*Paper presented at the 22nd Asian Conference on Remote Sensing, 5 - 9 November 2001, Singapore.*


# A MODIFIED TEXTURE FILTERING TECHNIQUE FOR SATELLITE IMAGES

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**KEY WORDS:** Texture Unit, Texture Spectrum, CDTM, Satellite Imagery

**ABSTRACT:** 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 papers deals with extraction of micro texture unit of 3X3 as well as 5X5 window to represent the local texture unit information of a given pixel and its neighbourhood. In this technique, the texture unit comprising of eight neighbourhood 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.

## 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 an satellite imagery of an area, where an array or group of pixels characteristically represent 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 ( Haralick, 1979 and 1986; Matsuyama et al, 1980; Wang and He, 1990). Both the approaches are found to have certain limitations. Several textural features have been widely used in textural analysis. Some of these are: gray level co-occurrence matrix (GLCM), markov random fields (MRF), two dimensional auto-regressive (2D-AR), gabor filters, fractals, texture spectrum (TS), wavelet transform, complexity curve, run length matrices, cross diagonal texture matrix ( Cross and Jain, 1983; Keller et al, 1989; Bovik et al, 1990; Davis, 1981; Kartikeyan and Sarkar, 1991, Chang and Kuo, 1993). Weszka et al (1976), and Ohanian and Dubes (1992) have carried out comparative studies among some of these proposed textural features to evaluate their performances.

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

## 2. METHODOLOGY

### 2.1 Texture Spectrum

The basic concept of textural spectrum method for analysis was introduced by He and Wang (1990, 1991a, and 1991b) is that a texture can be extracted from a neighbourhood of 3X3 window, which constitute the smallest unit called 'texture unit'. In the neighbourhood 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 $V_0$ is the central pixel value, and $V_1, \ldots, V_8$ are the values of neighbouring pixels within the window (Figure 1). 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,

$$E_i = \begin{cases} 0 & \text{if } V_i < V_0 \\ 1 & \text{if } V_i = V_0 \\ 2 & \text{if } V_i > V_0 \end{cases}$$

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 ( $3^8$ , i.e., 6561 possible values). The texture units are labeled by using the relation,

$$N_{TU} = \sum_{i=1}^{8} E_i \, 3^{i-1} \qquad \text{..........................(1)}$$

where $N_{TU}$ is the texture unit value. The occurrence distribution of texture unit is called the texture spectrum (TS). Each texture unit represent 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 (He and Wang, 1991).

**2.2 Cross Diagonal Texture Matrix**

Al-Janobi (2001) has proposed a cross-diagonal texture matrix technique, in which the eight neighbouring 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 ($3^4$, i.e., 81 possible values).

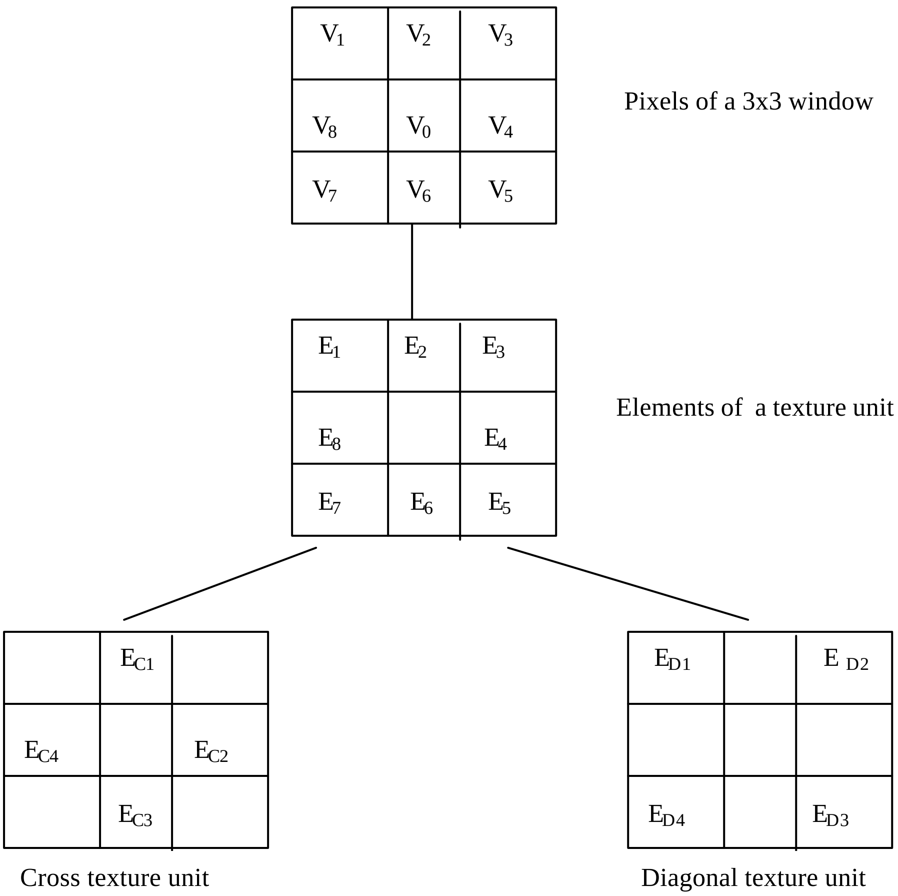



Figure 1. Formation of cross and diagonal texture units

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

$$N_{CTU} = \sum_{i=1}^{4} E_{ci}\ 3^{i-1} \qquad \text{..............(2)}$$

$$N_{DTU} = \sum_{i=1}^{4} E_{di}\ 3^{i-1} \qquad \text{...............(3)}$$

where $N_{CTU}$ and $N_{DTU}$ are the cross texture and diagonal texture unit numbers respectively; $E_{ci}$ and $E_{di}$ are the ith element of the texture unit.

### 2.3 Modified Texture Filter

In the proposed method, $N_{CTU}$ and $N_{DTU}$ 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.

$$N_{TU} = N_{CTU} * N_{DTU} \qquad \text{.... .................(4)}$$

$$N_{TU} = \frac{1}{4}\sum_{j=1}^{4} N_{CTU} * N_{jDTU} \qquad \text{.....................(5)}$$

$$N_{TU} = \frac{1}{4}\sum_{i=1}^{4} N_{iCTU} * N_{DTU} \qquad \text{....................(6)}$$

$$N_{TU} = \frac{1}{16}\sum_{i=1}^{4}\sum_{j=1}^{4} N_{iCTU} * N_{jDTU} \qquad \text{....................(7)}$$

$$N_{TU} = N_{CTU} - N_{DTU} \qquad \text{....................(8)}$$

$$N_{TU} = N_{CTU} + N_{DTU} \qquad \text{....................(9)}$$

$$N_{TU} = 81*N_{CTU} + N_{DTU} \qquad \text{................(10)}$$

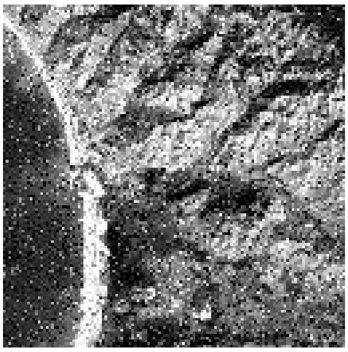
where $N_{iCTU}$ and $Nj_{DTU}$ are the ordering ways for evaluation of $N_{CTU}$ and $N_{DTU}$.

After obtaining the CDTM values of 3x3 window through entire image the occurrence frequency of each CDTM values are recorded. For the texture units having same CDTM values, two different procedures have been carried out to replace the pixel values of these units. These procedures are ‘mean’ and ‘median’. In the ‘mean’ procedure, all the pixel values of corresponding locations in 3X3 window having same CDTM value are averaged. This ‘mean’ pixel value is then assigned to the respective pixel locations. In the ‘median’ procedure, the median of the pixel values of the corresponding locations are selected, and substituted for all the pixels of the windows having same CDTM value for the corresponding texture units. Same procedure has been followed with 5x5 window also.

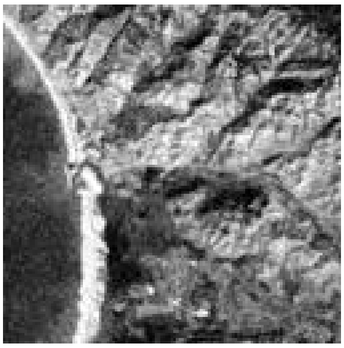
The techniques described above have been applied on several satellite imagery spiked with induced noises of different percentages. The results obtained after applying mean and median procedures with 3x3 window and 5x5 window for one satellite imagery corrupted with three induced noises (25%, 50% and 90%) have been shown in Figures 2, 3 and 4.

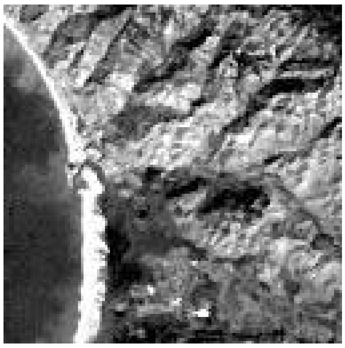
## 3. CONCLUSIONS:

From the results obtained after the application of the mean and median with 3X3 and 5X5 windows on several satellite imagery data corrupted with different percentages of induced noise, it is found that the median filter with 3x3 window is comparatively more effective in removing the noises from the imagery data than that by the 3x3 mean, 5x5 mean and 5x5 median texture filters. It is also observed that, in general, the noise removal is very good in case of low noise data (around 30%), which decreases with increase of noise percentage becoming very poor in case of very high noise data (around 90%). Another very important advantage of the proposed technique is the substantial reduction in the computational time involved.

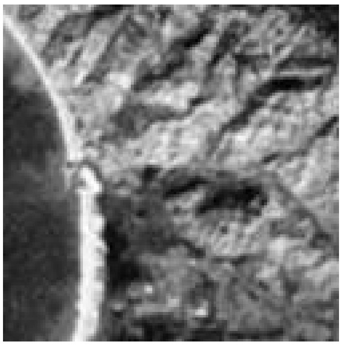


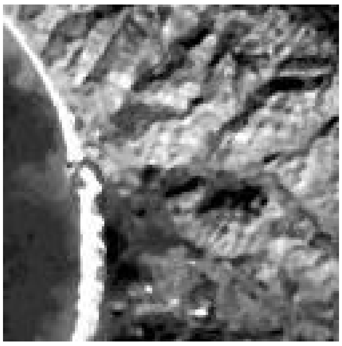
**Original Satellite Image** **Image with 25% random noise**





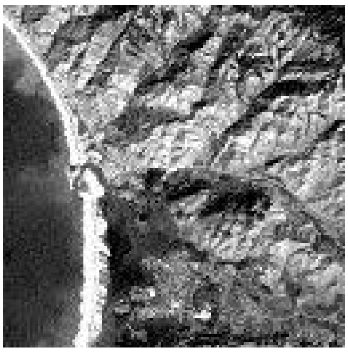
**Mean with 3x3 window** **Median with 3x3 window**



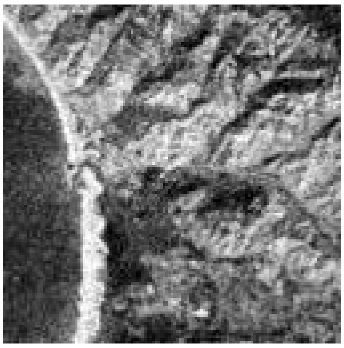


**Mean with 5x5 window** **Median with 5x5 window**

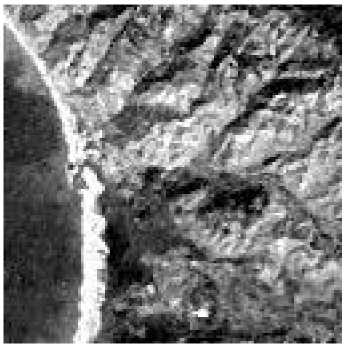
**Figure 2. Mean and median texture filtering on a Landsat image with 25% noise**



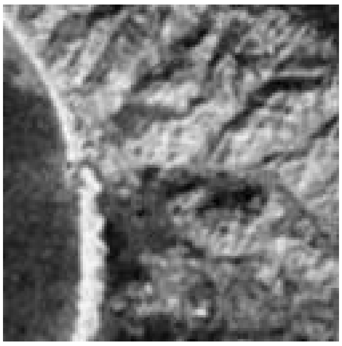
**Original Satellite Image** **Image with 50% random noise**



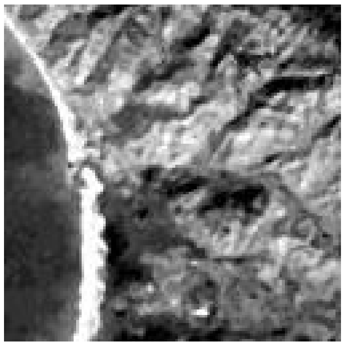
**Mean with 3x3 window**



**Median with 3x3 window**



**Mean with 5x5 window**

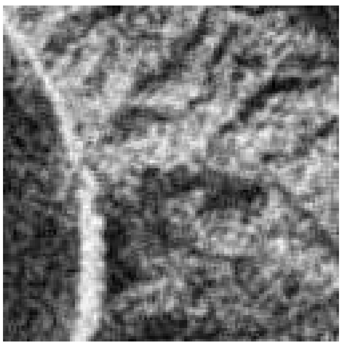


**Median with 5x5 window**

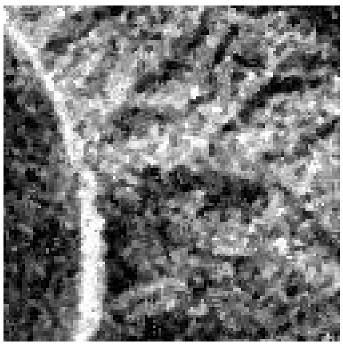
**Figure 3. Mean and median texture filtering on a Landsat image with 50% noise**

**Original Satellite Image**

**Image with 90% random noise**

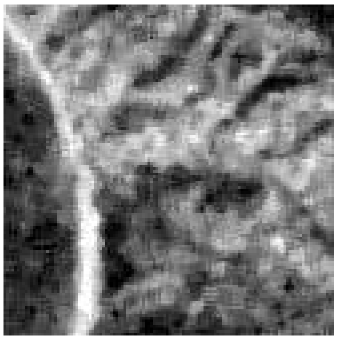


**Mean with 3x3 window**



**Median with 3x3 window**

**Mean with 5x5 window**



**Median with 5x5 window**

**Figure 4. Mean and median texture filtering on a Landsat image with 90% noise**

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