

Texture Analysis for Recognition of Satellite Cloud Images Using Orthogonal Polynomial Model

A.SUDHA¹, V.VAITHIYANATHAN²
School of Computing, SASTRA University,
Thanjavur, Tamil Nadu, India
Getsudha30@gmail.com¹

ABSTRACT: The main aim of this work is to classify the satellite cloud images with high accuracy and good recognition rate using texture as a feature. This work is based on Orthogonal Polynomial Transformation (OPT) to extract the low level feature like texture. Texture is a central feature especially for classifying homogeneous images. For achieving high accuracy the multi resolution technique is used with rotation invariant characteristics. Multiresolution is achieved in some existing methods with high complexity rate. In the proposed work complexity level is reduced by means of reordering coefficients in the form of sub bands. Then, the global feature is constructed and the optimized result is achieved for classifying the cloud.

Keywords: Multiresolution, Orthogonal, Rotation invariant, Texture.

I. INTRODUCTION

For a Meteorological application like weather prediction, the geostationary satellite provides an outstanding stage (images) for examining the clouds. These cloud data obtained from the geostationary satellites have been interpreted by the meteorologists and is used along with the weather forecast tools for daily usage. The satellite data are taken from METEOSTAT 7 in the IR band of region $10.5-12.5\mu m$.

Initially these data can be manually segmented by the meteorologist into different types of cloud based on its shape and its evolutionary process [1]. The different types of cloud can be observed from the satellite images. They are:

1. Stratus
2. Cumulonimbus
3. Cirrus-cirrostratus
4. Clear condition
5. Stratocumulus

The manually segmented image from the meteorologist is used as input for the proposed work. From these data, statistical features set can be calculated and global features are formed for each and every types.

There are various low level features like shape, color, texture etc. Texture arises where regularity and coarseness presents. Majority of the homogeneous images like cloud, rocks can be classified by means of texture. In the existing system, texture feature is used to achieve the Multi resolution characteristics but the complexity rate is high and redundancy of data is present. For that, literature review is done on the existing methods. Tsong Hwang et al.[2] Proposed a model in which texture feature is extracted using gabor wavelets, it is combined with PCA and NDVI in order to achieve accuracy. It is based on frequency based transform. Initially in gabor wavelets multiresolution is not achieved but in later it is invoked in [3] Ju Han et al. proposed a method in which texture can be extracted through gabor wavelets, and multiresolution is achieved with rotation invariant and scaling invariant Scheme. Complexity is reduced for specific rotation and scaling effect. J. Zhang et al.[4] proposed a model in which circular symmetric version of gabor is attained to form efficient texture segmentation. Desheng Fu et al. [5] proposed a system in which texture feature is take out using gabor and texture feature set has been classified using Neural networks. Pun et al. [6] proposes polar transform for retrieving the texture feature, here energy signature also computed for the formation feature. B.S. Manjunath et al.[7] have proposed a method for getting data from multimedia database using gabor wavelets. multiresolution is achieved for limited scale and orientation to reduce complexity. This work has been compared with pyramid wavelets to achieve better performance. Cui et al.[8] proposed a model named as Radon transform in which both the rotation and scale invariant feature set are focused. Also it reflects different energy distribution values of the texture image. Due to absence of orthogonality, problem exists in the above existing methods.

Section 3 refers achieving multiresolution using orthogonal model. Section 4 defines calculating statistical features. The proposed work is concluded at Section 5.

II. CHARACTERISTICS OF VARIOUS CLOUD SYSTEM BASED ON MANUAL OBSERVATION

Generally clouds are classified into three systems: low, middle and high clouds based on its top air pressure and distance from the base earth. High cloud includes cirrostratus type, middle cloud includes alto cumulus type, and low cloud has stratus, clear sky, cumulonimbus types.

A. High cloud:

It includes high altitude, low temperature, and having transparency to visible region of light. It is easily distinguishable when compared with the other two types.

B. Middle cloud:

It includes wide region, the shapes here can be in the form line, comma, or it may be of swirl shapes and it can include IR regions.

C. Low cloud:

It shows cumulonimbus and stratus types. Cumulonimbus seems to be white in sea regions and color of gray in land area. For stratus it may be of color from deep gray to normal gray.

III. APPLYING TRANSFORM ON SEGMENTED IMAGE AND ACHIEVING MULTI RESOLUTION CHARACTERISTICS

Polynomial based transformation and achieving multiresolution structures are described in [9]. The point Spread operator $G(p,q)$ is an real value function named for $(p,q) \in P \times Q$, P and Q are considered as real values with ordered divisions. For gray-level images with the size (nxn) , where P (rows) has predetermined set, for understanding it can be marked as $\{0, 1, 2, \dots, n-1\}$, the function $G(p,q)$ lessen to be a functions with sequence.

$$G(i,t)=v_i(t), \quad i,t=0,1,2,\dots,n-1 \tag{2}$$

The 2-D linear Transformation can be described with the point spread operator $G(p,q)(G(i,t)=u_i(t))$ as

$$B'(\alpha, \eta) = \int_{x \in X} \int_{y \in Y} G(\alpha, p) G(\eta, q) I(p, q) dx dy \tag{3}$$

Here α can be considering as an invariant texture feature vector. P and Q are assumed to be a finite set of values $\{0,1,2,\dots,n-1\}$, Eq. (3) has been carved in the following matrix format

$$|B'_{ij}| = (G \otimes G)' |I| \tag{4}$$

Here α is the outer product, B'_{ij} are matrices of size n^2 . The coefficients of the B'_{ij} are point spread operator G and its transpose and the input image I . The point spread operator G can be of the form as follows

$$|M| = \begin{vmatrix} v_0(t1) & v_1(t1) & \dots & v_{n-1}(t1) \\ v_0(t2) & v_1(t2) & \dots & v_{n-1}(t2) \\ \vdots & \vdots & \ddots & \vdots \\ v_0(tn) & v_1(tn) & \dots & v_{n-1}(tn) \end{vmatrix} \tag{5}$$

The $v_0(t1), v_1(t1), \dots, v_{n-1}(t1)$ are orthogonal polynomials having degree $0, 1, \dots, n-1$, to form the point spread operator of different sizes from the Eq.(4), the size of n can be greater than 2, the order to be used in the powers of 2. The formula for generating the polynomial is as follows:

$$v_{i+1}(t) = (t-\rho)v_i(t) - b_i(n)v_{i-1}(t) \quad \text{for } i \geq 1$$

$$v_1(t) = t - \rho, \text{ and } v_0(t) = 1 \tag{6}$$

Here

$$b_i(n) = \frac{(v_i, v_i)}{(v_{i-1}, v_{i-1})} = \frac{\sum_{t=1}^n v_i^2(t)}{\sum_{t=1}^n v_{i-1}^2(t)} \quad \& \quad \rho = \frac{1}{n} \sum_{t=1}^n t. \quad \text{values of } t_i \text{ can be assumed to be equals to } i. \quad i=1,2,3,4,\dots,n,$$

from these we can form

$$b_i(n) = \frac{i^2(n^2 - i^2)}{4(4i^2 - 1)}, \quad \rho = \frac{1}{n} \sum_{t=1}^n t = \frac{n+1}{2}$$

A. Performing Orthogonal Polynomial Transform

Using the above formula, the Point Spread Operator is constructed as below:

$$|G| = \begin{vmatrix} v_0(x_0) & v_1(x_0) & v_2(x_0) \\ v_0(x_1) & v_1(x_1) & v_2(x_1) \\ v_0(x_2) & v_1(x_2) & v_2(x_2) \end{vmatrix} = \begin{vmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{vmatrix}$$

The example taken is of the size 3x3, in the proposed work operator size has been taken as 4x4, formation of this operator is having same procedure as 3x3. Linear transformation has been performed for forming B_{ij}.

The operator and its transpose are formed and multiplied with input of size in the powers of 2 results in the formation of Forward Transform. This output will highlight the texture area.

For Performing Inverse Transform for B_{ij} it needs to form 9 polynomial basis operators for size 3x3, these set of operators can be formed as O_{ij}ⁿ=v_i⊗v_j^t here v_i is (i+1)th column of the polynomial operator.

The basic polynomial operators can be

$$|O_I| = \begin{vmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{vmatrix} \quad |O_{II}| = \begin{vmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{vmatrix} \quad |O_{III}| = \begin{vmatrix} 1 & -2 & 1 \\ 1 & -2 & 1 \\ 1 & -2 & 1 \end{vmatrix} \quad |O_{IV}| = \begin{vmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{vmatrix}$$

$$|O_V| = \begin{vmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{vmatrix} \quad |O_{VI}| = \begin{vmatrix} -1 & 2 & -1 \\ 0 & 0 & 0 \\ 1 & -2 & 1 \end{vmatrix} \quad |O_{VII}| = \begin{vmatrix} 1 & 1 & 1 \\ -2 & -2 & -2 \\ 1 & 1 & 1 \end{vmatrix} \quad |O_{VIII}| = \begin{vmatrix} -1 & 0 & 1 \\ 2 & 0 & -2 \\ -1 & 0 & 1 \end{vmatrix}$$

$$|O_{IX}| = \begin{vmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{vmatrix}$$

This basic operator can be an orthogonal and also linear independent completely. After performing Inverse transform the original image is obtained, the transformed output will highlight the texture area.

B. Enriching Orthogonal polynomial Transform with Multiresolution characteristics

Multiresolution is obtained by means of reordering the coefficients in the forms of subband like structure. The transformed coefficients B'_{ij} can be obtained from the above section has been reordered into subbands; the size of the block can be in the power of 2. Total number of subbands formation depends on the size of the block. Total subbands formed by means of using this formula (3log₂N+1) so that 7 subbands can be obtained s₀,s₁,s₂,s₃,s₄,s₅,s₆ for N of size(4x4).For each and every block of output obtained by the previous section has been formed into seven subbands individually ,the coefficients can be reordered by means of following assumptions. Assume the coefficient of this range 2^{u-1} ≤ i < 2^u and 2^{v-1} ≤ j < 2^v where u and v assumed to be an integers and I value, J value assumed to be from 0,1,...(N-1) are taken. After that it can be positioned into exact subband s_x , where x can be computed as:

$$x = \begin{cases} 0 & \text{for } m = 0 \\ 3(n-1) + 2 \left(\frac{u}{n} \right) + \left(\frac{v}{n} \right) & \text{otherwise} \end{cases} \quad (7)$$

Hence 2-level decomposition has been achieved here. In this computation n =max (u,v). Loop this process for every block (NXN) of entire image with height h and width w. Size of an entire image is (h x w). The location of reordered coefficient can be obtained by using function of block B(a,b), where a and b values of the rows and the column.

$$W = (2^{n-1}a + i - 2^{u-1}, 2^{n-1}b + j - 2^{v-1}) \quad (8)$$

four (4x4) output blocks of an above transform for a single image can be reordered as one (8x8) likewise this process is repeated for an entire image. The system architecture for the proposed work is shown in fig. 1.

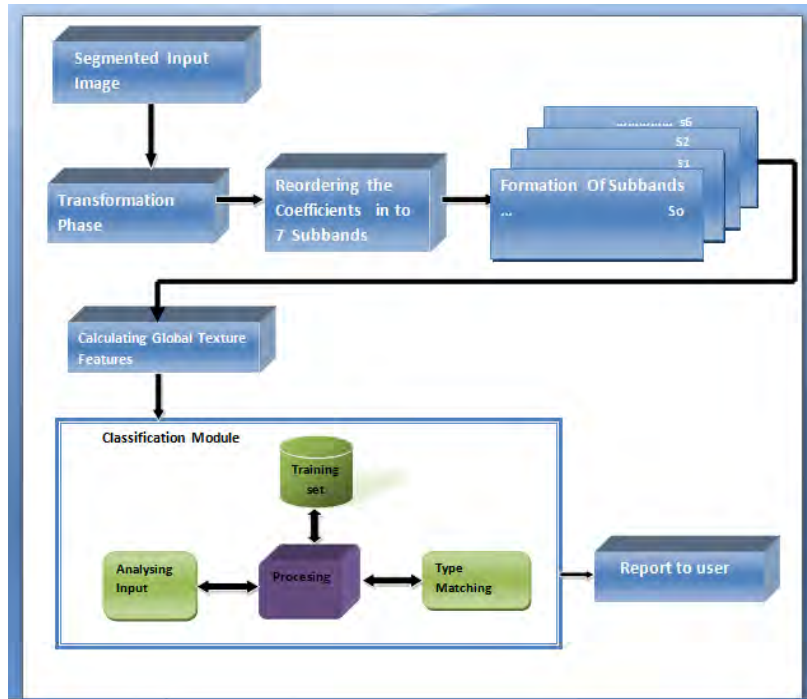


Fig.1. Overall system architecture.

The rotation invariant feature can be achieved easily in it by means of using orthogonal polynomial transform. If any block of size in the order of 2 is taken from the input image, then it is transformed by using orthogonal polynomial transform and then applying multiresolution reordering techniques. It results in reordered coefficients. If we rotate this resultant to any angle means it will result in same coefficients with changes only in its sign and location not in magnitude. Here the Complexity is completely reduced.

IV. TEXTURE FEATURE EXTRACTION

In the previous section the output as many 8x8, total number depends up on the size of an image is provided. The texture feature with rotation invariant characteristics such as statistical feature such as mean, standard deviation, energy are calculated for each (8x8) previous section output block of an image for every subband s0....s6. This process is repeated for the entire image. So that features set can get formed for every image. The contrastness also gets calculated for the s₀ band of each 8x8. Then using all the local contrast value for a single image, global coarseness is calculated for each image.

Statistical features such as mean (μ_s), standard deviation (σ_s), energy(E_s) has been calculated for all subbands using the formulae:

The mean can be calculated for every subband:

$$\mu = \frac{1}{XY} \sum_{i=0}^X \sum_{j=0}^Y |B'_{ij}|$$

The standard deviation can be calculated as

$$\sigma = \frac{1}{XY} (\sum_{i=0}^X \sum_{j=0}^Y |B'_{ij} - \mu_s|)$$

The Energy is formulated as

$$E_k = \sum_{i=0}^X \sum_{j=0}^Y |B'_{ij}|$$

Then the total feature set is calculated for all the subbands for each block, that is consider as a local set. From that global set can get formed.

Contrastness:

The Local contrast can gets calculated as

$$L_{cont}(i, j) = \frac{\max_{c \in DxD}(C) - \min_{c \in DxD}(C)}{\max_{c \in DxD}(C) + \min_{c \in DxD}(C)}$$

where C indicates the subband s_0 , i, j represent rows and column values, and (DxD) indicates neighborhood matrix size.

Then global value can gets calculated as

$$G_{cont} = \frac{1}{XY} \sum_{i=1}^X \sum_{j=1}^Y L_{cont}(i, j).$$

V. RESULTS

Recognition of satellite cloud images using texture with Orthogonal Polynomial Transform enriched by multiresolution characteristics has been experimented with the images obtained from the meteorologists [1]. The image of size(256×256) is taken(known Type), then these images can be subdivided into (4x4) blocks. The sub blocks are transformed by using Orthogonal Polynomial Transform. The obtained coefficient can be reordered to achieve Multiresolution characteristics, it outcome as an blocks of size (8x8). Here 2-level decomposition is obtained with 7 subbands for every (8x8) block. Then the statistical values such as mean, standard deviation, energy and contrastness are calculated for every block. Then these local values are used to form a global feature.

After calculating all features for two or more samples of the same category, approximate value is calculated for each and every type. Then the new samples are given as input for comparing with threshold values. Finally we are able to predict the type of cloud accurately with the help of the statistical value. The below table comprises of approximate threshold values calculated for contrastness, energy, and statistical feature which include mean and standard deviation of cloud images namely like stratus, cirrocumulus, clear, cumulonimbus, cirro stratus. The fig.2 shows some manually segmented image by the Meteorologist.

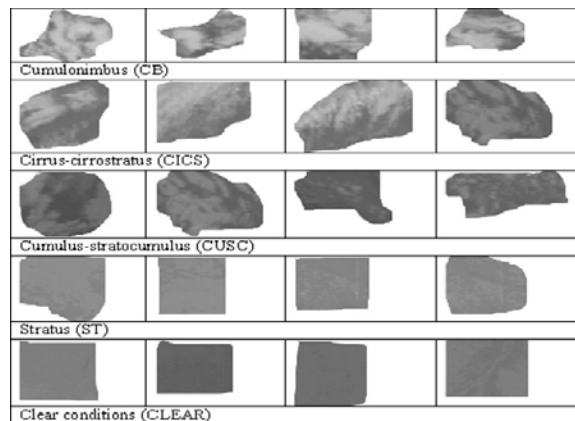


Fig.2.Manually segmented Cloud image Types

Table: 1 Texture feature set calculation

	Stratus	Cirrocumulus	Clear	Cumulonimbus	Cirro stratus
Energy	25	44	17	39	36
Statistical feature set	40	43	20	42	30
Contrast ness	42	22	34	24	23

The probability for achieving this threshold value is given above, for example the probability of stratus cloud to achieve energy can range of 25, statistical feature can be in the range is 40, and contrastness in the range is 42. This computation can be formed for two samples of each category of cloud.

VI. CONCLUSION

In this paper, satellite image has been predicted using orthogonal polynomial transform improved with the multiresolution characteristics for better understanding about the types of cloud images. The recognition accuracy is achieved with less computational complexity. In Future Coarseness feature also gets included to get more accuracy.

VII. REFERENCES

- [1] Christodoulos I. Christodoulou, Silas C. Michaelides, and Constantinos S. Pattichis, "Multifeature Texture Analysis for the Classification of Clouds in Satellite Imagery," *IEEE Transaction on Geoscience and remote sensing*, VOL. 41, NO. 11.
- [2] Jin-Tsong Hwang, Kuan-Tsung Chang, Hun-Chin Chiang, "Satellite Image Classification Based on Gabor Texture Features and SVM," *IEEE 2011 Supported by the National Science Council of Taiwan (No. NSC-99-2410-H-305-075)*.
- [3] Ju Han, Kai-Kuang Ma, "Rotation-invariant and scale-invariant Gabor features for texture image retrieval," *Elsevier*, 2006.
- [4] J. Zhang, T. Tan, L. Ma, "Invariant texture segmentation via circular Gabor filters," in: *Proceedings of 16th International Conference on Pattern Recognition*, vol. 2, 2002, pp. 901–904.
- [5] Desheng Fu, Lijuan Xu, "Satellite cloud image texture feature extraction based on Gabor wavelet," *International Congress on Image and Signal processing*, 2011, pp. 248-250.
- [6] C. Pun, "Rotation invariant texture feature for image retrieval," *Computer Vision and Image Understanding*, 2003, pp. 24-43.
- [7] B.S. Manjunathi and W.Y. Ma, "Texture Features for Browsing and Retrieval of Image Data," *IEEE Transaction*, 1996.
- [8] P.Cui, J.Li, Q.Pan, H. Zhang, "Rotation and scaling invariant texture classification based on radon transform and multiscale analysis," *Pattern Recognition Letters*, 2006, pp. 408 - 413.
- [9] R. Krishnamoorthi, S. Sathiya devi, "multiresolution approach for rotation invariant texture image retrieval with orthogonal polynomials model," *Elsevier*, 2011, pp.18-30.