PROBABILISTIC DISTANCE APPROACH FOR SIMILARITY MEASURE IN SAR IMAGES

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CERTIFICATE

This is to certify that work entitled "**Probabilistic Distance Approach For Similarity Measure In SAR Images**" submitted by SANDEEP KUMAR SINGH (2K12/ISY/27), to Delhi Technological University, Delhi for the award of the degree of Master of Technology is a bonafide record of research work carried out by him under my supervision.

The content of this thesis, in full or parts, have not been submitted to any other institute or university for the award of any degree or diploma.

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ABSTRACT

Measuring similarity between two Synthetic aperture radar (SAR) images becomes challenging when there is no universal method used to measure the similarity in the two SAR images. Presence of speckle noise makes it difficult to follow the usual rule as for the optical images. Speckle noises are multiplicative in nature which makes it difficult to directly compare with another SAR images. For this reason it is interesting to study of several types of noises and their impact on the images.

This thesis introduces the concept of Renyi entropy and Renyi mutual information in SAR images and its case study over different value of alpha and noise variance under the various noise models. Here we are trying to predict approximate similarity between two SAR images by calculating Renyi mutual information. We could observe that the measuring similarity is not an absolute measure as there are different sensors working over different climatic conditions and different temperatures. Here we tried to simulate the results with various noise models at different noise variance. It is very difficult to generalize a single method for all but the effort is to make it to the best possible results. The experiment to measure the similarity in SAR images is performed and validated.

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CHAPTER 1

SYNTHETIC APERTURE RADAR IMAGES

1.1 Introduction

Monitoring of environment, Mapping of resources[1], and imaging for military system requires images of high resolution. Many times images required in different atmospheric condition, in different weather or at any time day or night. The SAR images provide such a capability. It takes advantage of long range propagation of radar signals and complex information processing for such a high resolution images. SAR Images have application in different field such as earth mapping, surface surveillance and search and rescue[2]. A light beam sends by radar towards the earth's surface through a small aperture. The beam passed through various layers and enters into the atmosphere. The beam hit the surface of earth and reflected fully or partially. During the process of entering and reflecting it undergone pass through various environmental condition that result in the presence of speckle noise in SAR images.

In general every SAR image is affected by speckle noise and this makes it difficult to deal with[3]. The information provided by SAR images is of great importance, but the presence of speckle noise degrades the quality of information. In SAR images the goal is removal or minimizing the effect of speckle noise and preserves the entire textural feature.

1.2 Basic Principles of rRadar And SAR

The basic principle of radar is based on echo ranging. Anyone who has shouted and getting the reflected voice back is the fundamental of echo system. The similar concept is used by the radar for imaging. In radar system the basic principle is transmitting high bandwidth pulse and then using pulse compression technique [1][2]. In radar we transmit a narrow beam to illuminate a certain portion on the ground.

The points are discriminating based on their distance from the radar. Here the discriminatory power of an optical system in all directions of scene is proportional to the lens size. The resolution of SAR images are not related to the aperture size as it based on echo ranging. The cross range resolution for conventional radar is calculated as

$$\rho = \frac{\lambda R}{D} \tag{1.1}$$

Here λ is the wavelength of the illuminating source, R is the target range, and D is the Width of the antenna aperture or the diameter of the lens. The wavelength of the microwave is 104 times that of visible light.

Synthetic aperture radar sends the multiple pulses from a number of observation points, and receiving the information coherently to obtain a high-resolution 2-D description of the scene. Actually current SAR systems can produce imagery with a spatial resolution that begins to approach that of remote optical imagers, while avoiding its limitations like night time and cloud-cover Image captures.

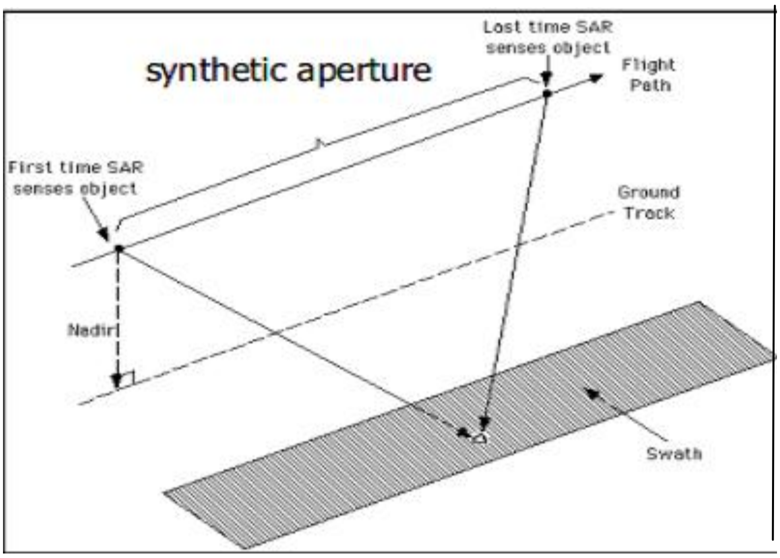

Figure 1.1 (a) Principle of SAR

Echo effect in RADAR Principle

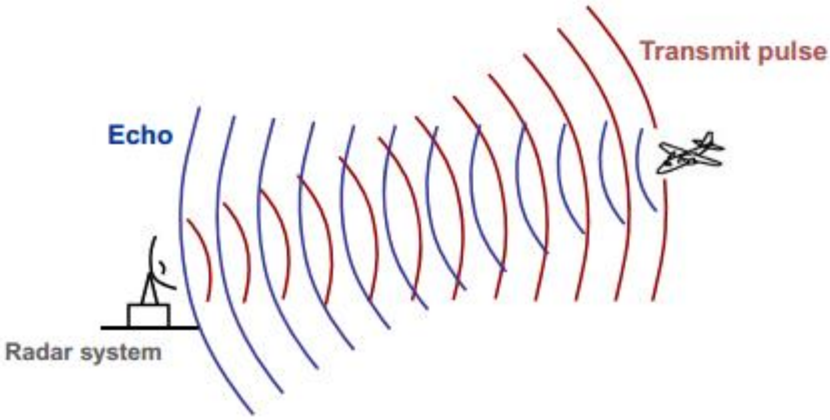

Figure 1.1 (b) Radar Principle 1

1.2.1 Scattering mechanism

1.2.1.1 General scattering

SAR images represent the back scattering of radar from the certain area on the ground. Few of them are high backscatter and few of them are low backscatter, darker portion of the image represents the low backscatter while brighter area represents the high backscatter. When large fraction of radar energy was reflected back to radar more brightness will appear while dark feature imply that only a small part of energy was reflected back. Backscattering depends on the various many factors like size of the target scattered area, target moisture content i.e. wetter the object brighter the appearance and drier the object darker the appearance. Apart from these wavelength, polarization of SAR pulses and observation angle also affect the backscattering[4][5].

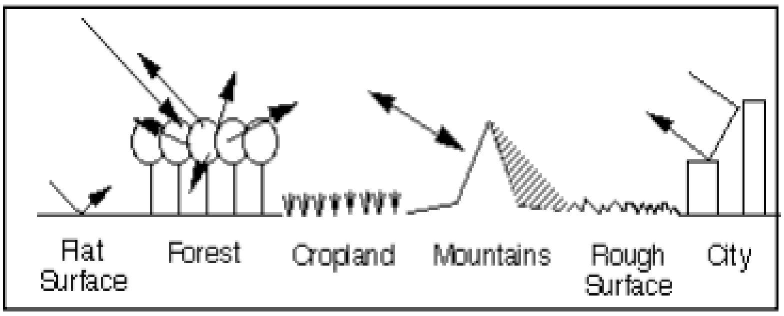

Figure 1.2 General Scattering

1.2.1.2 Surface and Volume Scattering

There are two types of surfaces rough or smooth. In case of rough surfaces the scattering is high, it appears bright in the image. Where flat surface reflects little or no light so appears dark in the images [3].

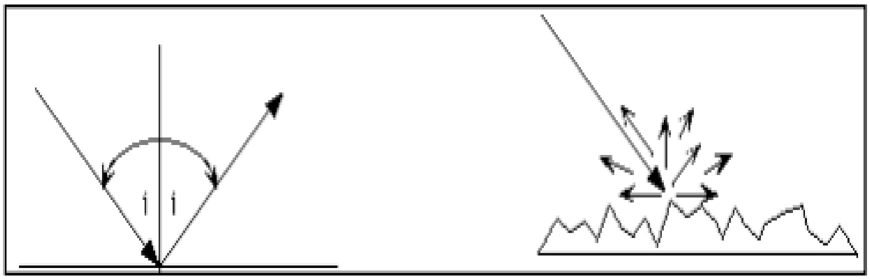

Figure 1.3 surface scattering

Vegetation partially reflects, so it appears grey or light grey in the images.

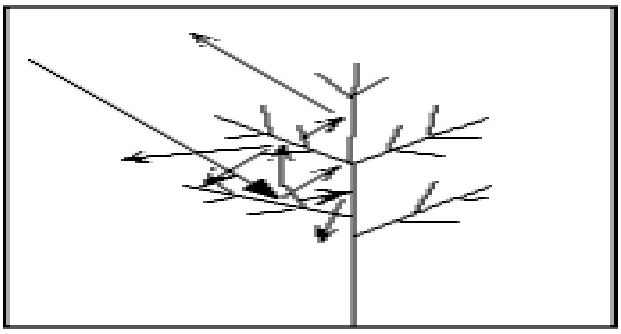

Figure 1.4 vegetation scattering

1.2.1.3 Double bounce

Inclined surfaces scatter more than slope away surfaces, so it tends to appear bright in a radar image. Shadow are like back side of mountains will not be illuminated by the radar and it appears dark. Some sequence of building tends to scatter double times and received by radar, it also appear white or bright in SAR images. Flat surfaces like open ground, roofs, and roads appear dark. Finally some surfaces are which are not lined up will appear grey in image.

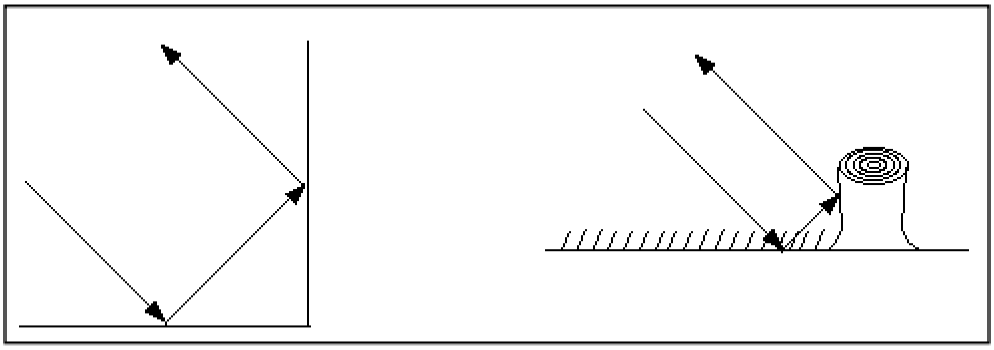

Figure 1.5 Double bounce

1.3 SAR Models

Statistical model helps in the interpretation of the SAR images. It reveals the characteristic of SAR. Images through which one can understand the scattering mechanism. Various statistical models have been illustrated and to describe the SAR image data.

Statistical models have been divided into parametric and non-parametric models[6].

1. Parametric model
2. Non- Parametric model

1.3.1 Parametric model

Parametric models assumes that the underlying probability distribution for SAR Imaged data is known. The paticular form of distribution ensures the estimation of various parameters by adopting fixed statistical techniques like moment method, Maximum Likelihood estimation (MLE) etc.

The main task is to find out the optimal distribution. Various moment parametric models required a theoretical model which could provide the mathematical form of the distribution. This class of model can be categorized in four following as

1. Empirical model
2. Gaussian type model
3. roduct model

4. Models based on Rician distribution, Joint distribution etc.

1.3.2 Non-parametric model

In non-parametric model the underlying probability distribution is not specified. In this model information about the data is not known prior the calculation. The probability distribution functions can be computed from the data. Non – parametric model used Parzen window method, support vector to estimate the probability distribution function. Thus various attempts have been made to adopt non- parametric models because knowing everything in advance is very difficult.

1.4 SAR Sensors Vs. Optical Sensors

SAR Sensors are different in many respects with optical sensors, as optical sensors also records electromagnetic energy. Still There are many differences between the SAR and Optical sensors as follows

1. SAR uses wavelength of 1cm to 1m while optical sensors uses wavelength of 1 micron near that of visible light.

2. SAR uses wavelength of 1cm to 1m while optical sensors uses wavelength of 1 micron near that of visible light.

3. SAR can capture images in cloudy and stormy weather while optical can't reflect the light properly during this condition. Scattering mechanism of electromagnetic waves is different for different wavelength and frequency.

4. Optical sensors works well in sun's illumination while SAR sensors works equally at any time in day and night.

5. SAR projections in all directions while optical sensors look straight down

Every sensor has pros and cons. For example SAR imaging is better for taking images of Iceland because optical sensor snow and ice appears bright white which makes images featureless.

1.5 Organization Of Thesis

This thesis contains five chapters. **Chapter 1,** Contains the introduction of SAR images and its principle. In the last of chapter there is comparison between Radar vs. Optical image. In **Chapter 2,** This chapter totally dedicated to Information theory, mutual information and Entropy. **Chapter 3**, In this chapter survey based on SAR images change detection and similarity measure for those images. **Chapter 4,** Illustrate the proposed work in which similarity found between two co-registered multi-temporal images using probalistic approach.and results are presented to support the theory. **Last chapter**, gives conclusion and future aspect of related work.

CHAPTER 2

ENTROPY AND MUTUAL INFORMATION

2.1 ENTROPY (UNCERTANITY OR COMPLEXITY)

In 1948 Claude Shannon[7][8] introduced the concept of entropy and publishing a paper in the field of Mathematical theory and its Communication which provided the fundamentals of the information theory. Shannon introduced and explained the term like channel capacity, entropy and mutual information and shows its significance in communication theory. The entropy measures the uncertainty, surprise, or information on the outcome of a situation. For example, the reception of a message or the outcome of the event. Shannon coined the term Entropy and evaluated it for the development of communication theory. It is the most commonly used in measure of information in signal and image processing. Entropy will have a maximum value of H when all the symbols have equal probability.

$$H(X) = -K\sum_{i=1}^{n} Pi \log Pi$$

$$= K\sum_{i=1}^{n} Pi \log \frac{1}{Pi} \qquad (2.1)$$

Where K is a constant.

The value of H(x) must be greater or equal to zero. It lies between zero and one.

$$H(X) \geq 0$$
$$0 \leq H(X) \leq 1$$

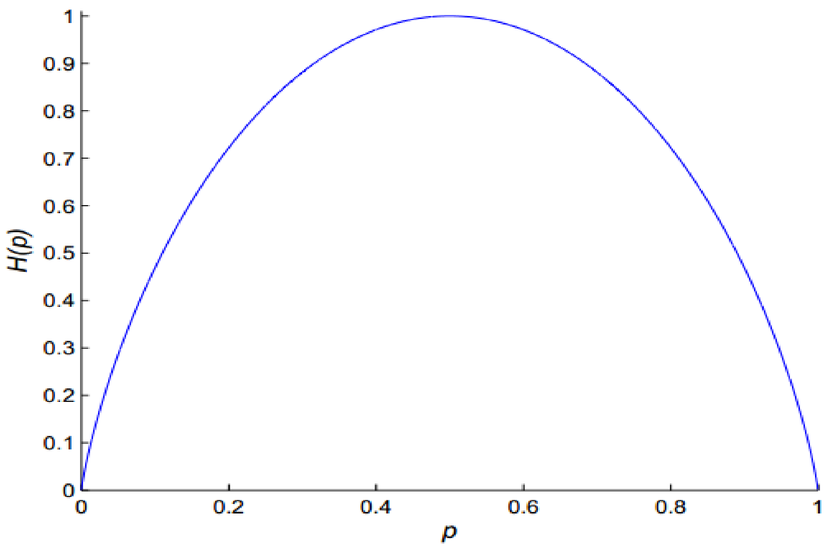

Figure 2.1 Variation of Entropy function with probability

when p = 0 or p = 1 the value of entropy = 0. Hence it is maxium is at p = 0.5 and varies between the value of range between 0 and 1. If the probability of occurring is p = x then its probability of non- occurring is $p' = 1\text{-}x$.

2.1.1 Joint Entropy

The joint Entropy H(X, Y) of a pair of variable is defined [9] as

$$H(X,Y) = -\sum_i \sum_j p(x_i, y_j) \log p(x_i, y_j) \tag{2.2}$$

Joint probability of two random variable x_i, y_j is defined as

$$p(x_i, y_j) = P(X = x_i, Y = y_j)$$

$$i = 1, \ldots\ldots, n$$

$$j = 1, \ldots\ldots, n$$

Directly we can calculate the joint entropy that is associated with bivariate vector

(X,Y) which is defined same as the joint entropy of two variable (2.2).

$$H(X,Y) = -\sum_i \sum_j p(x_i, y_j) \log p(x_i, y_j)$$

Marginal distributions of probability function are defined as

$$p_X(x_i) = \sum_j p(x_i, y_j)$$

$$p_Y(y_j) = \sum_i p(x_i, y_j) \tag{2.3}$$

For independent variables, we have

$$p(x_i, y_j) = p_X(x_i).p_Y(y_j) \tag{2.4}$$

Put these values this in formula (2.2), we get

$$
\begin{aligned}
H(X,Y) &= -\sum_i \sum_j p_X(x_i) p_Y(y_j) \log\left[p_X(x_i) p_Y(y_j) \right] \\
&= -\sum_i \sum_j p_X(x_i) p_Y(y_j) \log p_X(x_i) \\
&\quad - \sum_i \sum_j p_X(x_i) p_Y(y_j) \log p_Y(y_j) \\
&= -\sum_i p_X(x_i) \log p_X(x_i) \sum_j p_Y(y_j) \\
&\quad - \sum_i p_X(x_i) \left[\sum_j p_Y(y_j) \log p_Y(y_j) \right]
\end{aligned} \qquad (2.5)
$$

$\sum_j p_Y(y_j) = 1$ and $\sum_i p_X(x_i) = 1$,

we have

$$H(X,Y) = H(X) + H(Y)$$

2.1.2 Conditional Entropy

In case of conditional entropy we observe that the $Y = y_j$ in a bivariate distribution. Hence the value of entropy will reduce. This is the situation that required for introduction of conditional entropy when giving uncertainty outcome of X once we have observed $Y = y_j$ i.e.

$$H(X \mid Y = y_j) = -\sum_{i=1}^{n} p(x_i \mid Y = y_j) \log(p(x_i \mid Y = y_j)) \qquad (2.6)$$

Finding the average of all y_j, gives the value of conditional entropy

$$
\begin{aligned}
H(X \mid Y) &= \sum_j p_Y(y_j) H(X \mid Y = y_j) \\
&= -\sum_i \sum_j p_Y(y_j) p(x_i \mid Y = y_j) \log p(x_i \mid Y = y_j) \\
&= -\sum_i \sum_j p(x_i, y_j) \log p(x_i \mid y_j)
\end{aligned} \qquad (2.7)
$$

Using this we find

$$
\begin{aligned}
H(X|Y) &= -\sum_i \sum_j p(x_i, y_j)\log\frac{p(x_i, y_j)}{p_Y(y_j)} \\
&= -\sum_i \sum_j p(x_i, y_j)\log p(x_i, y_j) \\
&\quad + \sum_i \sum_j p(x_i, y_j)\log p_Y(y_j) \\
&= H(X,Y) - H(Y)
\end{aligned}
$$

(2.8)

$H(p_1, p_2, ..., p_n) = H(X)$ represent the average value of uncertainty that is associated with random variable X.

2.2 Mutual Information(MI)

Mutual information measures the amount of information that one random variable contains about another random variable. It reduces the uncertainty of one random variable due to the knowledge of the other. Shannon first presented the functional form of mutual information between sender and receiver in the field of communication.

Let us consider a method in which we are taking input variable is X and output variable is Y. The random variables are preassumed to be correlated to each other. The difference $H(X) - H(X|Y)$ shows the uncertainty in input variable X after that output variable Y is observed. This could be taken as mutual information between the input variable X and output variable Y[10].

$$I(X;Y) = H(X) - H(X|Y) \tag{2.9}$$

Mutual information derived in form of joint probability mass function is stated as[11]

$$
\begin{aligned}
I(X;Y) = & -\sum_i p_X(x_i)\log p_X(x_i) \\
& +\sum_i\sum_j p(x_i,y_j)\log\frac{p(x_i,y_j)}{p_Y(y_j)} \\
= & -\sum_i\sum_j p(x_i,y_j)\log p_X(x_i) \\
& +\sum_i\sum_j p(x_i,y_j)\log p(x_i,y_j) \\
& -\sum_i\sum_j p(x_i,y_j)\log p_Y(y_j)
\end{aligned}
\tag{2.10}
$$

Hence we can get

$$
I(X;Y) = \sum_i\sum_j p(x_i,y_j)\log\left[\frac{p(x_i,y_j)}{p_X(x_i)p_Y(y_j)}\right] \tag{2.11}
$$

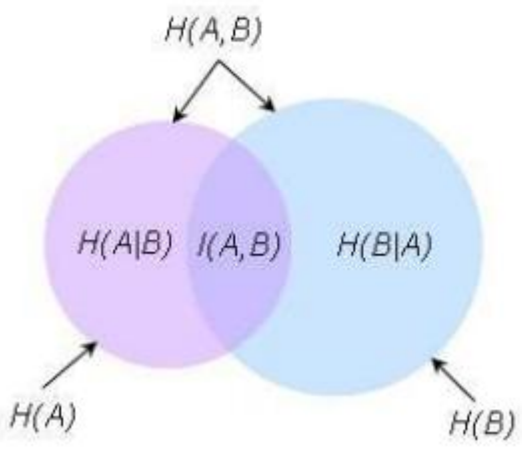

Figure 2.2 Relationship between entropy and mutual information

In th above figure mutual information correspond to the I (A,B), intersection of H(A) and H(B).

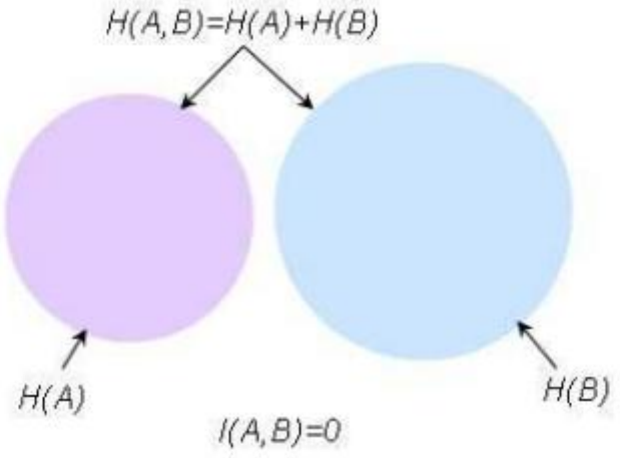

Figure 2.3 Relationship between joint entropy and MI of totally unrelated image

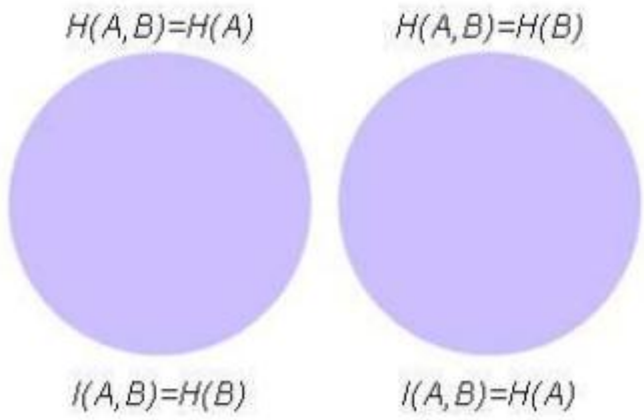

Figure 2.4 Relationship between joint entropy and MI of totally related images

Here is no mutual information between A and B as A and B are totally dependent, that is outcome of an event in A gives exact knowledge of the outcome the event of B . In this case joint entropy of of teo images equivalent to the entropy of image A or B separately. So the mutual information would br either H(A) or H(B).

$$I(A,B) = H(A) + H(B) - H(A,B)$$

H(A) and H(B) are the entropy of the two images and H(A,B) is the mutual information. As the images are independent value of H(A,B)=0.

CHAPTER 3

LITERATURE REVIEW

Measuring Changes or similarity in SAR images help in forest and vegetation monitoring[12]. It also helps in finding natural disaster affected area like flood[13]. The change detection[14] or similarity measure technique require two co-registered multitemporal images. First image is treated as master image and second image which is taken over different span of time is required which used for comparison is known as slave image. Major problem in detecting differences through normal process like as used in optical images is difficult because of presence of speckle noise in SAR images. Noise occurs in SAR images due to certain technical and climatic measure. Minimizing the effect of speckle noise in images is proposed by using Mean ratio detector. In this method a small portion of 3×3 window is taken and after that calculate the mean of this nine pixels and in last calculate mean ratio[15].

Change detection can be done by two techniques: Unsupervised and Supervised. In case of supervised technique, the knowledge of prior statistics is required while in unsupervised techniques, the detection is given more focus than the classification of the change.

The aim of change detection techniques is to generate a change indicator for each pixel of the region of interest. This change indicator is due to the application of local similarity measure to the images. We take large number of samples to perform high quality of results. In case of small sample one should know prior know the statistics of SAR image. Some of the commonly used similarity measure techniques based on images statistics are:

1. Mean Ratio Change Detector (MRCD)
2. Correlation coefficient of two image
3. Similarity measure in SAR images
4. Simiarity measure in multisensor images

3.1 Mean Ratio Change Detector

SAR Images is more prone to speckle noise which is multiplicative in nature. Mean ratio change detector (MRCD) used to minimize the effect of speckle noise for measuring change detection in SAR images. Here we take a fix size window in both master and slave images and calculate the mean of both the windows. Let us take two co-registered multi-temporal SAR images I_X and I_Y captured at two different dates T_X and T_Y respectively The MRCD produce a binary image for spotting the places where changes have occurred in the images over the time T_X and T_Y. Our goal is to generate a binary image corresponding to the two classes: change and no change. This process helps in change-detection analysis of images. The remaining part of problem can be solved via one more step that is the thresholding of the change image in a particular order. For calculating the MRCD we follow the steps as[15]:

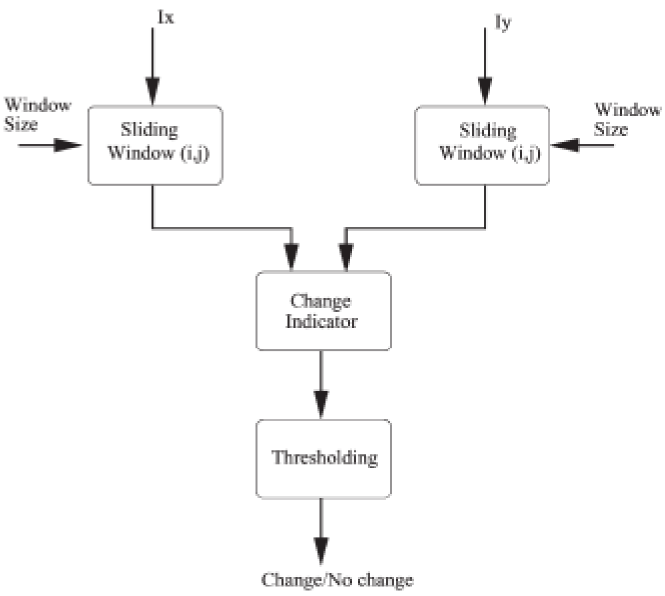

Figure 3.1 Block Diagram For Change Detection

Difficulty occurs in multi-temporal analysis of SAR images is due to presence of speckle noise. The speckle noise is different from one image to another image and its makes the change detection more difficult.

Property maximize the high number of false alarm rate in change detection. The nature of speckle is multiplicative and MRCD uses a classical approach in SAR images. Let R and S be reference image and secondary image, respectively and μ_r and μ_s be local mean values in R and S, then mean ratio detector is defined as

$$r_{MRD} = 1 - \min\left\{ \frac{\mu_r}{\mu_s}, \frac{\mu_s}{\mu_r} \right\} \tag{3.1}$$

SAR image 1

SAR image 1

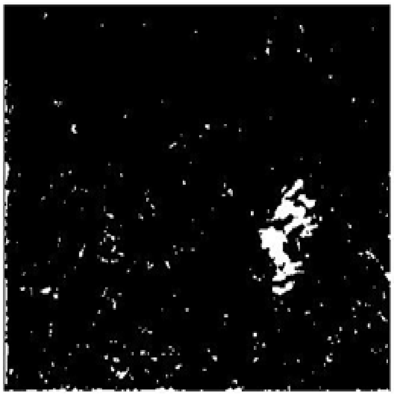

Figure 3.2 Binary Image Shows Changes in SAR Image 1 and SAR Image 2

The major drawback of this technique is that if change occurs at global level it does not detect it locally because of preservance of local statistical properties. As SAR sensors are independent of sunlight and atmospheric condition. Which makes it more interesting.

There are unsupervised approach change detection divided into three steps [18]

1. Image processing
2. Producing difference image between the multi-temporal images
3. Analysis of the difference image

In image processing we do co-registration, geometric correction and noise reduction of the images[16], In second step we compare the image pixel to pixel and generate the difference image. In SAR images the differencing and rationing operator are two major tool for generating of binary image. In case of pixel to pixel, changes are produced by subtracting intensity values pixel by pixel. In case of mean ration operator we take a window size and calculate the mean by using 3.1. MRCD is more robust to change detection in presence of speckle noise.

In order to get the more robust result we can take fusion of two approcahes mean ratio and log ratio[17].

$$X_m = 1 - \min\left(\frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1}\right)$$

$$X_l = \left|\log\frac{X_2}{X_1}\right| = |\log X_2 - \log X_1| \qquad (3.2)$$

Xl is the log ratio operator.

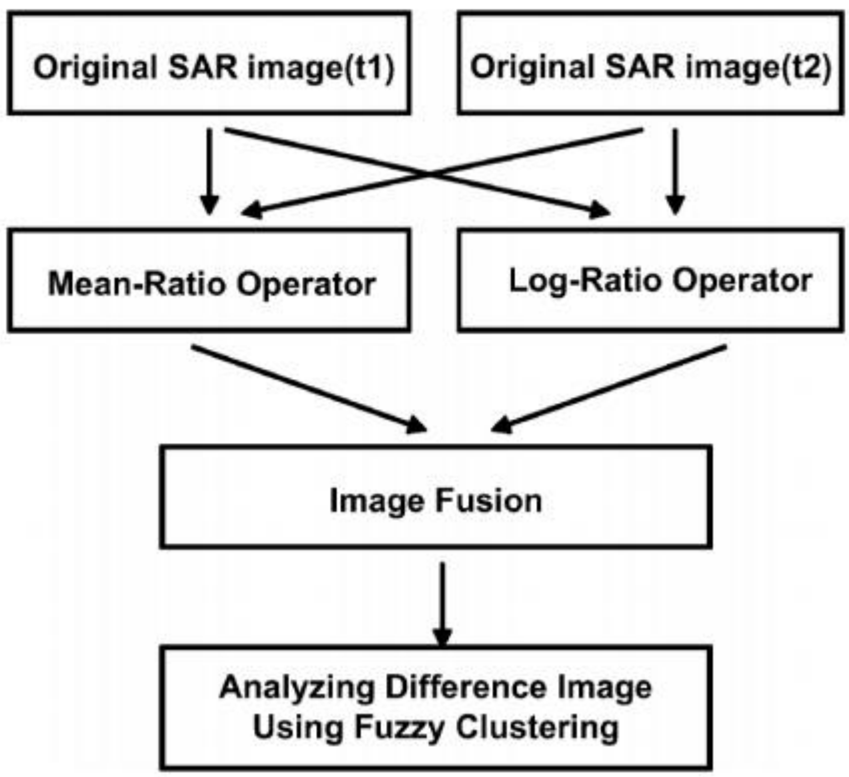

Figure 3.3 Proposed Fusion of Mean Ratio And Log Ratio

Fusion of these two operator is done by using the Discrete wavelet transform(DWT) for the pixel level image fusion. The DWT isolates frequencies in both space and time, allowing to extract detailed information from images. For the fusion DWT is better than others like curvelets , contourlets .

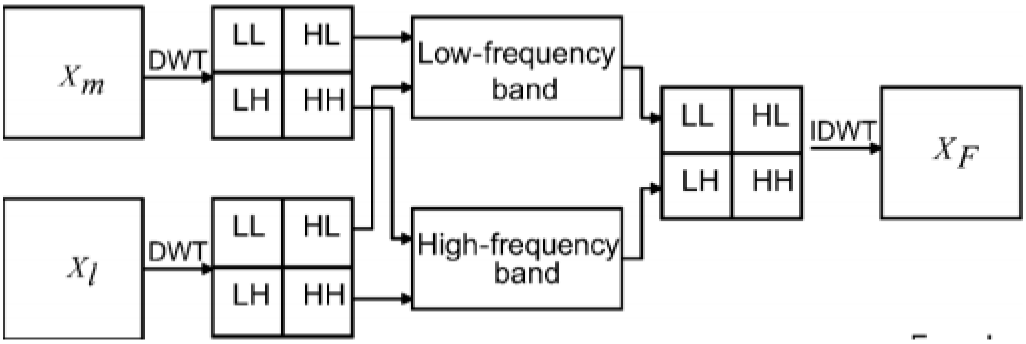

Figure 3.4 Image Fusion Based on DWT

Here the images are divided into four parts as shown in above figure and the selection for the fusion is done in high frequency and low frequency band respectively and the resultant is the fused image generated. The fusion rule is described as

$$D_{\mathrm{LL}}^{F} = \frac{D_{\mathrm{LL}}^{m} + D_{\mathrm{LL}}^{l}}{2}$$

$$D_{\varepsilon}^{F}(i,j) = \begin{cases} D_{\varepsilon}^{m}(i,j), & E_{\varepsilon}^{m}(i,j) < E_{\varepsilon}^{l}(i,j) \\ D_{\varepsilon}^{l}(i,j), & E_{\varepsilon}^{m}(i,j) \geq E_{\varepsilon}^{l}(i,j) \end{cases} \qquad (3.3)$$

Figure 3.5 Generating Fused Image

Where m and l are mean ratio and log ratio image respectively and D_{LL} is low-frequency coefficient constant. D_e(i,j) represents the three high frequency coefficient at point (i,j).

Suppose we take two SAR images and its fused image will be generated as

SAR Image 1

SAR Image 2

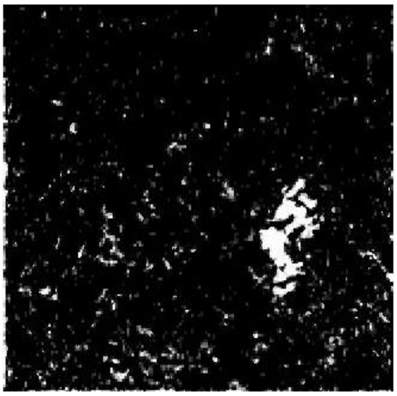

Figure 3.6 Binary Fused Image

3.2 Correlation Coefficient of Two Images

It uses variance or second order statistics for compution of the similarity measure between two SAR images. If Im and I_S are spell as master and slave images respectively, then the correlation coefficient between them is calculated as

$$\rho = \frac{\sum_{i,j \in Neighborhood} Im(i,j) \cdot I_s(i,j)}{\sigma_m^2 \cdot \sigma_s^2} \tag{3.4}$$

where σm and σ_s are variance of estimated window of master image (Im) and slave image (I_S) respectively.

3.3 Similarity Measure in SAR Images

Similarity measures is process of summarizing two images of the same scene captured with different sensors and at different time. Both images have different radiometric properties one is captured by the optical sensor and other is by radar . Since both the images are not same and nohaving the similar properties which makes it difficult to find the similarity between two images. In registration of both the images goal is to find a spatial transformation related to two images.

A simple way is to extract the features from each images with a segmentation step and try to minimize the distance criterion between these measured features. Now a days it is directly based on the intensity of the pixel and there is no need of the preliminary feature extraction. topics.

Let us conside the two images X and Y , to measure the similarity the function is defined as f(X,Y,c) , it shows on the basis of the variable c that how much both the images are similar. Since the similarity measure is measured only with the help of probability density and with the help of both probability density and radiometric properties.

Let $p_x(i)$, $p_y(j)$ is probability of image window size of image X and Y . $p_{xy}(i,j)$ is the joint probability of both the images. For statistical indendence we find

$$p_{xy}(i,j) = p_x(i) \times p_y(j) \qquad (3.5)$$

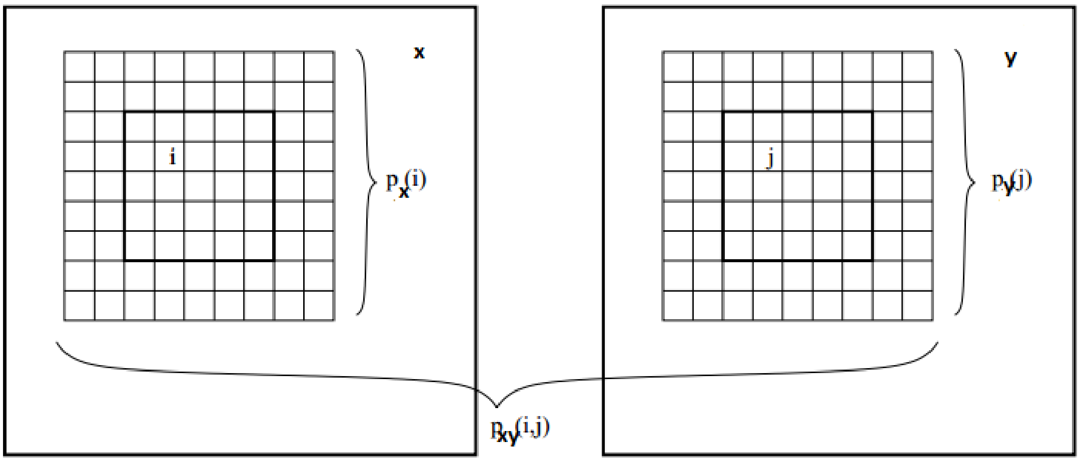

Figure 3.7 Image to Finding Out Absolute And Joint Probabilities

There are many approachs to measuring similarity between the two SAR images , We can broadly classify the methods in two main category.

3.3.1 Measuring similarity using the probabilities

3.3.1.(a) By mutual information

3.3.1.(b) CRA (cluster reward algorithm)

3.3.1.(c) Independence distance

3.3.2. Measuring similarity by combining both radiometric values and probabilities

3.3.2.(a) Woods criteria

3.3.2.(b) Correlation ratio

3.3.1.(a) By Mutual Information

Shannon introduced the concept of information theory, which is based on the log values. It measures the uncertainity of the event X and Y.When a particulare event is certain then its probability is equal to unity and its maxium values lies when all the event have same probability. The entropy of the images can be calculated as given by the Shannon formula[19].

$$H(X) = -K\sum_{i=1}^{n} Pi \log Pi \tag{3.6}$$

And its mutual information[20] of both the images is calculated as

$$\begin{aligned} MI(X,Y) &= H(X) + H(Y) - H(I,J) \\ &= H(X) - H(I/J) \\ &= H(Y) - H(J/I) \end{aligned} \tag{3.7}$$

$H(X,Y)$ is the joint entropy of the images X and Y, $H(X/Y)$ or $H(Y/X)$ is the conditional entropy of the images with respect to X and Y.

3.3.1.(b) CRA (Cluster Reward Algorithm)

The CRA(X,Y) has a large value when there is little dispersion between the joint histogram . If there is little disersion between the image intensities of the generated histogram , this can be considered as a good result and there is possibility to predict the values of the one image from those of another images[21].

Let $H_{R,S}(r,s)$ be the joint histogram of master image and slave image, and let $H_R(r)$ and $H_S(s)$ be the marginal histogram of master image and slave image respectively. N is the number of pixels then CRA this measure can be defined as

$$I_{CRA} = \frac{\frac{\Phi}{G} - \frac{G}{N^2}}{1 - \frac{G}{N^2}} \tag{3.8}$$

$$\text{where, } \Phi = \sum_{r=0}^{N-1} \sum_{s=0}^{N-1} H_{R,S}^2(r,s)$$

$$G = \sqrt{h_R h_S}$$

$$h_R = \sum_{r=0}^{N-1} H_R^2(r)$$

$$h_S = \sum_{s=0}^{N-1} H_S^2(s)$$

3.3.1.(c) Independence Distance

In the independent distance we calculate the difference of the both terms marginal probability and joint probability which measures directly the degree of indepence of the both images.

$$DT(X,Y) = \sum \frac{(p_{xy}(i,j) - p_x(i).p_y(j))^2}{p_x(i).p_y(j)} \tag{3.9}$$

3.3.2.(a)Woods Criteria

Sometimes probability value is not predicting the exact information about the similarity in images , then we need to consider the radiometric value of both the images also. Estimate the correlation between two images[22].

mean:

$$M(X/j)=\frac{1}{p_y(j)}\sum i.p_{xy}(i,j) \tag{3.10}$$

And conditional variance

$$\sigma^2(X\mid j)=\frac{1}{p_y(j)}\sum (M(I\mid j)-i)^2.p_{XY}(i,j) \tag{3.11}$$

By calculating the mean it is easy to define the pixel intensity variability in one image with respect to other images. If there is difference in images then variability is larger otherwise smaller.

$$V(X\mid Y)=1-\sum \frac{\sigma(X\mid j)}{M(X\mid j)}p_y(j) \tag{3.12}$$

3.3.2.(b) Correlation Ratio

Correlation ratio is define as conditional mean and variance:

$$CR(X\mid Y)=1-\frac{1}{\sigma_X^2}\sum \sigma^2(X\mid j).p_y(j) \tag{3.13}$$

Here σ_x^2 is the variance of the radiometric properties of one of the images.

3.3 Similarity Measure for Multiple Sensor Image

Every type of sensor is different in its operational time,revisting period and capturing properties etc. many times for accurate analysis we take multiple images of same scene with different sensors. There are difference between the images acquired by the same sensor it can be automatically co-registered but in case of multiple sensor two approach are used [23]

1. Extracting common feature from the image and used them for registration.

2. Similarity measure between radiometry between the two images.

For the purpose of change detection we normailly prefer the images of same radiometric properties but if we want to compare th images of different radiometric properties we need to extract some common feature and patten matching algorithms or finding the dependency between the both images. To compare similarity measure we need to find 4 different similarity measure

A.Co-relation coefficient of two images both master and slave. It defines as

$$\eta = \frac{\sum_{i,j\varepsilon Neighbourhood} I_m(i,j).I_s(i,j)}{\sigma_m^2 \sigma_s^2} \tag{3.14}$$

B. Cluster reward algorithm

Let $H_{MS}(k,l)$ be joint histogram of master and slave image. $H_M(k)$ is histogram of master image. $H_S(k)$ is histogram od slave image. Then the similarity measure will define as

$$I_{CRA} = \frac{\frac{\phi}{F} - \frac{F}{P^2}}{1 - \frac{F}{P^2}} \tag{3.15}$$

where

$$\phi = \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} H_{MS}^2(k,l)$$

$$F = \sqrt{h_m h_s}$$

$$P = N \times N$$

$$h_M = \sum_{k=0}^{N-1} H_M^2(k)$$

$$h_S = \sum_{k=0}^{N-1} H_S^2(k)$$

Value of I_{CRA} have a high value when there is little dispersion in joint histogram.Here dispersion is related to co-relation of the data or clustering of the data. Now we will easure the Mutual Information of two random variables using 2.5. It act as the generalization of correlation.

3.4.1 Fusion of Information of Multiple Sensors

Analysis of SAR image or finding the change detection in SAR images is becomes difficult ewhen land cover type/ surface material is spectrally similar. This makes extremely difficult to analyse the scene using single sensor[24]. Therfore the more then one sensor data is needed , here extraction of data and fusion of data of both the sensors helps to predict it in efficient way.

For such a fusion cases we follows three steps

1. Image preprocessing and registration
2. Image fusion
3. Image change detection

Image registration is done for the images taken by more than two different type of sensors of the same scene. Calculting mutual information is provided stastical. dependencey between two randon variable. We can calculate the entropy of two images and find the mutual information or maxium statistical dependency between two images.

Image fusion done for obtaining information of greater quality by using dissimilar information form multiple sensors. For the fusion wavelet packet transform (WPT) is used.

Image change detection algorithm takes the two images as input and generate the output as a binary imagewhich identify the change pixels or the region where change has occurred over the period of time.

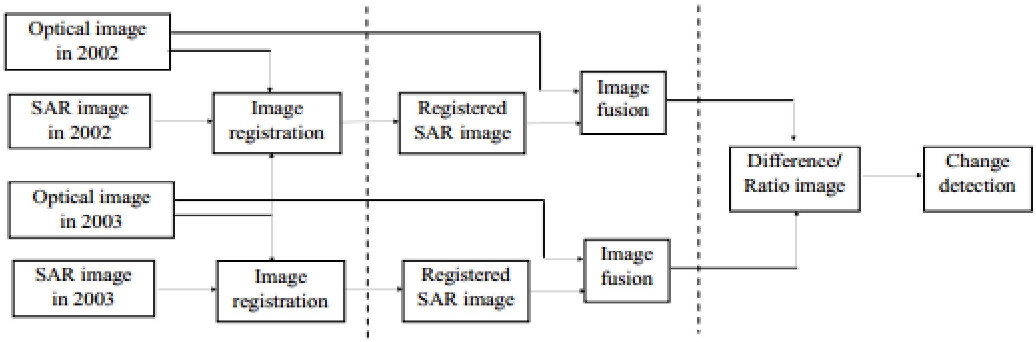

Figure 1.8 Diagram For Change Detection System

This diagram shows that the process of information fusion of data of different–different sensors.

CHAPTER 4

EXPERIMENTAL SETUP AND RESULT ANALYSIS

This chapter presented in two part. In the first part we make experimental setup and in the second part we do result analysis by considering certain variation in noises.

4.1 Experimenal Setup

Here we take a master image and will make a slave image by adding certain noises in that SAR image and then measure the similarity between the two images by using Renyi entropy. Here we considered that these particular noises are present in SAR images data. Noises have its cause to happen.We have considered that every cause that makes presence of noises in SAR images. Here we have taken three noises and their behaviour in measuring similarity with Renyi entropy.

4.1.1 Gaussian Noise

Gaussian noise occurred in images during the acquisition of images. It mainly caused by the high temperature, poor source of illumination and transmission of signal. Gaussian noise can also caused by natural sources like black body radiation from the earth, thermal vibration in conductors or from earth object like sun rays.

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \qquad (4.1)$$

Model of Gaussian noise is additive in nature and independent of each pixel and signal intensities. In images the main cause of this noise is sensor heat and illumination.

4.1.2 Salt and Pepper Noise

Salt and pepper noise also known as Fat-tail distribution or implusive noise or spike noise. Image with salt and pepper noises have dark pixel in bright region and vice-versa. It occurs due to transmission error i.e misplacing of bits or conversion from analog to digital.

4.1.3 Speckle Noise

Speckle noise is multiplicative noise.This type of noises are inherently exists and degrades the quality of SAR image. It generally occured by the fluctuation in return signal from the target and coherent backscattering of signal from multiple target which is random in nature. It increases the mean grey level of local area in images which makes it difficult to interpretate. General model of speckle noises are

$$G(m,n) \times U(m,n) + \eta(m,n) \tag{4.2}$$

Where, $G(m,n)$ is the observed image, $U(m,n)$ is the multiplicative component and $\eta(m,n)$ is additive component of speckle noise. Here m and n are axial and lateral indices of the images component.

4.3.4 Renyi Entropy and Renyi Mutual Information

Alfred renyi generalizes the Shannon, Hartley, Min- entropy, and the collision entropy. Basically entropy quantifies the uncertainty, diversity or randomness of the system. Renyi entropy of order α, where $\alpha \geq 0$ and $\alpha \neq 1$ is defined as

$$H_\alpha(X) = \frac{1}{1-\alpha} \log\left(\sum_{i=1}^{n} p_i^\alpha\right) \tag{4.3}$$

Here X denotes the discrete random variable with possible outcomes 1,2 …upto n and probability p_i for i=1 to n.

The mutual information of Renyi Entropy between two discrete random variable X and Y is $I(X,Y)$ with a joint probability mass function $f_{xy}(X,Y)$ and marginal prbability function $f_x(x)$ and $f_y(y)$ is calculted by the relative entropy between the joint distribution and the product of marginal distribution.

$$I_\alpha = \frac{1}{1-\alpha} \log \sum_{x\varepsilon X} \sum_{y\varepsilon Y} \frac{f_{xy}^\alpha(x,y)}{f_x^{1-\alpha}(x) f_y^{1-\alpha}(y)} \tag{4.4}$$

When X and Y are independent if $f_{xy}(X,Y) = f_x(x) f_y(y)$

4.2 Result Analysis

In the first section, the slave image with Gaussian noise has been analyzed and plotted at varying noise variance. In the second section, slave image with the salt and pepper noise at different noise variance has been analyzed and plotted. In the last section, the slave image with speckle noise is carried out at varying noise density and plotted.

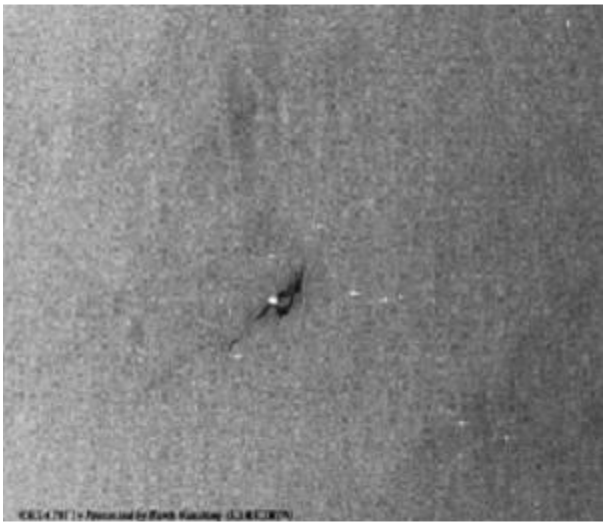

Figure 4.1 Master SAR Image

4.2.1 For Gaussian Noise

In this section we obtained the slave image is by adding zero-mean Gaussian noise in the master image. The plotting of graph of Renyi mutual information vs. varying noises value v =0.01 to v =1 and α value α = 0.1 to α = 2.0 .

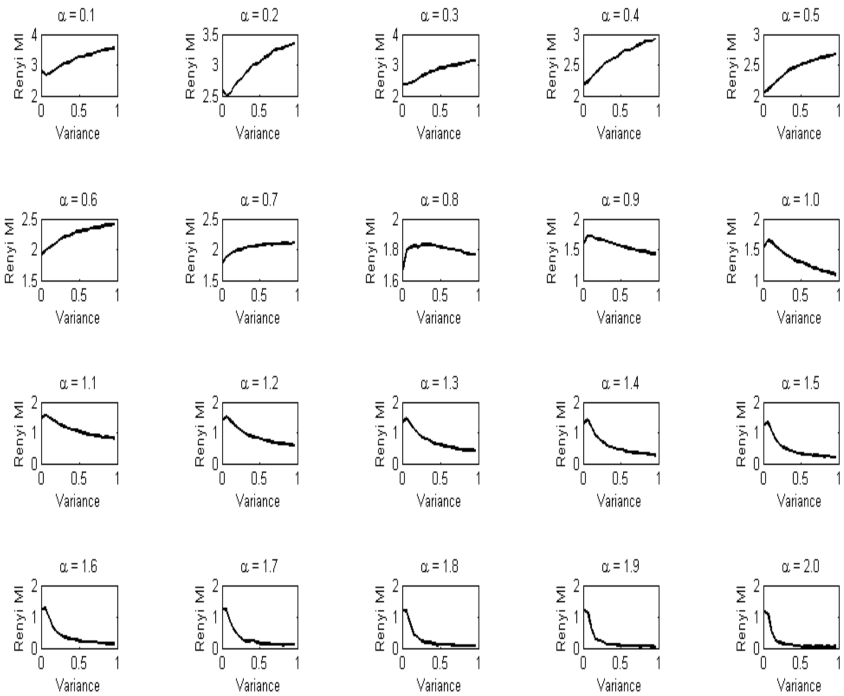

Figure 4.2 Analysis of Renyi MI with Different α For Gaussian Noise

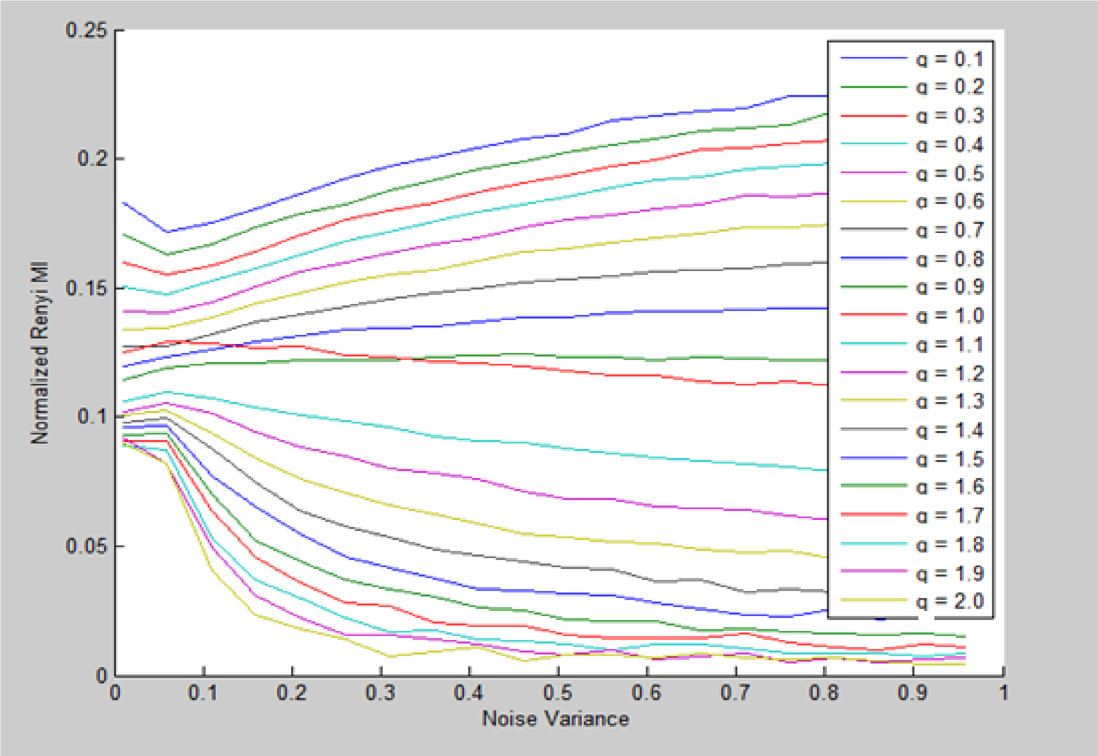

Figure 4.3 Aggregate Analysis of Renyi MI for Different α For Gaussian Noise

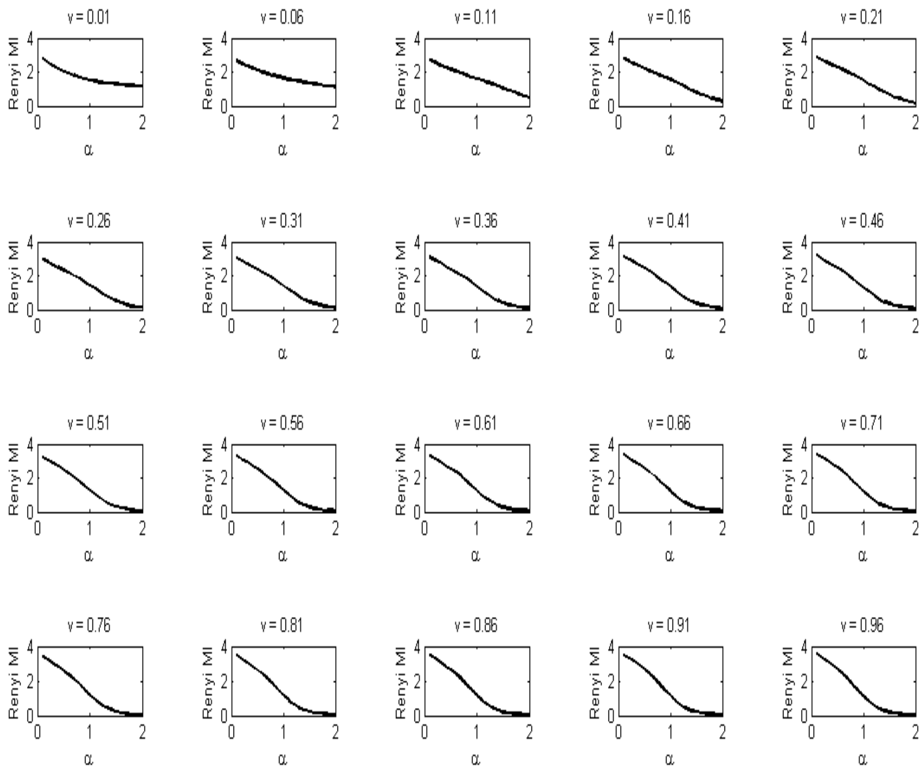

Figure 4.4 Analysis of Renyi MI With Different Gaussian Noise Variance

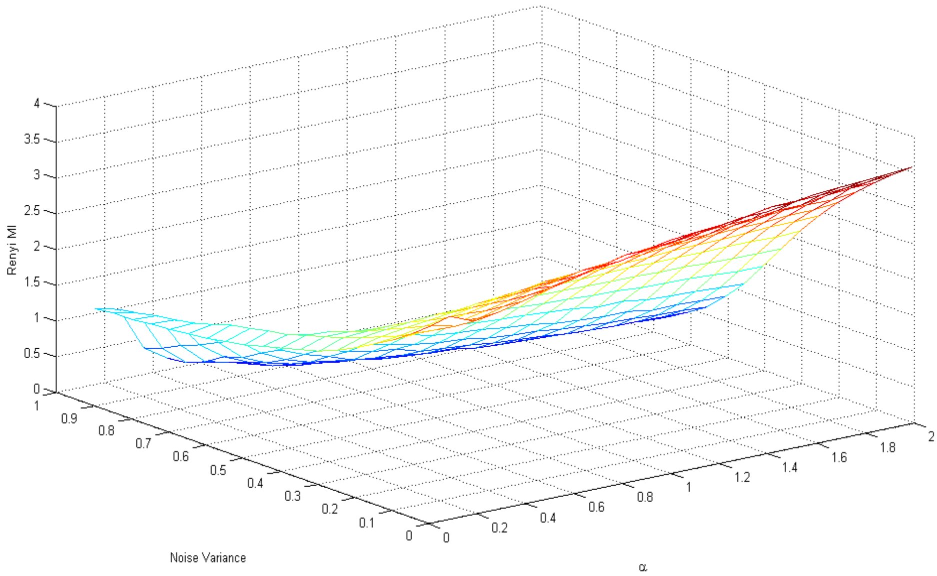

Figure 4.5 Mesh Plot of Renyi MI For Varying Gaussian Noise Variance And Varying α

4.2.2 For Salt and Pepper Noise

In this section we obtained the slave image is by adding noise density in the master image. The plotting of the slave image at different noises density value d =0.05 to d =1 and value of α varying from α =0.1 to α = 2.0 as shown below.

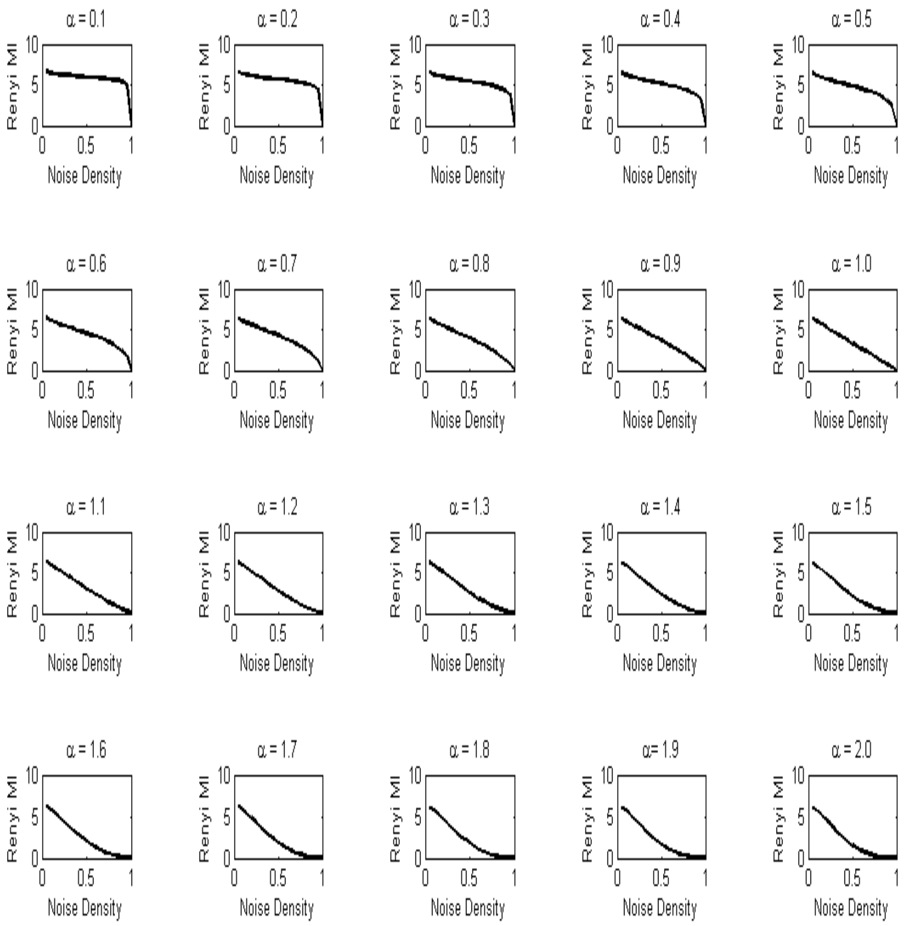

Figure 4.6 Analysis of Renyi MI With Different α For Salt And Pepper Noise

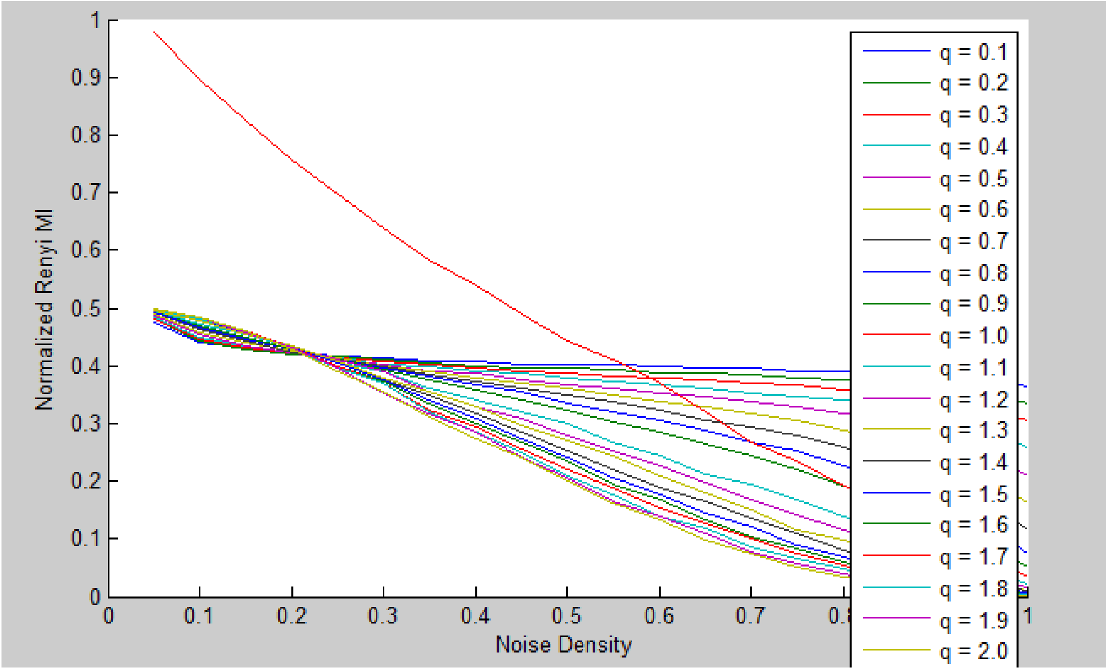

Figure 4.7 Aggregate Analysis of Renyi MI For Different α For Salt And Pepper Noise

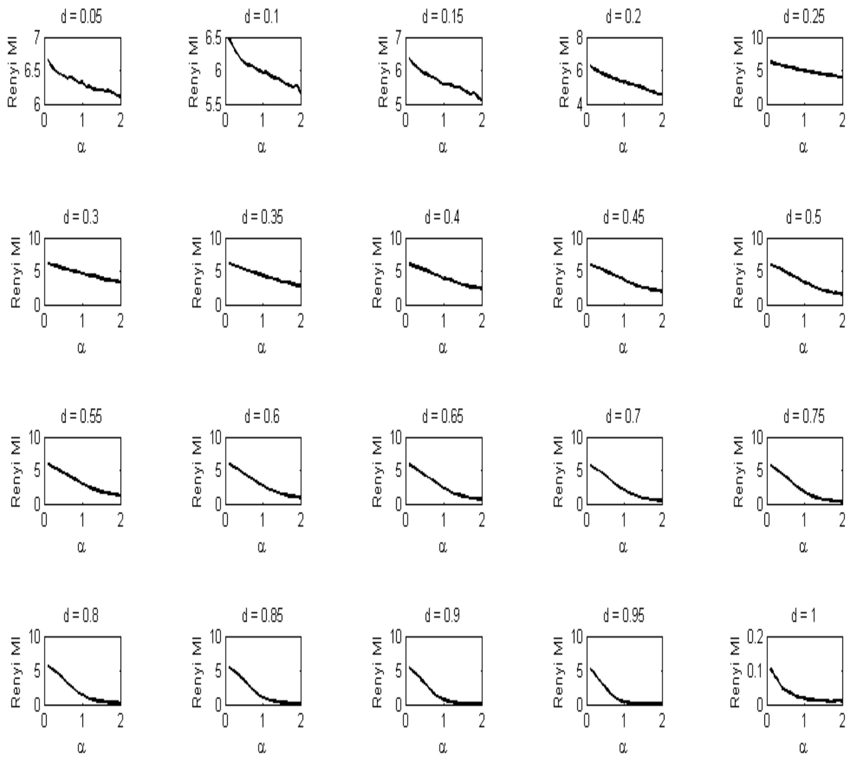

Figure 4.8 Analysis of Renyi MI With Different Salt And Pepper Noise Intensity

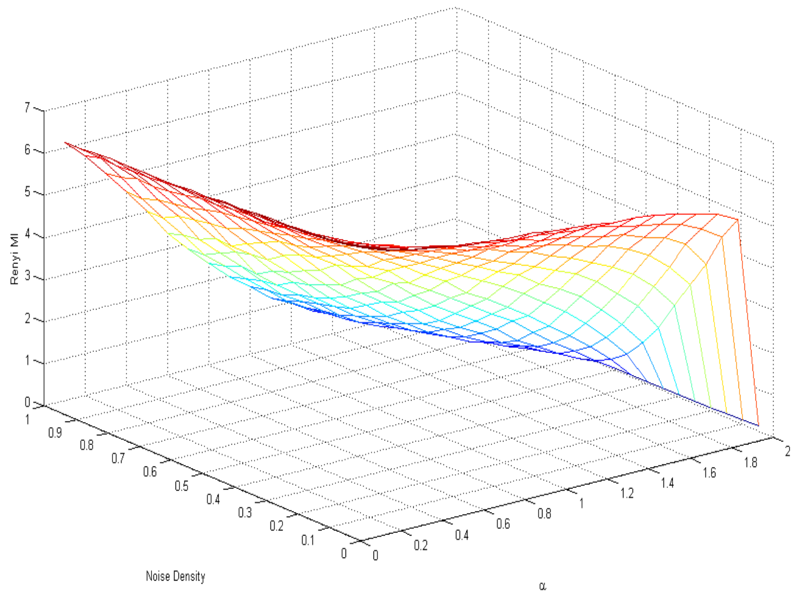

Figure 4.9 Mesh plot of Renyi MI For Different Salt And Pepper Noise Variance And Various α

4.2.3 For Speckle Noise

In this section we obtained the slave image is by adding speckle noise in the master image. Here the value of noises variance varying $v = 0.01\ to\ v = 1$ and value of α varying from α =0.1 to α =2.0 as shown below.

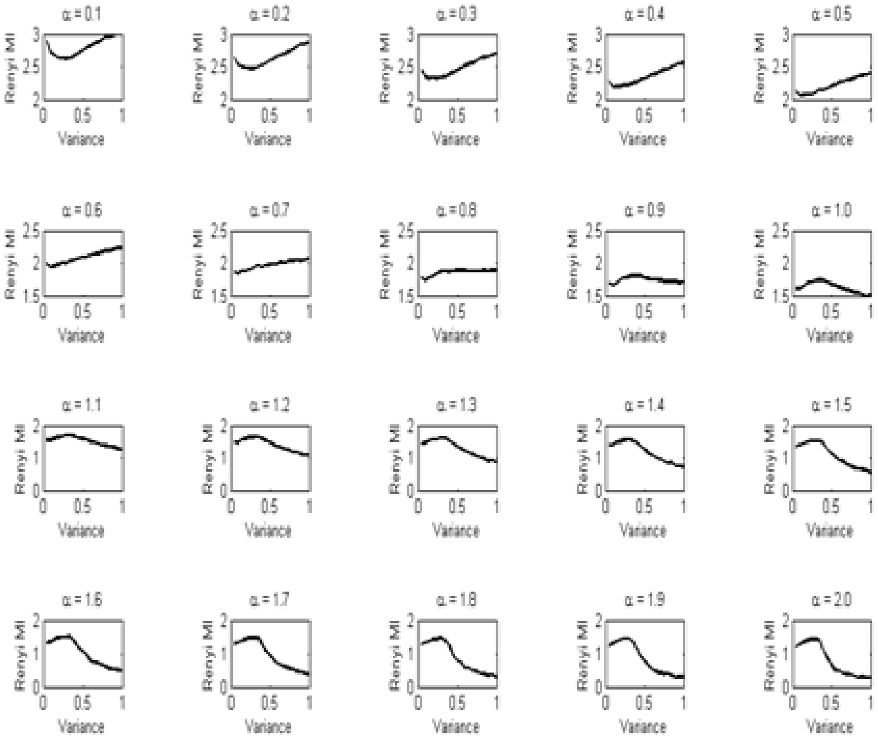

Figure 4.10 Analysis of Renyi MI With Different For a Speckle Noise

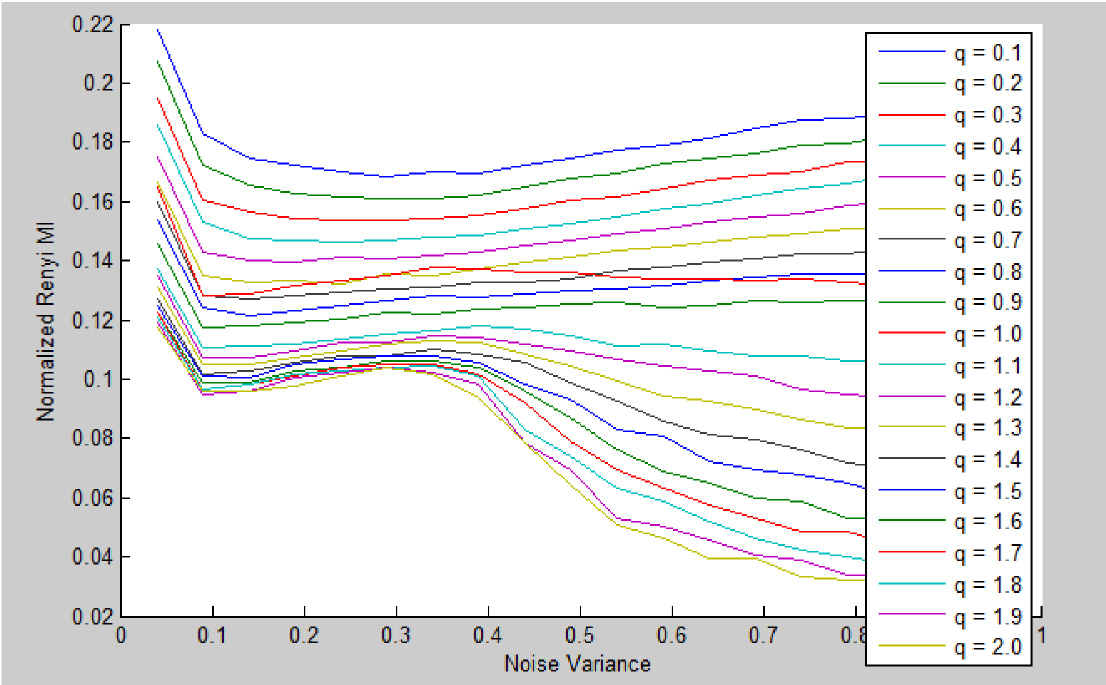

Figure 4.11 Aggregate Analysis of Renyi MI For Different α For Salt And Pepper Noise

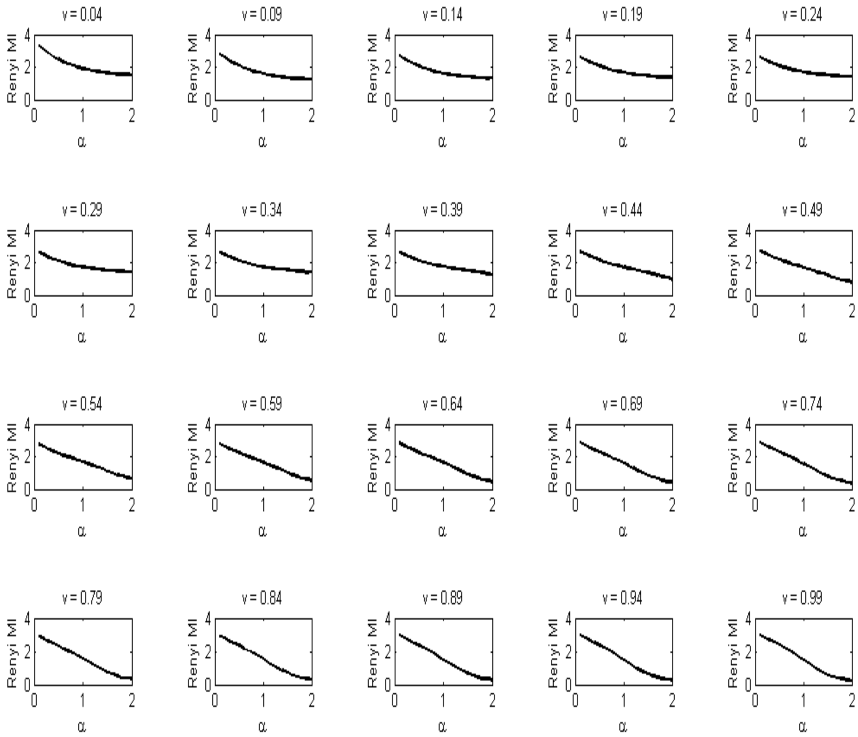

Figure 4.12 Analysis of Renyi MI With Varying Speckle Noise

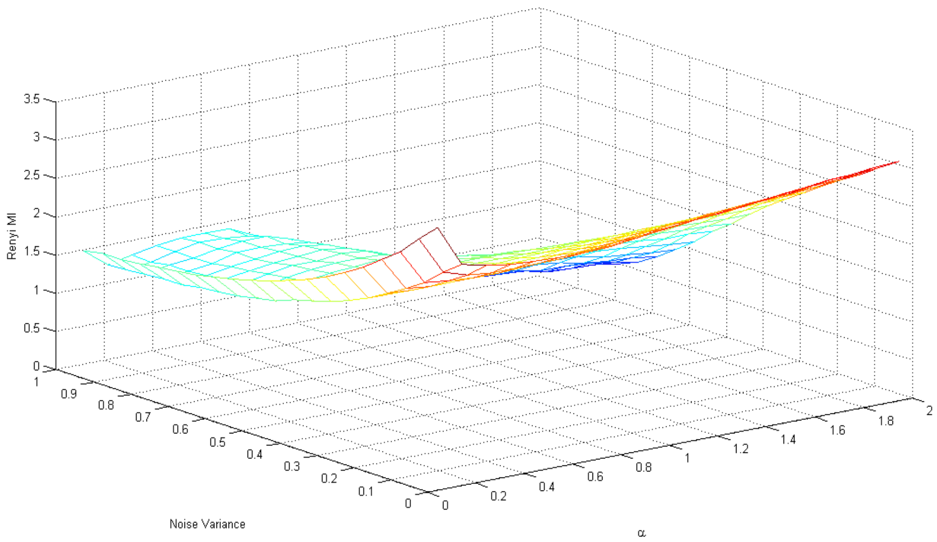

Figure 4.13 Mesh Plot of Renyi MI For Varying Speckle Noise And Various α

CHAPTER 5

CONCLUSION AND FUTURE WORK

CONCLUSIONS

This thesis presents an efficient approach to find out the similarity between the SAR images. We have analyzed the similarity measure for all value α in Renyi entropy and its mutual information. Generally $\alpha \to 1$ converges as Shannon entropy. Measuring the similarity between the images helps to predict the geographical changes that have occurred over the period of time. Addition of noise at any stage at the time of acquisition, due to heating of sensors, or in transmission makes it difficult to predict the similarity in images. Study of noises and its impact on the similarity measure properly simulated in this thesis. The method presented in this paper is a robust approach for various types of noises.

In future we can also use this method in case of shifting of pixels for measuring similarity.

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