

# Image Watermarking Based on Contourlet in a Noisy Environment Using Optimum Detector

Devi. P

adidevi\_mp@yahoo.co.in

Prakash.V

venkatprakash01@gmail.com

**Abstract** – Digital watermarking is an emerging technique to protect data security and intellectual property right. Identification or verification of watermarking patterns can be achieved by detecting watermarks in received signals. Watermarking is applied in the contourlet domain, which represents image edges sparsely, as the human visual system is less sensitive to the image edges. The contourlet transform is a new two-dimensional extension of the wavelet transform using multiscale and directional filter banks. In the presented scheme, watermark data is embedded in directional sub-band with the highest energy. By modeling the contourlet coefficients with General Gaussian Distribution (GGD), the distribution of watermarked noisy coefficients is analytically calculated. At the receiver, based on the Maximum Likelihood (ML) decision rule, an optimum detector by the aid of channel side information is proposed. In the next step, a blind extension of the suggested algorithm is presented using the patchwork idea.

**Keywords** – Contourlet Transform, Maximum Likelihood Detector, Multiplicative Image Watermarking.

## I. INTRODUCTION

Digital watermarking has attracted increasing interest from many areas as the data security and copyright protection issues are becoming increasingly important. It embeds hidden secondary data into digital multimedia products for copyright notification and protection, content authentication, transaction-tracing, and covert communication. The main advantage of watermarking is that it provides a way to deliver side information through primary multimedia contents in a seemingly innocuous and standards-compliant fashion, such that much novel functionality can be enabled.

In steganography or security applications, secret messages may be transmitted covertly through a perceptually innocent image or audio. In multimedia database retrieval, watermarking patterns associated with annotations or keywords may be imprinted seamlessly into host media to facilitate future accurate access. In broadcast monitoring and copy control techniques, watermarking can actively and cost-effectively identify specific multimedia contents in digital TV, audio, or video broadcasting or playing back such that royalty collection can be automated or illegal copying prevented. Since the inception of digital watermarking around the early 1990s, there have been a variety of methods proposed in the literature, and there are many ways to classify them. For example, some approaches deal with the signals in the sample (spatial or time) domain, while others deal with transformed data. Some private watermarking schemes need the knowledge of host multimedia signals in decoding, whereas blind watermarking schemes do not. The watermarking is viewed as the following information system with side

information available only to the embedder. A secret message or pattern is encoded by an encoder or embedder into a watermark and hidden into the host medium within an embedding distortion level. The composite signal is then input into the watermarking channel, where an attacker attempts to disrupt the watermark by introducing additional distortions. The channel output is a corrupted or noised composite signal. A decoder decodes the watermark bit by bit or symbol by symbol, or a detector detects or verifies the existence of a specific watermarking pattern or specific message.

## II. CONTOURLETS

For piecewise continuous 1-D signals, wavelets have been established as a right tool in generating efficient representation. However, natural images are not simply stacks of 1-D piece-wise smooth scan-lines, but they have many discontinuity points. Along smooth curves and contours. Thus, separable wavelets cannot capture directional information in two dimensions. To overcome this shortcoming, many directional image representations have been proposed in recent years.

Implementing the idea of combining subband decomposition with a directional transform, Do and Vetterli introduced a multidirectional and multiscale transform known as the contourlet transform, which consists of two major stages: the sub-band decomposition and the directional transform. Laplacian Pyramid (LP) filters are used as the first stage and Directional Filter Banks (DFB) as the second stage.

First, for the multiscale decomposition it uses Laplacian Pyramid (LP) filters. The LP decomposition at each level generates a downsampled lowpass version of the original and the difference between the original and the prediction, resulting in a bandpass image. Fig. 1(a) and (b) depicts the decomposition and reconstruction processes, where H and G are orthogonal analysis (lowpass) and synthesis filters, respectively, and M is the sampling matrix. The process can be iterated on the coarse (downsampled lowpass) signal.

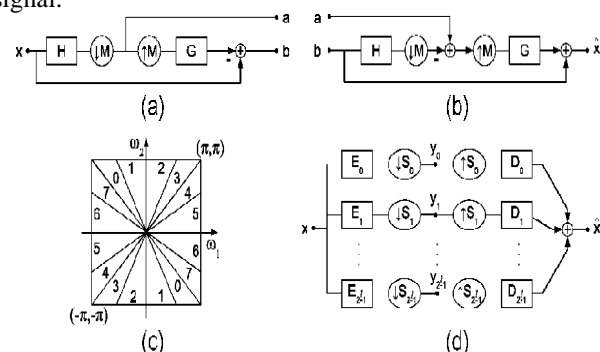


Fig.2.1. (a), (b) Laplacian pyramid one level of decomposition and reconstruction; (c), (d) directional filter bank frequency partitioning and the multichannel view of tree-structured directional filter bank.

The directional decomposition stage is also constructed based on the idea of using an appropriate combination of shearing operators together with two-direction partition of quincunx filter banks at each node in a binary tree-structured filter bank, to obtain the desired 2-D spectrum division as shown in Fig. 1(c). It is instructive to view an level tree-structured DFB equivalently as a  $2^l$  parallel channel filter bank with equivalent filters and overall sampling matrices as shown in Fig. 1(d), where the equivalent (directional) synthesis filters are represented by  $D_k^{(l)}, 0 < k < 2^l$ . The corresponding overall sampling matrices is shown in to have the following diagonal forms:

$$S_k^{(l)} = \begin{cases} \text{diag}(2^{l-1}, 2) & \text{for } 0 \leq k < 2^{l-1} \\ \text{diag}(2, 2^{l-1}) & \text{for } 2^{l-1} \leq k < 2^l \end{cases} \quad (1)$$

This basis exhibits both directional and localization properties. Combining the Laplacian pyramid and the directional filter bank into a double filter bank structure the contourlet transform is developed.

Bandpass images from the LP are fed into a DFB to capture the directional information. By iterating this scheme on the coarse image, the image decomposes into directional subbands at multiple scales. This cascade structure helps the user to decompose different scales into different directions.

The contourlet transform is a two-dimensional extension of the wavelet transform using multiscale and directional filter banks. Contourlet transform provides a flexible multi-resolution, local and directional expansion for images. Contourlet transform is obtained by combining the Laplacian pyramid with a directional filter bank. In a contourlet transform there are two stages – a Laplacian pyramid followed by directional filter bank (DFB). Laplacian pyramids provide a multi-resolution system while directional filter banks give a directional nature to the contourlet transform. The Laplacian pyramid decomposition at each level generates a down-sampled low-pass version of the difference between the original and the prediction resulting in a band-pass image. Band-pass images from the Laplacian pyramid are fed into a DFB so that the directional information can be captured.

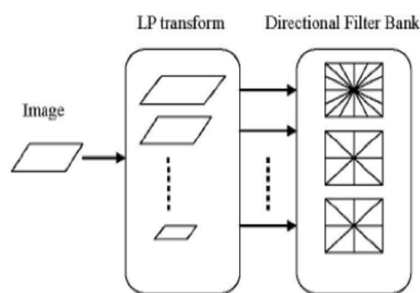


Fig.2.2. Contourlet transform

### III. PROPOSED WORK

#### A. Watermark embedding

Imperceptibility of the watermarking algorithm is commonly achieved by exploiting the weaknesses of the HVS. As demonstrated in HVS, the human eye is less sensitive to high entropy blocks instead of smooth ones as there are usually stronger edges in the high entropy blocks. For this purpose, N blocks are selected with the highest entropy in the whole image for the watermarking purpose. The contourlet transform is applied to each selected block. Calculating the energy of the coefficients in each directional subband of the finest scale, we choose the directional subband with the highest energy for embedding purpose.

This way, the code in the most significant direction of each block is hidden. The data in these coefficients are embedded using a multiplicative based approach. In the multiplicative watermarking, the samples with large values are expected. Thus, the transforms are applied to concentrate the energy of the image in a few coefficients. The contourlet coefficients are well modeled by random variables with Generalized Gaussian Distribution (GGD). Applying the inverse contourlet transform, we reconstruct the watermarked block. Repositioning each block in its position in the image, we create the watermarked image. The block positions and the GGD parameters ( $\alpha$  and  $\beta$ ) should be sent along with the watermarked image, where  $\alpha$  is the standard deviation of  $x$ , and  $\beta$  is the shape parameter. Special cases of the GGD density function include the Gaussian distribution with ( $\beta=2$ ), and the Laplacian with ( $\beta=1$ ). The block diagram of watermark embedding is shown in the following figure.

A single bit of “0” or “1” is embedded in each block by manipulating the coefficients  $x_i$  in the most energetic directional subband based on the following strategy :

$$W_i = x_i * f_1(x_i), \text{ for embedding 1} \quad (2)$$

$$W_i = x_i * f_0(x_i), \text{ for embedding 0} \quad (3)$$

Where  $f_1(x)$  and  $f_0(x)$  are strength functions.

The strength functions are considered to be even and monotonically exponential functions and they are given as,

$$f_1(x) = a_1 e^{a_2 \text{mod } x} + a_3$$

$$f_0(x) = b_1 e^{b_2 \text{mod } x} + b_3$$

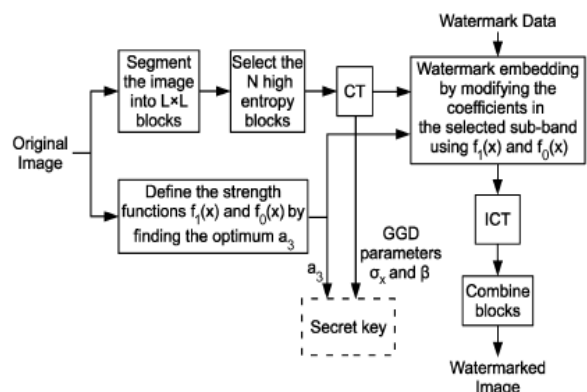


Fig.3.1 Block diagram of watermark embedding

**B. Watermark detection**

For detecting the watermark data in each block, we suggest a detection scheme based on an optimum detector. Suppose that  $x_i$  represents the contourlet coefficients of the most energetic directional subband of a specific block. These coefficients are assumed to be independently and identically distributed as  $GGD(\sigma, \beta)$ .

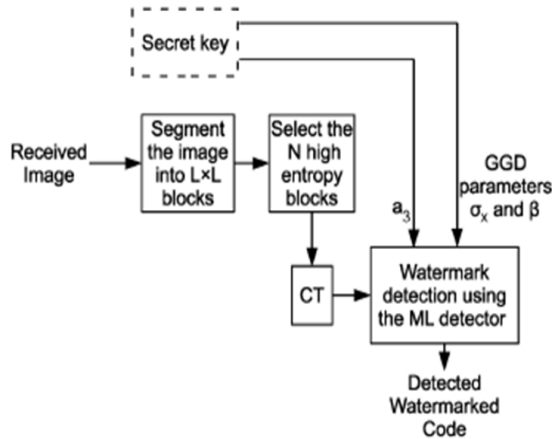


Fig.3.2 Block diagram of watermark detection

In order to have ML decision, the condition that has to be satisfied is

$$P(y_1, y_2, \dots, y_m | 1) >_0 P(y_1, y_2, \dots, y_m | 0)$$

where the left term is the distribution of the coefficients in a specific block with  $m$  coefficients for "1" embedding and the right term is the same distribution for "0" embedding. The block diagram of the watermark detector is shown as follows,

**C. Parameter optimization**

The strength functions  $f_1(x)$  and  $f_0(x)$  have critical role on the performance of the watermarking scheme. These functions can affect two factors in the watermarked image: visibility and robustness. Since  $f_0(x)$  can be calculated from  $f_1(x)$ , the effect of  $f_1(x)$  is only considered. First, larger values of  $f_1(x)$  can cause more distortions in the image due to the watermark. On the other hand, larger values of  $f_1(x)$  increase the robustness of the watermarked image against various attacks. Therefore, there is a trade-off between visibility and robustness. Henceforth a multi-objective optimization technique is utilized to select an appropriate strength functions ensuring imperceptibility with acceptable robustness.

The effect of the strength function on the visibility using the image quality index  $Q$  is modeled. In this quality assessment method, any image distortion is modeled as a combination of three factors considering the properties of the HVS: 1) loss of correlation, 2) luminance distortion, and 3) contrast distortion. This image quality index outperforms traditional quality assessment methods such as MSE due to its conformity to HVS and subjective tests. Thus the quality index is calculated using,

$$Q = \left( \prod_{j=1}^M Q_j \right)^{\frac{1}{M}} \dots \dots (4)$$

**IV. SIMULATED RESULTS**

In the proposed method, the mean Peak Signal to Noise Ratio (PSNR) between the original and the watermarked images are 39.63, 43.20, 40.40, and 36.48, respectively. The results for the block size of  $16 \times 16$  which delivers a suitable robustness against different attacks along with an appropriate transparency of the watermark data. The performance of the proposed contourlet base method over similar DWT based approach for different block sizes to find the efficiency of implementation of contourlet. The small block size of  $16 \times 16$  there is a notable difference between the performance of contourlet and wavelet transform. Wavelet as a separable 2-D multi resolution transform just follows the curves as horizontal-vertical lines and essentially cannot represent 2-D directional discontinuity which is common in image edges. Thus, contourlet has advantage over the wavelet transform in proposed method, in which the great performance is obtained where the transform coefficients are sparse. Gray scale image (Barbara image) with  $512 \times 512$  is given as the input image.



Fig.4.1 Input image



Fig.4.2. Contourlet transform of the barbara image.

The image is decomposed into two pyramidal levels, which are then decomposed into four and eight directional subbands. Small coefficients are showed by black while large coefficients are showed by white.

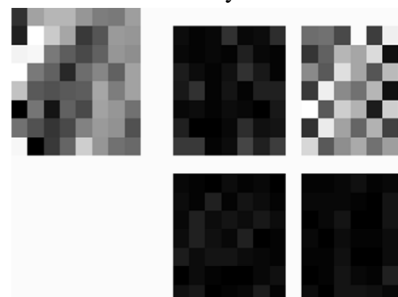


Fig.4.3. CT Block output

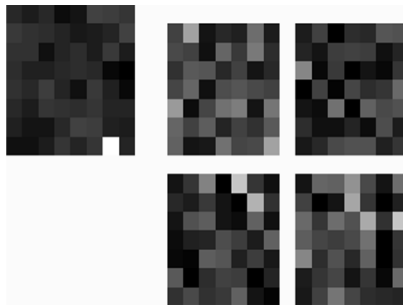


Fig.4.4. Inverse contourlet transform



Fig.4.5. Watermarked image

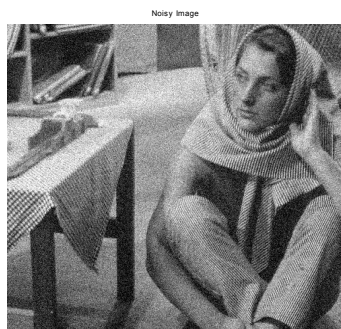


Fig.4.6. Noisy image

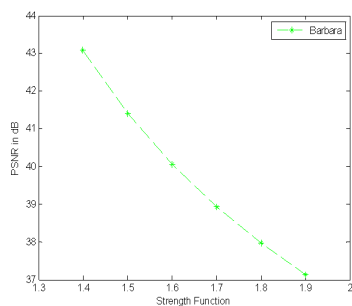


Fig.4.7. Strength function vs psnr

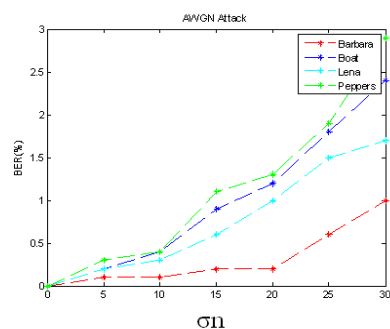


Fig.4.8. AWGN Attack for Various Test Images

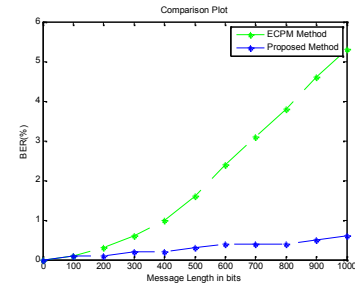


Fig.4.9. Comparison between proposed method and MWT-EMD method:

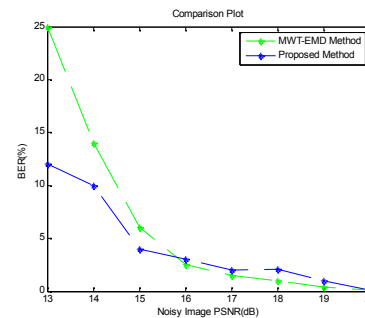


Fig.4.10. Comparison between proposed method and ECPM method:

## V. CONCLUSION

The properties of the contourlet coefficients of natural images is studied. It is found that similar to wavelets, contourlet coefficients are highly non-Gaussian and exhibit Markovian dependencies in the form of local clustering and persistence across scales. Moreover, coefficients across adjacent directions show more significant mutual dependencies compared to wavelets. Thus, contourlet coefficients exhibit dependencies across all of scale, space, and direction. Conditioned on these generalized neighborhood coefficient magnitudes, contourlet coefficients are approximately Gaussian. A robust multiplicative image watermarking technique in the contourlet transform domain is introduced. The proposed algorithm is presented in both semi-blind and blind versions. Since the contourlet transform focuses the image energy in the limited number of edge coefficients, using multiplicative approach in this domain yields high robustness accompanied by great transparency. To have better control on both imperceptibility and robustness, the strength functions are selected optimally by multi-objective optimization approach. The distribution of contourlet coefficients is modeled by GGD. Then, the distribution of watermarked noisy coefficients is calculated analytically. Using ML decision rule, the optimum detector has been proposed. The optimal detector guarantees that the suggested method is well suited for high noisy environment. Experimental results over several images confirm the excellent resistance against common attacks in the semi-blind version. In the blind version the proposed method outperforms recently proposed techniques in AWGN and rotation attacks, while it has competitive results in JPEG attacks.

## REFERENCES

- [1] Mohammad Ali Akhaee, Mohammad Ebrahim Sahraeian and Farokh Marvasti, "Contourlet-Based Image Watermarking Using Optimum Detector in a Noisy Environment," IEEE Transactions on Image Processing, vol. 19, no. 4, April 2010.
- [2] N. Bi, Q. Sun, D. Huang, Z. Yang, and J. Huang, "Robust image watermarking based on multiband wavelets and empirical mode decomposition," IEEE Trans. Image Process., vol. 16, no. 8, pp. 1956-1966, Aug. 2007.
- [3] D. D.-Y. Po and M. N. Do, "Directional multiscale modeling of images using the contourlet transform," IEEE Trans. Image Process., vol. 15, no. 6, pp. 1610-1620, Jun. 2006.
- [4] J. Seitz, Digital Watermarking for Digital Media. Arlington, VA: Information Science Publishing, 2005.
- [5] 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, Dec. 2005.
- [6] Q. Cheng and T. S. Huang, "Robust optimum detection of transform domain multiplicative watermarks," IEEE Trans. Signal Process., vol. 51, no. 4, pp. 906-924, Apr. 2003.
- [7] M. Barni, F. Bartolini, A. De Rosa, and A. Piva, "Optimum decoding and detection of multiplicative watermarks," IEEE Trans. Signal Process., vol. 51, no. 4, pp. 1118-1123, Apr. 2003.
- [8] M. Barni, F. Bartolini, A. De Rosa, and A. Piva, "A new decoder for the optimum recovery of nonadditive watermarks," IEEE Trans. Image Process., vol. 10, no. 5, pp. 755-766, May 2001.

## AUTHOR'S PROFILE



### P. Devi

received the BE degree in Electronics and Communication Engineering from VLB Janakiammal College of Engineering and Technology, Anna University Chennai in 2009 and the ME degree in Communication Systems from Sri Krishna College of Engineering and Technology, Anna University Coimbatore in 2011. Currently working in Sri Ramakrishna Institute of Technology as an Assistant Professor in ECE Department. She has one year teaching experience. She has presented the papers in the national conference. Under her guidance, the final year students are doing their project in various fields. Her field of interest is Digital Image Processing.



### V. Prakash

received the BE degree in Electronics and Communication Engineering from Sri Ramakrishna Institute of Technology, Anna University Coimbatore in 2012. He is an active member of IETE. He had presented national conferences and international conferences in various fields. He had done the project in the area of Digital Image Processing. His area of interest is Vehicular technology, Digital Electronics, Digital Image Processing.