 4, pp. 532–540, 1983.

[4] E. J. Candes and D. L. Donoho, "New tight frames of curvelets and optimal representations of objects with piecewise-C2 singularities," Commun. Pure Appl. Math., vol. 57, pp. 219–266, 2002.

[5] M. N. Do and M. Vetterli, "Wavelet-based texture retrieval using generalized Gaussian density and," IEEE Trans. Image Process., vol. 11, no. 2, pp. 146–158, 2002.

[6] M. N. Do and M. Vetterli, "Rotation invariant texture characterization and retrieval using steerable wavelet-domain hidden Markov models," IEEE Trans. Multimedia, vol. 4, no. 4, pp. 517–527, 2002.

[7] M. N. Do and M. Vetterli, Contourlets, Beyond Wavelets, G. V. Wellard, Ed. New York, NY, USA: Academic, 2003.

[8] Z. He and M. Bystrom, "Color texture retrieval through contourlet based hidden Markov model," in Proc. IEEE Int. Conf. Image Processing, 2005, pp. 513–516.

[9] M. N. Do and M. Vetterli, "The contourlet transform: An efficient directional multiresolution image representation," IEEE Trans. Image Process., vol. 14, no. 12, pp. 2091–2106, 2005.

[10] Z. Yifan and X. Liangzheng, "Contourlet-based feature extraction on texture images," in Proc. Int. Conf. Computer Science and Software Engineering, 2008, pp. 221–224.

[11] Mohammad H. Rohban, and Shohreh Kasaei, "Skin Detection using Contourlet-Based Texture Analysis," IEEE Fourth International Conference on Digital Telecommunications, pp. 59-65,2009

[12] Ali Mosleh, Farzad Zargari, Reza Azizi,"Texture Image Retrieval Using Contourlet Transform," IEEE conference on Image Processing, 2009

[13] Sherin M. Youssef, Ezzat A. Korany, Rana M. Salem, "Contourlet-based Feature Extraction for Computer Aided Diagnosis of Medical Patterns," 11th IEEE International Conference on Computer and Information Technology, pp. 481-487, 2011

[14] Zhiling Long, and Nicolas H. Younan, "Contourlet Spectral Histogram for Texture Classification," IEEE conference on image processing, pp. 31 -36, 2006