*International Journal on Emerging Technologies* **5**(2): 73-78(2014)

**ISSN No. (Print) : 0975-8364**
**ISSN No. (Online) : 2249-3255**

# Contourlet Cryptography: A Better Description for Pattern Recognition

***Dr. S.K. Yadav, Pooja Jain and Manoj K. Thakur***
*JJT University, Rajasthan, India*

*(Corresponding author: Pooja Jain)*
*(Received 05 August, 2014 Accepted 06 October, 2014)*

**ABSTRACT: In the application of Computer vision research, Wavelets have enjoyed widespread popularity. In recent perspective some new age transforms like the corex transform, steerable Pyramid, ridgelets, contourlets and curvelets are theoretically appearing to the better image description for pattern recognition. These new transforms have been applications in the area of compression, denoising, watermarking and digital signature systems. In this work we will compare the performance of wavelets and contourlets for the purpose of pattern recognition cryptography. The results are based on well known database experiments viz USPS database of handwritten numerals and the Essexface database. We chose K-Nearest Neighbor and Probabilistic Neural Network for the purpose of classification. The result indicates that although contourlets surpass wavelets for other image processing tasks like compression and denoising, they are not good as wavelets for the purpose of pattern recognition until or unless cryptography is involved.**

**Keywords:** Contourlet, Wavelet, Optical Character Recognition, Face Recognition, Firewalls, Proxying.

## I. INTRODUCTION

According to study of Human Visual System and Image statistics, the image representation should satisfy the following conditions. (The mechanical and cryptographic versions):

(i) **Multiresolution:** The representation should allow images to be successively approximated, from course to fine resolutions.

(ii) **Localization:** The basis elements in the representation should be localized in both the spatial and the frequency domains.

(iii) **Critical Sampling:** For some applications, the representation should form a basis, or a frame with small redundancy.

(iv) **Directionality:** The representation should contain basis elements oriented at a variety of directions, much more than the few directions that are offered by separable wavelets.

(v) **Anisotropy:** To capture smooth contours in images.

The Multiresolution, Localization and critical sampling are successfully provided by separable wavelets, while Directionality and Anisotropy require Private key and public key cryptography. Key sequence is shared between communication parties. This has inspired researchers to search for new methods for image representation. This led to the development of Steerable Pyramids [1] Corex Transforms [2] Ridgelets [3] Contourlets [4] Curvelets [5], Cryptographic Techniques [29] Polymonphic Tools and Firewalls [29] These new transforms have outperformed wavelets and related traditional transforms in image denoising [6, 7]. Image compression [8], Watermarking [9] etc. At all event, these new multiscals transforms hardly found applications in problem related to pattern recognition. Steerable Pryamids [10], Ridgelets [11], Contourlets [12] and Curvelets [13] all have been used for texture classification. Apart from texture classification the above transforms have enjoyed a little exposure to the other pattern recognition application like character and face recognition. Later on Naumauich [14] and Athisha [15] worked on the pattern, under PKT.

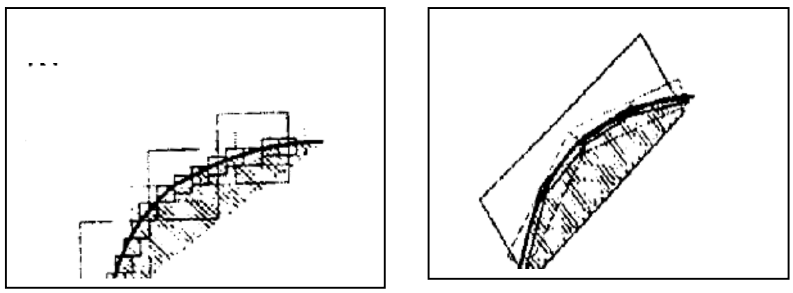
## II. FEATURE EXTRACTION

Since the thrust of this paper is on contourlet cryptography for pattern recognition problem using wavelets and contourlets. Ideally both the wavelet and contourlet transforms are necessary to be discussed. The interested readers can go through the works of Meyer [16], Daubechis [17, 18] and Mallat [19] to have a thorough understanding of wavelets and contourlets. Different families of wavelets like Hear, Daubechies, Symlets, Coiflets, to name a few exists. He [20] showed that for the purpose of pattern recognition the recognition accuracies of different wavelet families at different resolutions are significantly different.

*A. Contourlet Transform*

It is basically a 2D transform defined in the discrete form to capture the contour information in all directions. It is basically in cryptic form, which is very suitable for image processing. Contourlet transform can be compared of wavelet transforms and can be coded in neural network and encrypted again.

The wavelet transform is to use the square shaped brush strokes along the contour to paint the contour, with different brush sizes corresponding to the multiresolution structure of the wavelets. As the resolution becomes finer, the wavelet transform uses dots (small squares) to capture the contour. The contourlet transform uses different elongated stapes in a variety of directions following the contour to paint the contour with more flexibility. The contourlet transform uses contour segments to realize the local, multi-resolutional and directional image expansion; As a result the transform is known as contourlet transform. The efficiency of a representation is defined as the ability of it to capture the information of an object in interest using fewer description. With parabolic sealing and sufficient directional vanishing moments, the contourlets achieve the optional approximations rate for a 2D piecewise smooth functions with twice continuously differentiable contours. With dyadic scaling and sufficient vanishing moments, the wavelets can approximate any two continuously differentiable 2D functions with arbitrary accuracy, the efficiency of the wavelet transform may not be as high as contourlet transform if the contour is not horizontally or vertically efficient as illustrated by Fig. 1.



Wavelet Contourlet

**Fig. 1.**

Conceptually the contourlet transform firstly utilizes a wavelet like transform for edge detection such as the Laplacian Pyramid, and then the contourlet transform utilizes a local directional transform for contour segment detection such as the directional filter bank to link point discontinuities into the linear structure therefore contourlets may have elongated supports at various scales, directions and ratios. Contourlet segments have cryptic point to form images. The image in first decomposed into sub bands by Laplacian Pyramid and then each detail image is analyzed by the directional filter banks.

This cryptic scheme discussed have been implemented by Eslami and Radha [21]. The most improvements of cryptography are formed in two steps viz. sends inverse structure for reconstruction (robust in presence of noise) and Simplification of traditional directional filter bank by first sharing the image by certain angles them passing the shared image through two fan filters (one for vertical direction and other for horizontal direction). This shows that the contourlet transform is true 2D digital transform for cryptography.

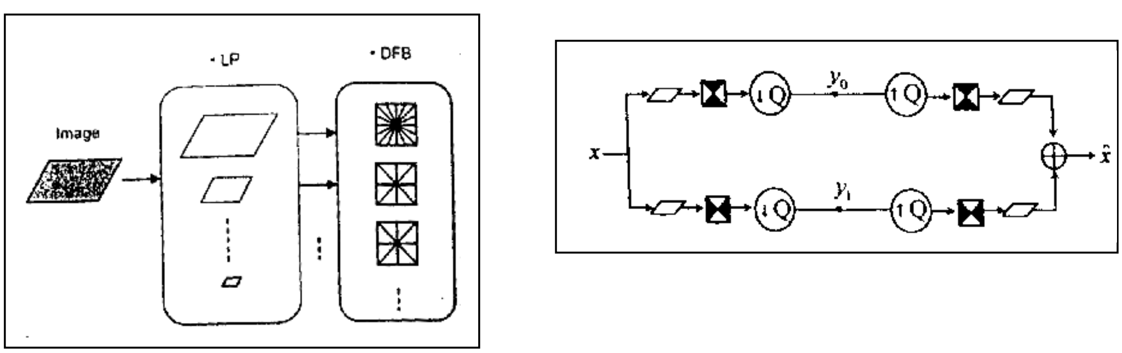



**Fig. 2.** Flow graph of the contourlet transforms.

The cryptography of above figure is:

(i) The parallelogram represents the sharing operator.

(ii) The quincunx represents the vertical or horizontal filter.

(iii) The circle with Q inside represents down sampling or up sampling.

(iv) The left half is to expand the image by the contourlet transform.

(v) The right half is reconstruction.

*B. Modern Cryptography*

The history of modern cryptography starts with the dressing of military ciphers. The shift operations were the earliest work. The mono-alphabetic, poly-alphabetic and poly-graphic substitutions ciphers were based on the concept of substitution, where the set of plain alphabets were replaced by cipher alphabets. Transposition (cryptographic technique) involves the rearrangement of letters occurring in the text, making it unintelligible.

Cryptography can be classified as (i) Private Key (ii) Public Key Cryptography. In Private key cryptography, key sequences is shared between communicating devices. Pseudorandom noise sequence generators, linear feed back shift registers, block permutators were some of the complex key generation mechanism. The aim of initiating a programs to develop a single cryptographic algorithm which could be adopted as a standard by all organization led to the development of Data Encryption Standard (DES). Most encryption algorithms assure date privacy, a way to prevent remove other than the intended recipient from reading or modifying the message code in form of contourlets.

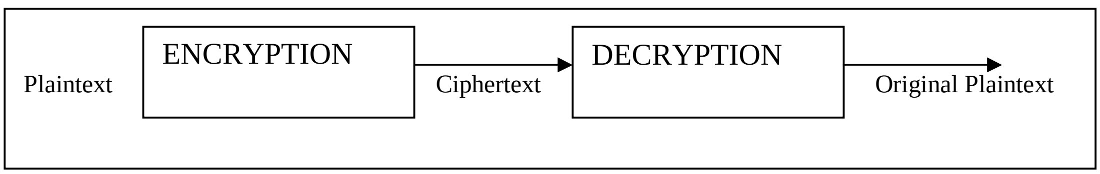



**Fig. 3.** General view of Cryptographic Algorithm

*C. Firewalls*

The initial layer of defence against external threats and attaches to networks is called firewall. It helps to reduce the risk to an acceptable layer (level). Firewall technology is a set of mechanism that collectively enforce a security policy on communication traffic entering or leaving the guarded network domain. Firewalls protect material such as stored data, computation and communication resources. The packet-fittings mechanism operates primarily on the network layer. Operating on the transport layer is the circuit level proxy mechanism, while the application specific proxy mechanism operates on top three layers.

At all seven layers cryptographic mechanism can be applied. Though firewalls guard any network domain they do impose some problems in the form of decreased data throughout and increased delay and jitter. The integrity and authenticity of these products can not be controlled without contourlets. However technologies do exist to bypass firewalls configurations such as IPP (Internet Printing Protocol) and Web DAV (Web-based Distributed Authoring and Versioning).

| | | |
|---|---|---|
| Application Layer<br>Presentation Layer<br>Session Layer | Application Specific<br>Proxy Mechanism | |
| Transport Layer | Circuit Level Proxy | Contourlets |
| Network Layer<br>Datalink Layer<br>Physical Layer | Packet Filtering | |

Some protocols marketed as firewall friendly are in reality, designed to bypass firewall configurations.

*D. Proxying*

Proxying provides Internet access to a single or a small number of hosts. A proxy server for a particular set of protocols runs on a dual-homed lost.

## III. CLASSIFICATION

Even though the focus of this study in on the feature extraction by contourlets and the intention is not increasing the classification accuracy up, but to study the relative performance of contourlet cryptography as bases of pattern recognition. We carry out the experimented with two different classifiers viz. K-Nearest Neighbour and Probabilistic Neural Network.

It is not possible to go into the details of these two classifiers in this limited scope of the paper. But we will give a brief overview of both these classification schemes in the following two subsections.

*A. K-Nearest Neighbour Classifier*

The K Nearest Neighbour (KNN) classifier is one of the most simplest classifiers. A detailed discussion on the KNN classification technique can be obtained in the works of Dasarathy *et al* [22]. A short but formal definition for KNN classification can be as follows:
Given a set of prototype vectors, $T_{xy} = \{(x_1, y_1), (x_2, y_2), \ldots\ldots, (x_i, y_i)\}$, the input vectors being $x_i$, $\varepsilon\ X \subseteq R^n$ and corresponding targets being $y_i$, $\varepsilon\ Y = \{1, 2, \ldots.., c\}$.

Let $R^n(x) = \{x' : \| x - x' \| \leq r^2\}$ be a ball centered in the vector x in which lie K prototype vectors $x_i$, $i\ \varepsilon\{1, 2, \ldots..,l\}$ i.e. $|\{x_i \mid : x_i\ \varepsilon R^n(x)\}| = K$. The K Nearest Neighbour Classification rule $q : X\ \varepsilon\ Y$ is defined as
$q(x) = \arg\max v(x, y)$,
Where $v(x, y)$ is number of prototype vectors $x_i$, with targets
$Y_i = y$ which lie in the ball $x_i\ \varepsilon R^n(x)$.

*B. Probabilistic Neural Network*

A Probabilistic Neural Network (to be called PNN henceforth) is an implementation of kernel discriminant analysis [23]. It is a multi-layered feedforward network with four layers: a) Input layer, b) Pattern layer, c) Summation layer and d) Output layer. Even though PNN has a large memory requirement and executes slower than the standard Backpropagation network the advantages that is brought forward are a) Faster Training, b) Inherently parallel structure and c) No local minima issues.
The basic decision rule for a PNN is:
If the probability density function (pdf) of each of the populations is known, then an unknown, X, belongs to Class "i" if $f_i(X) > f_j(X)$, all $I \neq j$ $f_k$ is the pdf for class k.
The pdf is estimated from the samples of the training set. For a single sample (in the population the pdf becomes $1/\sigma W(x - x_k/\sigma)$, where x is the unknown input, $x_k$ is the $k^{th}$ sample, W is the weighting function and σ is the smoothing parameter.
The pdf for a single population can be estimated using Parzen's pdf estimator. The population pdf is Average of the pdf's for "n" samples of the population. The estimated pdf approaches the true pdf as the training set size increases and as long as the true pdf is smooth.
The weighting function W provides a "sphere of influence" – the function should be such that its value is large for small distances between the unknown input and the training sample while it should rapidly decrease to zero as the distance increases.

$$\frac{1}{n\sigma}\sum_{k=1}^{n} W\left(\frac{x - x_k}{\sigma}\right)$$

The commonly used weighting function is the

Gaussian funcation, g(x) = $$g(x) = \frac{1}{n\sigma}\sum_{k=1}^{n} e^{-\frac{(x-x_k)^2}{\sigma^2}}$$

The actual input to the PNN is a vector (X). Taking into account the Gaussian weighting function the pdf for a single sample (in a population) is

$$\frac{1}{(2\pi)^{p/2}\,\sigma^p}\, e^{\frac{|X - X_1|^2}{2\sigma^2}}$$

where X is the unknown input, $X_i$ is the $K^{th}$ sample, σ is the smoothing parameter and p is the length of the vector.
As before the pdf for a single population can be calculated to be

$$g_i(X) = \frac{1}{(2\pi)^{p/2}\sigma^p n_i}\sum_{k=1}^{n_i} e^{\frac{|X - X|^2}{2\sigma^2}}$$

(average of the pdf's for the n, samples in the $i^{th}$ population). Following the above discussion the classification rule will be $g_i(X) > g_i(X)$, all $i \neq j$

$$g_i(X) = \frac{1}{n_1}\sum_{k=1}^{n_i} e^{\frac{|X - X|^2}{2\sigma^2}}$$

(eliminating common factors).
As the training set increases in size the PNN asymptotically converges to the Bayes Optimal Classifier.

## IV. DATABASES

The experiments were carried out on some benchmark databases. A brief discussion on the databases will entail in the following paragraphs.

*A. USPS Database [24, 25]*

The US postal service database (USPS) consists of 9298 handwritten numerals of size 16 x 16 pixel with intensity values varying between 0 and 2.7291 samples constitute the training set and the rest 2007 images consist of the testing set.

**Fig. 4.** Samples from the USPS Database.

*B. Essex Face Databases [26]*

The Essex Face Database is held in four directories viz., faces94, faces95, faces96, grimace; in order of increasing difficulty, Faces96 and Grimace are the most difficult, though for two different reasons (variation of background and scale, versus extreme variation of expressions).

The 4 datasets have both male and female subjects, and have representatives from 4 different races. The subjects are mostly university students but there are some subjects of an higher age range.

## V. RESULTS

All the experiments were performed on an AMD 64 Bit 3200 + machine with 1 GB RAM and running Windows XP 32 Bit. The programming environment of choice was that of Matlab 6.5.

**Fig. 5.** Image Description through Contourlet Cryptography & Wavelets.

As mentioned earliest the wavelet family of choice was Coiflets

1. Only the approximate coefficients at the first level of decomposition were used an image descriptors.

## CONCLUSION

Our work has been the first attempt for utilizing contourlet transform for addressing problems in pattern recognition. The above results show that the wavelets are almost better than contourlets for pattern recognition from images. However, the result of this work should not deter future research in this area. It must be remembered that, following traditional approaches, we have made use of only the approximate coefficients for pattern recognition. But studies from other related areas of image processing like denoising [6, 7] and compression [8] indicate that the detailed directional coefficients of the Multiresolution transforms carry important information. In future research, we will attempt to make use of the detailed directional coefficients for the purpose of pattern recognition. Such studies have not been attempted earlier, and appear to be an interesting area of research where the individual shortcomings of the detailed directional coefficients (it was mentioned earlier that the recognition accuracy with the detailed coefficients were very poor) can be removed by fusing the approximate and detailed transforms to achieve better results in computer vision. Already the new Multiresolution multidirectional transforms are proving their worth in texture classification.

This study proves that, by only using the approximate coefficient of contourlet transform, good recognition accuracy can not be obtained. In the future we should focus on the utilizing the detailed transformed coefficients for better pattern recognition accuracy.

## REFERENCES

[1]. E.P. Simoncelli, W.T. Freeman, E.H. Adelson and D.J. Heeger, “Shiftable multi-scale transforms”. IEEE Trans. Information Theory, Special issue on Wavelets. Vol. **38**, Issue 2, March 1992, pp. 587-607.

[2]. A.B. Watson, “The cortex transform: rapid computation of simulated neural images”, Computer Vision, Graphics, and Image Processing, Vol. **39**, Issue 3, Sept. 1987, pp. 311-27.

[3]. Key Technology in Information Security D.S. Athisha (Vol. **22** pp. 173-181) IETE (T.R.)

[4]. M.N. Do and M. Vetterli, “The contourlet transform: an efficient directional Multiresolution image representation”. *IEEE Transactions Image on Processing*, Vol. **14**, Issue 12, Dec. 2005, pp. 2091-2106.

**[5].** E.J. Candes and D.L. Donoho, “Curvelets – A Surprisingly Effective Nonadaptive Representation for Objects with Edges, Curves and Surfaces”, L.L. Schumaker et al (eds), Vanderbilt University Press, Nashville, TN, 1999.

[6]. J.L. Starck, E.J. Candes and D.L. Donoho, “The curvelet transform for image denoising”, *IEEE transactions on image processing*, Vol. **II**, Issue 6, 2002, pp. 670-684.

[7]. A.L. da Cunha, J. Zhou, and M.N. Do, “Nonsub sampled contourlet transform: filter design and application in image denoising”, *Proc. of IEEE International Conference on Image Processing, Genoa*, Italy, Sep. 2005.

[8]. A.N. Balbachir and P.M. Goebel, “The Contourlet Transform for Image Compression”, *Physics in Signal and Image Processing,* Toulouse, France, January, 2005.

[9]. F. Drira, F. Denis, A. Baskurt, F. Truchetet and O. Laligant, “Image watermaking technique based on the steerable pyramid transform”, Wavelet applications in industrial processing II, Philadelphia, PA, October 2004.

[10]. H. Greenspan and S. Belongie and P. Perona, "Invariant Texture Recognition Using a Steerable Pyramid", *Proceedings of IEEE International Conference on Image Processing*, Jerusalem, Israel, 1994.

[11]. G.Y. Chen, P. Bhattacharya, "Invariant Texture Classification Using Ridgelet Packets", *18th International Conference on Pattern Recognition*, 2006 pp. 464-467.

[12]. L. Shutalo, J Shawe-Taylor, A. Fred, T. Caelli, P.W. Duin Robert, A Campilho and D. de Ridder, "Texture classification by combining wavelet and contourlet features", *Joint IAPR international workshops SSPR 2004,* Vol. **3138**, pp. 1126-1134.

[13]. S. Arivazhagan, L. Ganesan an T.G. Subash Kumar, "Texture classification using Curvelet Statistical and Co-occurrence Features", *Proceedings of the 18th International Conference on Pattern Recognition,* Vol. **2**, 2006, pp. 938-941.

[14]. A. Majumdar, "Bangla Basic Character Recognition using Digital Curvelet Transform", accepted for publication in Journal for Pattern Recognition Research.

[15]. A. Majumdar, "Curvelets" A New Approach to Face Recognition", under review at *Journal for Machine Learning Research.*

[16]. Y. Meyer, "Principe d'incertitude, bases hilbertiennes at algebras d'operteurs", Seminaire Bourbaki, Vol. **662**, 1985-1989.

[17]. Daubechies, "Orthonormal bases for compactly supported wavelets", CPAM, Vol. **41**, 1988. pp. 909-996.

[18]. I. Daubechies, "Ten Lectures on Wavelets," CBMS-NSF Lecture Notes, Vol. 61, SIAM, 1992.

[19]. S. Mallat, "A Theory of Multiresolution signal decomposition: The wavelet representation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. **11**, 1989.

[20]. Haibo He, "Dynamically self reconfigurable systems for Machine Intelligence", PhD dissertation presented to the faulty of the Russ College of Engineering and Technology of Ohio University, 2006.

[21]. R. Eslami and H. Radha, "The Contoirlet Transform for Image De-noising Using Cycle Spinning", www.egr.mus.edu/waves/people/Radhu_files/2003/denoise_asilomar03.pdf.

[22]. B.V. Dasarathy, NN concepts and techniques, Nearest Neighbor (NN) Norms: NN Pattern Classification Techniques, B.V. Dasarathy (Ed.*), IEEE Computer Society Press*, 1991, pp. 1-30.

[23]. D.F. Specht, "Probabilistic neural networks", Neural Networks, Vol. **3**, Issue 1, 1980, pp. 109-118.

[24].http://www-stat-class.stanford.edu/-tibs/ElemStatLern/datasets/zip.train.gz.

[25].http://www-stat-class.stanford.edu/-tibs/ElemStatLern/datasets/zip.train.gz.

[26]. http://cswww.essex.ac.uk/mv/allfaces/index/html.

[27]. C.F. Chen, Y.S. Tseng and C.Y. Chen, "Combination of PCA and Wavelet Transforms for Face Recognition on 2.5 D Images", in Proc. Image and Vision Computing NZ, 2003, pp. 343-347.

[28].U. Bhattacharya and B.B. Chaudhuri, "Fusion of Combination Rules of an Ensemble of MLP Classifiers for Improved Recognition Accuracy of Hand printed Bangla Numerals", Eighth International Conference on Document Analysis and Recognition, August – September 2005.

[29]. Bruce Scheiner, Applied Cryptography John Wiley and sons pp. 11-13. 2001.