# A COMPARATIVE MODEL FOR IMAGE PROCESSING & TEXTURE CLASSIFICATION USING CROSS-DIAGONAL TEXTURE MATRIX (CDTM) & GREY-LEVEL CO-OCCURRENCE MATRIX (GLCM)

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## **ABSTRACT:**

The objective of this paper is to recognize different textures in an image, particularly a satellite image where properties of the image are not distinctly identified. Texture classification involves determining texture category of an observed image. The present study on Image Processing & Texture Classification was undertaken with a view to develop a comparative study about the texture classification methods. The algorithms implemented herein classify the different parts of the image into distinct classes, each representing one property, which is different from the other parts of the image. The aim is to produce a classification map of input image where each uniform textured region is identified with its respective texture class. The classification is done on the basis of texture of the image, which remains same throughout a region, which has a consistent property. The classified areas can be assigned different colours, each representing one texture of the image. In order to accomplish this, prior knowledge of the classes to be recognized is needed, texture features extracted and then classical pattern classification techniques are used to do the classification.

Examples where texture classification was applied as the appropriate texture processing method include the classification of regions in satellite images into categories of land use. Here we have implemented two methods namely- Cross Diagonal Texture Matrix (CDTM) and Grey-Level Cooccurrence Matrix (GLCM), which are based on properties of texture spectrum (TS) domain for the satellite images. In CDTM, the texture unit is split into two separable texture units, namely, Cross texture unit and Diagonal texture unit of four elements each. These four elements of each texture unit occur along the cross direction and diagonal direction. For each pixel, CDTM has been evaluated using various types of combinations of cross and diagonal texture units. GLCM, on the other hand, is a tabulation of occurrence of different combinations of pixel brightness values (grey levels) in an image. Basically, the GLCM expresses the spatial relationship between a gravlevel in a pixel with the gray-level in the neighboring pixels. The study focuses on extraction of entropy, energy, inertia and correlation features using several window sizes, which are calculated, based on the GLCM. A maximum likelihood supervised classifier is used for classification. While applying the algorithms on the images, we characterize our processed image by its texture spectrum. In this paper we deal with extraction of micro texture unit of 7X7 window to represent the local texture unit information of a given pixel and its neighborhood. The result shows that increasing the window size showed no significant contribution in improving the classification accuracy. In addition, results also indicate that the window size of 7x7 pixels is the optimal window size for classification. The texture features of a GLCM and CDTM have been used for comparison in discriminating natural texture images in experiments based on minimum distance. Experimental results reveal that the features of the GLCM are superior to the ones given by CDTM method for texture classification.

## 1. IMAGE PROCESSING

In computer science, image processing is any form of signal processing for which the input is an image like photographs or frames of video; the output of image processing can however be either an image or a set of characteristics or parameters related to the image.

Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

# 2. TEXTURE ANALYSIS

In many image-processing algorithms, simplifying assumptions are made about the uniformity of intensities in local image regions. However, images of real objects often do not exhibit regions of uniform intensities. For example, the image of a wooden surface is not uniform but contains variations of intensities that form certain repeated patterns called visual texture. The patterns can be the result of physical surface properties such as roughness or oriented strands that often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface.

Image texture, is defined as a function of the spatial variation in pixel intensities (gray values). One common application of image texture is the recognition of image regions using texture properties. Texture is the most important visual cue in identifying homogeneous regions. This is called **Texture Classification**. *The objective of texture classification is to produce a classification map of the input image where each uniform textured region is identified with the texture class it belongs to.*[6]

# **3. OBJECTIVE**

The objective is to recognize different textures in an image, particularly a satellite image wherein the properties of the image are not distinctly identified.

The algorithms implemented herein classify the different parts of the image into distinct classes, each representing one property that is different from the other parts of the image. The classification is done on the basis of texture of the image. The texture remains same throughout a region that has a consistent property. The classified areas can be assigned different colours, each representing one texture of the image.

# Some application of image processing-

- Computer vision
- Face detection
- Feature detection
- Medical image processing
- Microscope image processing
- Remote sensing

# 4. ADVANTAGES OF IMAGE PROCESSING

The "*Image Processing*" software will help Security personnel to use processed Images of the terrain, which are much clearer than the images taken by satellites. These images give a clear picture of the terrain by distinguishing the land region from the water bodies and other geographical regions on the earth such as desert, forest, hills etc. Thus classification of satellite images has following attributes:-

- The software would help in discriminating the features of an unknown image taken from a satellite.
- It helps in extracting the features of an image that are not visible from our naked eyes.
- It helps in locating the terrain at the time of war.

# 5. METHODS IIMPLEMENTING TEXTURE CLASSIFICATION

There are several methods already in use for texture classification, and new techniques are being constantly developed to classify Satellite Images of the terrain. Two of them are:

- Cross-Diagonal Texture Matrix (CDTM)
- Grey-Level Co-Occurrence Matrix (GLCM)

# 6. CROSS-DIAGONAL TEXTURE MATRIX

The present study was undertaken to develop a modified texture analysis algorithm based on the properties of texture spectrum (TS) domain for the satellite images. In texture analysis some specific spatial filters are required, which can transform the image based on the textural features instead of changing the spectral properties; the image is thus characterized by its texture spectrum. This study deals with extraction of micro texture unit of 3X3 window to represent the local texture unit information of a given pixel and its neighborhood. In this technique, the texture unit comprising of eight neighborhood elements is decomposed into two separable texture units, namely, cross texture unit and diagonal texture unit of four elements each. These four elements of each texture unit occur along the cross direction and diagonal direction. For each pixel, cross- diagonal texture matrix (CDTM) has been evaluated using several types of combinations of cross and diagonal texture units. This approach drastically reduces the computational time. The occurrence frequency of each CDTM value obtained in the entire image is recorded. Two different approaches, namely, mean and median, have been subsequently carried out while processing the data. It is observed that the median technique with 3X3 window shows best result in the reduction of noise in satellite data.[3]

## **6.1. INTRODUCTION**

Texture analysis plays an important role in image processing, image classification and in the interpretation of image data. Several publications (Haralick et al, 1973; He et al, 1988; Gonzalez and Woods, 1992; Chen et al, 1995) have appeared dealing with the technique and role of textural analysis in interpretation of image. From geological point of view, it is being increasingly used in the interpretation and understanding of terrain. In a satellite imagery of an area, where an array or group of pixels characteristically represents the terrain, it is imperative that analysis of textural features of the entire image must be undertaken.

Textural analysis has been used in image segmentation and in classification problems. In texture segmentation, the pixels are grouped together to form regions of uniform texture; while in textural classification the object is to partition the image into a set of sub-regions, each of which is homogeneously textured. Two different approaches have been proposed for textural analysis. One of them is the structural approach while the other is statistical approach. Both the approaches are found to have certain limitations.

The purpose of this study is to develop the cross-diagonal texture filtering technique using several approaches and examine its suitability in elimination of noise in satellite remote sensing data.[3]

# **6.2. METHODOLOGY**

#### 6.2.1 Texture Spectrum

The basic concept of textural spectrum method for analysis was introduced by He & Wang (1990, 1991a, and 1991b) is that a texture can be extracted from a neighborhood of 3X3 window, which constitute the smallest unit called 'texture unit'. In the neighborhood of 3X3 window comprising of nine elements respectively as  $V = [V_1, V_2, V_3, V_4, V_0, V_5, V_6, V_7, V_8]$  where V0 is the central pixel value, and  $V_1,..., V_8$  are the values of neighboring pixels within the window (Figure 3.5). The corresponding texture unit for this window is then a set containing eight elements surrounding the central pixel, represented as  $TU = (E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8)$  where  $E_i$  is defined as,

$$0 \text{ if } \underbrace{Y_i < V_0}_{Ei} = 1 \text{ if } \underbrace{Y_i = V_0}_{2 \text{ if } \underbrace{Y_i > V_0}}$$

and the element  $E_i$  occupies the corresponding  $V_i$  pixel. Since each of the eight elements of the texture unit has any one of these three values (0, 1 or 2), the texture unit value, TU, can range from 0 to 6560 (3<sup>8</sup>, i.e., 6561 possible values). The texture units are labeled by using the relation,

NTU = 
$$\sum_{i=1}^{8} E_{i} 3^{(i-1)}$$
 .....(1)

where, NTU is the texture unit value. The occurrence distribution of texture unit is called the texture spectrum (TS). Each texture unit represents the local texture information of a 3x3 pixels, and hence statistics of all the texture units in an image represent the complete texture aspect of entire satellite image. Texture spectrum has been used in texture characterization and classification, and the computational time depends on the number of texture units identified in the image.[3]

## **6.2.2 Cross Diagonal Texture Matrix**

Al-Janobi (2001) has proposed a cross-diagonal texture matrix technique, in which the eight neighboring pixels of a 3x3 window is broken up into two groups of four elements each at cross and diagonal positions. These groups are named as cross texture unit (CTU) and diagonal texture unit (DTU) respectively. Each of the four elements of these units is assigned a value (0, 1 or 2) depending on the gray level difference of the corresponding pixel with that of the central pixel of the 3X3 window. Now these texture units can have values from 0 to 80 (34, i.e., 81 possible values).[1]



Figure 1. Formation of cross and diagonal texture units

Cross texture unit (CTU) and diagonal texture unit (DTU) can be defined as:

N <sub>CTU</sub>	=	$\sum_{i=1}^{5} E_{Ci} 3^{(i-1)}$	
N <sub>DTU</sub>	=	$\sum_{i=1}^{4} E_{Di} 3^{(i-1)}$	

Where, NCTU and NDTU are the cross texture and diagonal texture unit numbers respectively;  $E_{ci}$  and  $E_{di}$  are the i<sup>th</sup> element of the texture unit.[1]

## 6.2.3 Modified Texture Filter

In the proposed method, NCTU and NDTU values have been evaluated which range from 0 to 80. For each type of texture unit, there can be four possible ways of ordering, which give four different values of CTU and DTU. Finally a cross diagonal texture matrix (CDTM) value for each pixel position is evaluated from corresponding CTU and DTU possible values. In the present work, several techniques of estimating CDTM values have been undertaken, which are listed below.

$N_{TU} = N_{CTU} * N_{DTU}$	
$N_{TU} = \frac{1}{4} \sum_{j=1}^{4} N_{CTU} * N_{jDTU}$	(5)
$NTU = \frac{1}{4} \sum_{i=1}^{4} N_{iCTU} * N_{DTU}$	(6)
NTU = $\frac{1}{16} \sum_{j=1}^{4} \sum_{j=1}^{4} N_{iCTU} * N_{jDTU}$	(7)
$N_{TU} = N_{CTU} - N_{DTU}$	(8)
$N_{TU} = N_{CTU} + N_{DTU}$	(9)
$N_{TU} = 81*N_{CTU} + N_{DTU}$	(10)

Where,  $N_{iCTU}$  and  $N_{jDTU}$  are the ordering ways for evaluation of NCTU and NDTU. After obtaining the CDTM values of 3x3 window through entire image the occurrence frequency of each CDTM values are recorded. This 'CDTM' value is then assigned to the respective pixel locations. Now based on the range of the CDTM values we divide the CDTM values into different classes and give specific colours to all the classes. Thus we obtain our resultant CDTM classified image. Same procedure has been followed with 7x7 windows also. The techniques described above have been applied on several satellite imagery spiked with induced noises of different percentages.





# 7. GREY-LEVEL CO-OCCURRENCE MATRIX

Basic of GLCM Texture considers the relation between two neighboring pixels in one offset, as the second order texture. The grey value relationships in a target are transformed into the co-occurrence matrix space by a given window size such as 3x3, 5x5, 7x7 and so forth.

In the transformation from the image space into the co-occurrence matrix space, the neighboring pixels in one or some of the eight defined directions can be used; normally, four direction such as  $0^{\circ}$ ,  $45^{\circ}$ ,  $90^{\circ}$ , and  $135^{\circ}$  is initially regarded, and its reverse direction (negative direction) can be also counted into account.[5]

Therefore, general GLCM texture measure is dependent upon matrix size and directionality, and known measures such as contrast, entropy, energy, angular second moment (ASM) and correlation are used.[5]

# 7.1 Introduction

Grey-Level Co-occurrence Matrix texture measurements have been proposed by Haralick in the 1970s. Its use improves classification of satellite images.

This study concerns some of the most commonly used texture measures, which are derived from the Grey Level Co-occurrence Matrix (GLCM). This involves:

- **Defining** a Grey Level Co-occurrence Matrix (GLCM)
- Creating a GLCM
- Using it to calculate texture
- Understanding how calculations are used to build up a texture image

## Textures in images quantify:

- Grey level differences (contrast)
- Defined size of area where change occurs (window)
- Directionality and its slope

<u>Definition:</u> The GLCM is a tabulation of how often different combinations of pixel brightness values (grey levels) occur in an image.

**Properties of the GLCM-**

- 1. It is square
- 2. Has the same number of rows and columns as the quantization level of the image
- 3. It is symmetrical around the diagonal

The GLCM is used for a series of "**second order**" texture calculations. **Second order** measures consider the relationship between *groups of two (usually neighboring) pixels* in the original image.

## 7.2 Steps in creating a symmetrical normalized GLCM:

- 1. Create a framework matrix
- 2. Decide on the spatial relation between the reference and neighbor pixel
- 3. Count the occurrences and fill in the framework matrix
- 4. Add the matrix to its transpose to make it symmetrical
- 5. Normalize the matrix to turn it into probabilities by using the formula-

$$P_{i,j} = \frac{V_{i,j}}{\sum_{i,j=0}^{N-1} V_{i,j}}$$

Where, i is the row number and j is the column number.

## 7.3 Creating a Texture Image

The result of a texture calculation is a single number representing the entire window. This number is put in the place of the centre pixel of the window, then the window is moved one pixel and the process is repeated of calculating a new GLCM and a new texture measure. In this way an entire image is built up of texture values.

Edge of image problems Each cell in a window must sit over an occupied image cell. This means that the centre pixel of the window cannot be an edge pixel of the image. If a window has dimension N x N, a strip (N-1)/2 pixels wide around the image will remain unoccupied. The usual way of handling this is to fill in these edge pixels with the nearest texture calculation.



## 7.4 Groups of texture measures

Now we calculate the GLCM Texture i.e. the compute and generate the types of texture measures such as- Contrast, Entropy, ASM (Angular Second Moment), Energy and Correlation. These are expressed as follows:

- Contrast Equation- $\sum_{i,j=0}^{N-1} P_{i,j} (i-j)^{2}$  $\sum_{i,j=0}^{N-1} P_{i,j} (-\ln P_{i,j})$ Entropy- $\sum_{i,j=0}^{N-1} P_{i,j} (-\ln P_{i,j})$

ASM (Angular Second Moment)- 
$$\sum_{i,j=0}^{N-1} P_{i,j}^{2}$$

Energy-  $Energy = \sqrt{ASM}$ 

• Correlation-
$$\sum_{i,j=0}^{N-1} P_{i,j} \left[ \frac{\left(i - \mu_i\right)\left(j - \mu_j\right)}{\sqrt{\left(\sigma_i^2\right)\left(\sigma_j^2\right)}} \right]$$

where, i and j are coordinates of the co-occurrence matrix space, P(i,j) is element in the co-occurrence matrix at the coordinates i and j.[5]

# 7.5 Implementation of GLCM

Stand-alone application program for GLCM texture measure and texture image creation is implemented in this study. In this program, general graphic image formatted as jpg, tiff, bmp can be used as input data. Also, a user determines two texture parameters such as window size and direction in the main frame. The grey value relationships in the target image are transformed into the co-occurrence matrix space by a given window size such as 3x3, 5x5, 7x7 and 11x11, the neighboring pixels as one of the four directions as East-West of 0°, North-East of 45°, North-South of 90°, North-West of 135°, and omni-direction will

be computed in the co-occurrence matrix space. Among them, texture image is obtained as the resultant GLCM classified image.[5]

## 7.6 Flowchart: GLCM



8. COMPARISON BETWEEN CDTM AND GLCM

**Cross-Diagonal Texture Matrix (CDTM)** 



Figure 2a. Input Image Grey-Level Co-occurrence Matrix (GLCM)



Figure 3a. Input Image

Figure 2b. Resulting CDTM Classified Image



Figure 3b. Resulting GLCM Classified Image

# CONCLUSION

Most previous studies for second order texture analysis have been directed toward the improvement of classification accuracy, with supervised or un-supervised classification methods, showing high accuracy [7]. Scope of this study is somewhat different from previous works. An application program for texture measures based on CDTM and GLCM is newly implemented in this study. By using this program, CDTM and GLCM based texture images by different quantization level, window size, and texture type are created with the high-resolution satellite image of the terrain. In application of feature characterization to texture measures, texture images is helpful to detect shadow zone, classify building types; and distinguishing the land, water, forest, desert etc. regions from one another which are not fully analyzed in this study.

In this paper we compare two different image texture classification techniques based on feature extraction by first and higher order statistical methods that have been applied on our images. The extracted features are used for unsupervised pixel classification with CDTM and GLCM algorithms to obtain the different classes in the image [4]. From the results obtained with 3x3, 5x5 and 7x7 windows on several satellite imagery data corrupted with different percentages of induced noise, it is found that the results with 7x7 windows are comparatively more effective in removing the noises from the imagery data than that by the 3x3 and 5x5 texture windows. Another very important advantage of the proposed technique is the substantial reduction in the computational time involved using CDTM method. Moreover,

- The algorithms work well for distantly clicked images such as satellite images.
- The algorithms can successfully recognize distinct regions in an image on the basis of textures extracted.
- When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features.
- The system helps in simplifying the amount of resources required to describe a large set of data accurately.

The extracted features are used for unsupervised pixel classification to obtain the different classes in the image, before using the algorithm. Two methods have been tested with very heterogeneous results [8]. The hypothesis took into account for the textural analysis methods are currently modified to justify them more accurately, especially concerning the number of classes and the size of the analysis window.

Another five parameters were calculated from the grey-level co-occurrence matrix (GLCM). The linear discriminant analysis was applied to sets of up to five parameters and then the performances were assessed. The most relevant individual parameter was the contrast (*con*) (from the GLCM algorithm).[2]

This paper presents a new texture analysis method incorporating with the properties of both the gray-level co-occurrence matrix (GLCM) and cross-diagonal texture matrix (CDTM) methods. The co-occurrence features extracted from the cross-diagonal texture matrix provide complete texture information about an image. The performance of these features in discriminating the texture aspects of pictorial images has been evaluated. The textural features from the GLCM and CDTM have been used for comparison in discriminating some of satellite images. Based on the resultant classified images of the

terrain it is observed that the features of the classified image in GLCM were more clear and vivid as compared to what we see in CDTM.

Although the GLCM approach is much less computationally intensive than the CDTM, it nonetheless requires massive amounts of calculation. Most of this computation time is spent in stepping through the input image and compiling the matrices themselves. Therefore, if the calculation time for these matrices could be reduced, the GLCM technique would become more practical.

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