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Change Detection Based on Hybrid Conditional Random Field Model with Applications to SAR Images Representation

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Abstract— **Change detection, which aims at identifying changed areas that occurred on the Earth's surface. Process of making a direct comparison of a pair of remote sensing images acquired over the same geographical area at different times. This paper proposes a hybrid conditional random field (HCRF) model for synthetic aperture radar (SAR) image change detection. The statistics of the log-ratio image derived from the two-temporal SAR images into conditional random field model. Proposed model is capable of integrating three kinds of information, including the texture features, the statistical distribution, and the spatial interactions. The HCRF model consists of three parts, namely, the unary potential, the pair wise potential, and the data term modelled by the statistics of the log-ratio image. Modification as a simple combination framework which uses the maps obtained by the mean filter and the median filter is proposed to generate a better change map. In future work k-means clustering algorithm is used to cluster it into two classes, changed area and unchanged area.**

Keywords— **Change detection, generalized Gamma distribution (GΓD), hybrid conditional random field (HCRF), Support Vector Machine (SVM), Synthetic Aperture Radar.**

I. Introduction

Environmental monitoring, earth-resource mapping, and military systems require broad-area imaging at high resolutions. Many times the imagery must be acquired in inclement weather or during night as well as day. Synthetic Aperture Radar (SAR) provides such a capability. SAR systems take advantage of the long-range propagation characteristics of radar signals and the complex information processing capability of modern digital electronics to provide high resolution imagery. Synthetic aperture radar complements photographic and other optical imaging capabilities because of the minimum constraints on time-of-day and atmospheric conditions and because of the unique responses of terrain and targets to radar frequencies. Synthetic Aperture Radar is a radar technology that is used from satellite or airplane. It produces high resolution images of earth's surface by using special signal processing techniques. Synthetic aperture radar has important role in gathering information about earth's surface because it can operate under all kinds of weather condition (whether it is cloudy, hazy or dark).However acquisition of SAR images face certain problems. SAR began with an observation by Carl Wiley in 1951 that a radar beam oriented obliquely to the radar platform velocity vector will receive signals having frequencies offset from the radar carrier frequency due to the Doppler Effect. Synthetic-aperture radar (SAR) is a type of radar in which a large, highly-directional rotating antenna used by conventional radar is replaced with many low-directivity small stationary antennas scattered over some area near or around the target area. The many

echo waveforms received at the different antenna positions are post-processed to resolve the target. Synthetic-aperture radar (SAR) can only be implemented by moving one or more antennas over relatively immobile targets, by placing multiple stationary antennas over a relatively large area, or combinations thereof.

In a typical SAR application, a single radar antenna is attached to the side of an aircraft. A single pulse from the antenna will be rather broad because diffraction requires a large antenna to produce a narrow beam. The pulse will also be broad in the vertical direction; often it will illuminate the terrain from directly beneath the aircraft out to the horizon. If the terrain is approximately flat, the time at which echoes return allows points at different distance to be distinguished. Distinguishing points along the track of the aircraft is difficult with a small antenna.

An appropriate coherent combination of several pulses leads to the formation of a synthetically enlarged antenna the so-called “Synthetic Aperture”. Maximum synthetic aperture size is the maximum distance travelled while target is illuminated.

II. EXISTING TECHNIQUES

Supervised kernel-based method for SAR image change detection. The intensity and texture information of the SAR images is employed to construct a composite-ratio kernel (CRK) that can integrate various features into high-dimensional space, thus handling the nonlinear problem. In the features derived from the difference image values are modeled as a Gaussian mixture model, and Bayesian inference is applied to obtain the change detection results by using conditional posterior probability. In this way, the contextual-information based intensity distribution of difference image is adequately considered, whereas the texture features are neglected. In the framework of Markov random field is used to achieve the change detection map, which exploits the contextual information and the statistical distribution of difference data. kernel methods are a class of algorithms for pattern analysis, whose best known member is the support vector machine (SVM).

The general task of pattern analysis is to find and study general types of relations in datasets. For many algorithms that solve these tasks, the data in raw representation have to be explicitly transformed into feature vector representations via a user-specified feature map: in contrast, kernel methods require only a user-specified kernel, i.e., a similarity function over pairs of data points in raw representation Training layers for the machine-learning classifier are assembled using data from field sites and other ancillary data. Layers currently being tested with the classifier include the interpreted canopy cover change (ground truth), transformed change data, cover type, tree density, harvest/fire history, local climate, slope, aspect, and time interval between acquisition dates.

Based on the discussion above, the aforementioned three kinds of information, namely, the texture features, the statistical distribution, and the spatial interactions, play a crucial role in SAR image change detection. In image analysis, the statistical models for image segmentation usually can be divided into four categories [4]: 1) descriptive models; 2) variants of descriptive models; 3) generative models; and 4) discriminative models. The descriptive models and variants of descriptive models are often integrated with generative models. In comparison, descriptive models and generative models are used as prior probabilities and likelihoods in the Bayesian framework, whereas discriminative models which relax the strong independence assumption and capture dependencies between observations, directly model the posterior probabilities based on local features.

III. PROPOSED TECHNIQUE

Change detection, which aims at identifying changed areas that occurred on the Earth's surface, is a process of making a direct comparison of a pair of remote sensing images acquired over the same geographical area at different times. Such a process is attracting a growing interest in various applications such as disaster management, environmental monitoring, urban studies, and forest monitoring. Compared with optical images, synthetic aperture radar (SAR) images are less insensitive to atmospheric and sun-illumination conditions. Therefore, SAR images are better sources of information for change detection. In comparison, descriptive models and generative models are used as prior probabilities and likelihoods in the Bayesian framework, whereas discriminative models which relax the strong independence assumption and capture dependencies between observations, directly model the posterior probabilities based on local features.

a) Image acquisition

Image acquisition in image processing can be broadly defined as the action of retrieving an image from some source, usually a hardware-based source, so it can be passed through whatever processes need to occur afterward. Performing image acquisition in image processing is always the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed and is the result of whatever hardware was used to generate it, which can be very important in some fields to have a consistent baseline from which to work. One of the ultimate goals of this process is to have a source of input that operates within such controlled and measured guidelines that the same image can, if necessary, be nearly perfectly reproduced under the same conditions so anomalous factors are easier to locate and eliminate.

If the hardware is not properly configured and aligned, then visual artifacts can be produced that can complicate the image processing. Improperly setup hardware also may provide images that are of such low quality that they cannot be salvaged even with extensive processing. All of these elements are vital to certain areas, such as comparative image processing, which looks for specific differences between image sets.max of directions for the linear SE.

b) Intensity Image

Intensity image is the equivalent to a "gray scale image" and this is the image that will mostly work with in this course. It represents an image as a matrix where every element has a value corresponding to how bright/dark the pixel at the corresponding position should be colored. There are two ways to represent the number that represents the brightness of the pixel.

The double class (or data type). This assigns a floating number ("a number with decimals") between 0 and 1 to each pixel. The value 0 corresponds to black and the value 1 corresponds to white. The other class is called uint8 which assigns an integer between 0 and 255 to represent

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he brightness of a pixel. The value 0 corresponds to black and 255 to white. The class uint8 only requires roughly 1/8 of the storage compared to the class double.

c) Binary Image

The image format also stores an image as a matrix but can only color a pixel black or white (and nothing in between). It assigns a 0 for black and a 1 for white. There are some advanced methods of image acquisition in image processing that actually use customized hardware. Three-dimensional (3D) image acquisition is one of these methods. Layers currently being tested with the classifier include the interpreted canopy cover change (ground truth), transformed change data, cover type, tree density, harvest/fire history, local climate, slope, aspect, and time interval between acquisition dates.

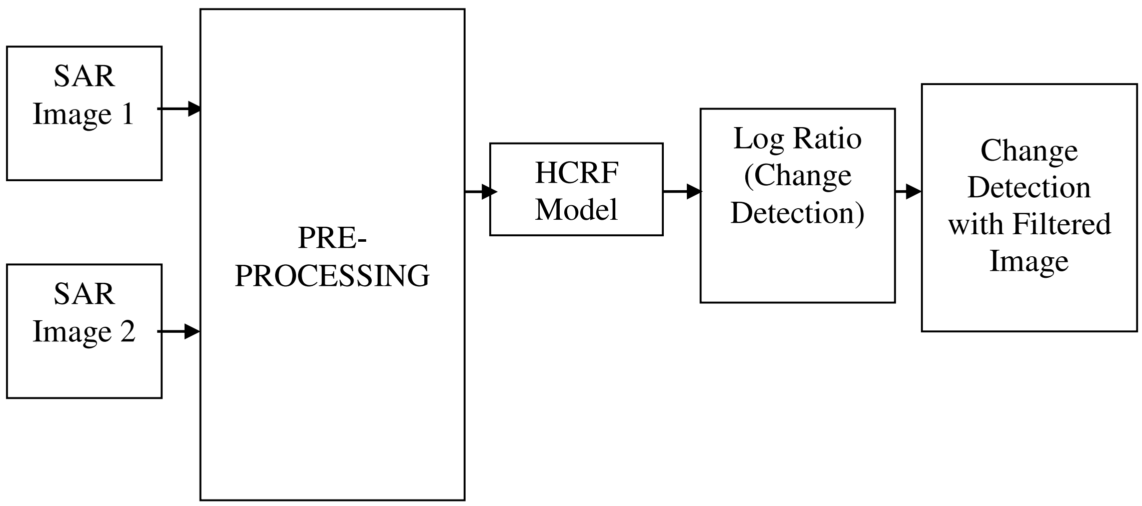

Fig 3.1 Proposed System

d) Preprocessing

After the image acquisition and creating the image database, the next step is image pre-processing. For the acquiring the original image data image pre-processing is step is very efficient process. In the pre- processing of image we suppress undesired distortion of these images and enhance some images features important for further processing and analysis task. In image pre-processing step it includes color space conversion, image enhancement and image segmentation.

- Image is converted to gray scale image in first step.
- Noise is removed if any
- The obtained image is then passed through a high pass filter to detect edges
- Then the obtained image is added to original image to enhance it.

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e) Gray Scale Image

A gray scale image (also called gray-scale, gray scale, or gray-level) is a data matrix whose values represent intensities within some range. MATLAB stores a gray scale image as an individual matrix, with each element of the matrix corresponding to one image pixel. By convention, this documentation uses the variable name I to refer to gray scale images. The matrix can be of class uint8, uint16, int16, single, or double. While gray scale images are rarely saved with a color map, MATLAB uses a color map to display them. For a matrix of class single or double, using the default gray scale color map, the intensity 0 represents black and the intensity 1 represents white. For a matrix of type uint8, uint16, or int16, the intensity in min (class (I)) represents black and the intensity in max (class (I)) represents white.

f) RGB Image

An RGB image, sometimes referred to as a true color image, is stored as an m-by-n-by-3 data array that defines red, green, and blue color components for each individual pixel. RGB images do not use a palette. The color of each pixel is determined by the combination of the red, green, and blue intensities stored in each color plane at the pixel's location. Graphics file formats store RGB images as 24-bit images, where the red, green, and blue components are 8 bits each. This yields a potential of 16 million colors. The precision with which a real-life image can be replicated has led to the nickname "true color image

g) Feature Extraction

HCRF model generalizes a conditional random field (CRF) model by incorporating the statistics of the log-ratio image derived from the two-temporal SAR images into the CRF model. In the HCRF model, given the texture features extracted from the two-temporal training samples, the unary potential is modelled by a support vector machine (SVM) which outputs the class conditional probability, and the pairwise potential is constructed by the multilevel logistical model to capture the spatial interactions of the log-ratio image in the change detection.

f) Unary Potential

In the HCRF framework, the unary potential as (yes, x) can be seen as the probability at site is taking the label yes given the observed data x

$$A_s (y_s,x)=\log〖 p (y_s/(f(x_s)))〗 \qquad (1)$$

where, $p (y_s/(f(x_s)))$ can be modeled by a local conditional model, and $f(x_s)$ denotes the feature vector at site s.

g) Support Vector Machine

The aim of a Support Vector Machine is to find good separating hyper planes in a high dimensional feature space. Distance from example to the separator is Examples closest to the hyper plane are support vectors. Margin ρ of the separator is the width of separation between support vectors of classes.

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Derivation of finding r:
Dotted line x’ − x is perpendicular to decision boundary so parallel to w.
Unit vector is w/|w|, so line is rw/|w|.
x’ = x – yr w/|w|.
x’ satisfies wTx’ + b = 0.
So wT(x –yrw/|w|) + b = 0
Recall that |w| = sqrt(wTw).
So wTx –yr|w| + b = 0
So, solving for r gives:
r = y(wTx + b)/|w|
Pairwise Potential

In the HCRF framework, the pairwise potential imposes the spatial interactions between neighboring sites in the label field. Here, the edge strength extracted from the log-ratio image by ROEWA operator is used to model the interactions.

h) *Statistical Distribution of the Log-Ratio Image*

The data term p(d(x)|y) is modeled by the statistics of the log-ratio image. GΓD, with Weibull distribution, exponential distribution, Rayleigh distribution, and Gamma distribution being its special cases, has been proven to fit the histogram of SAR image effectively.

IV. SIMULATION RESULTS

INPUT IMAGES

The input image is a temporal SAR data. It covers Australian landscape.

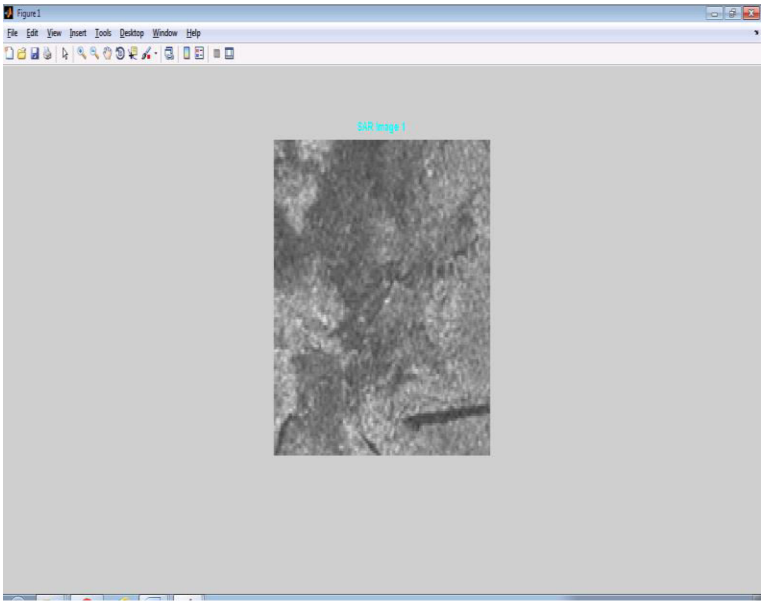

Fig 4.1 Input Image 1

The SAR image of Australian landscape after flooding is shown in fig.4.2.

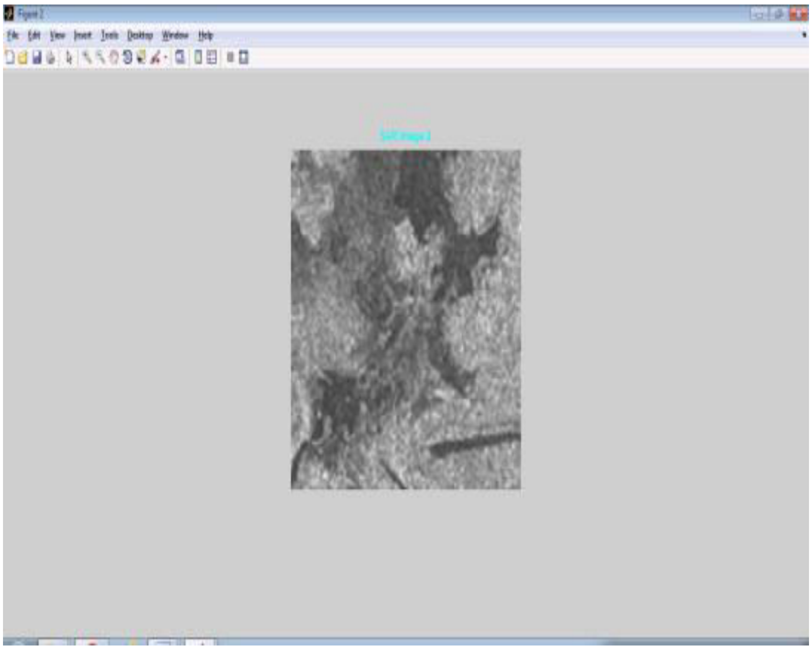

Fig 4.2 Input Image 2

UNARY POTENTIAL

The unary potential is extracted from two temporal SAR images. It is shown in fig.4.3.

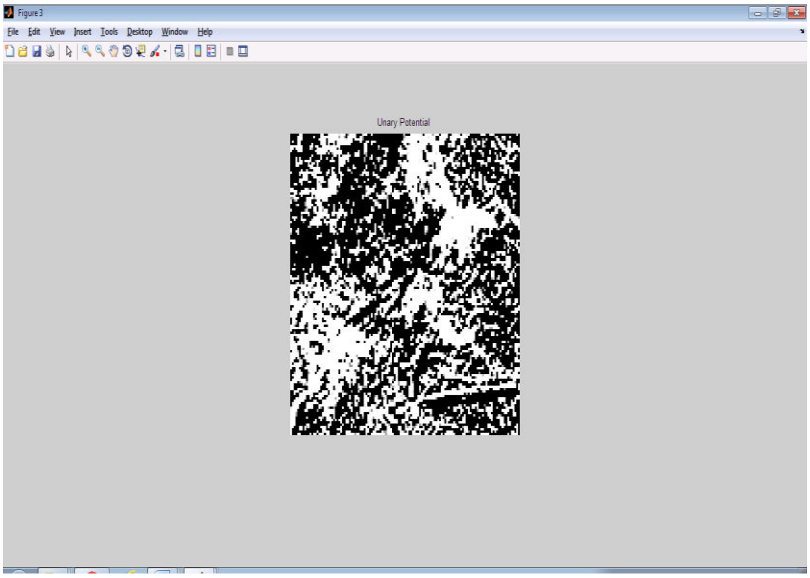

Fig 4.3 Unary Potential

PAIRWISE POTENTIAL

It is obtained from the spatial interaction of the log ratio images. It is shown in fig.4.4.

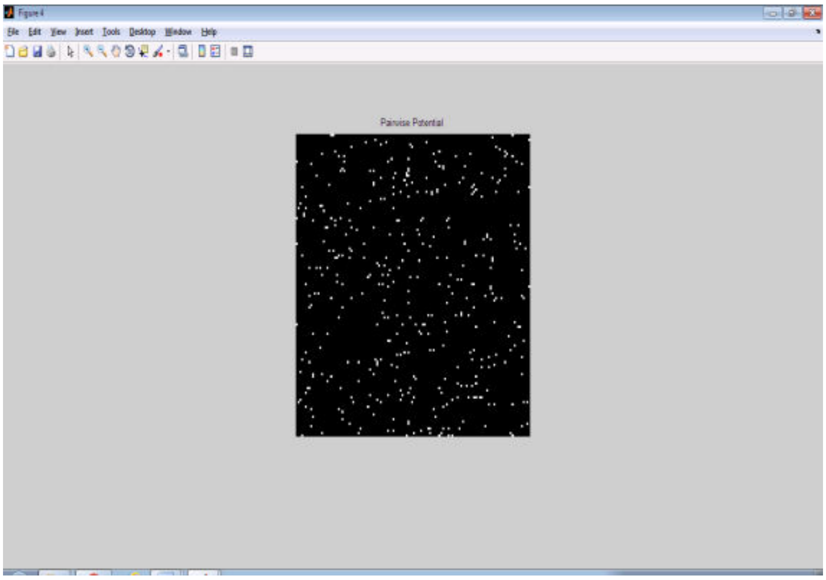

Fig 4.4 Pairwise Potential

CHANGED AREA

The changes occurred in unary and pairwise potential is shown in fig.4.5.

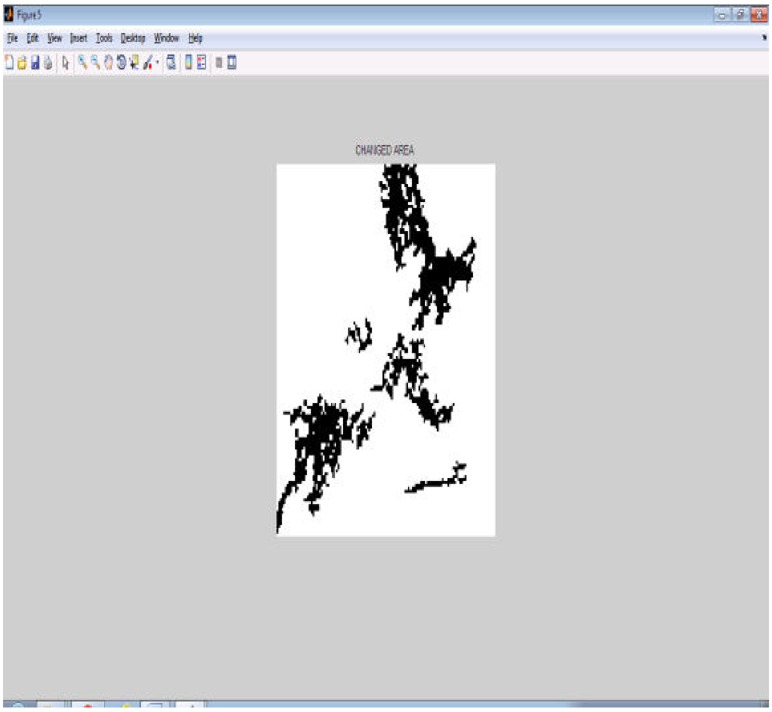

Fig 4.5 Changed Area

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MEAN FILTERED IMAGE

It is used to smoothen the image and to reduce the amount of intensity variation.

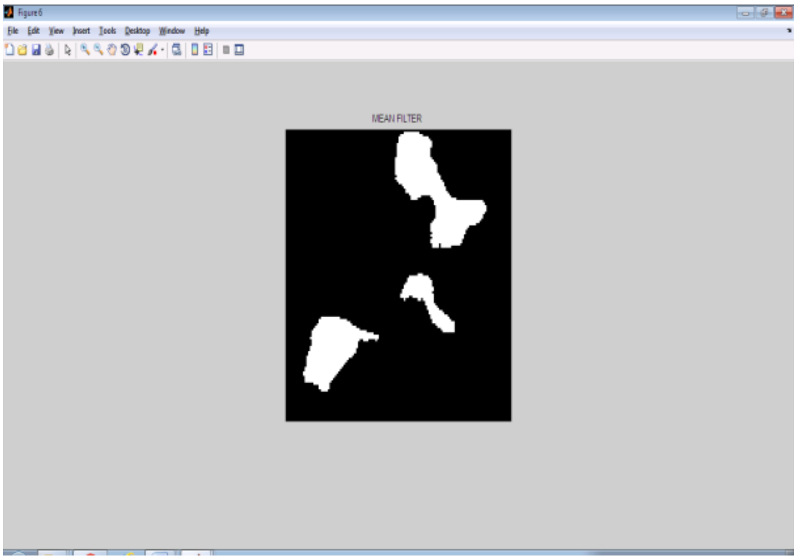

Fig 4.6 Mean Filtered Image

MEDIAN FILTERED IMAGE

The median filter is used to remove the salt and pepper noise. It is shown in fig.4.7.

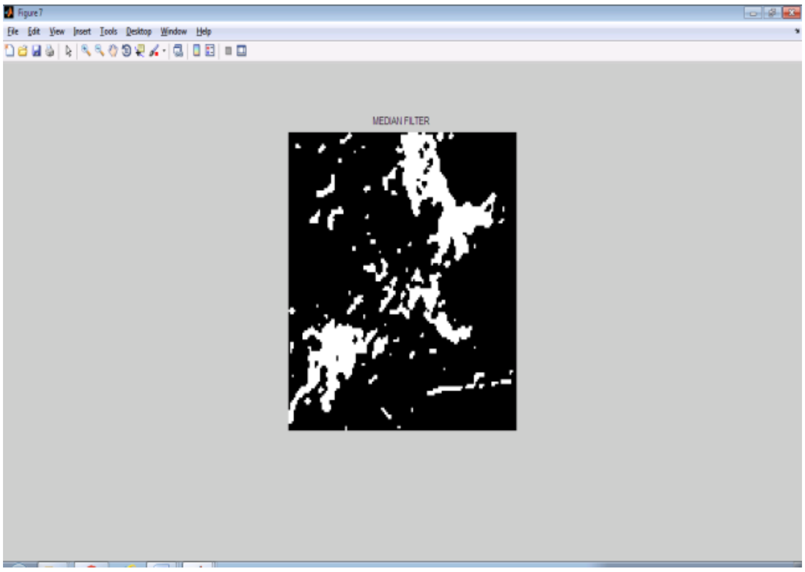

Fig 4.7 Median Filtered Image

COMBINATIONAL FRAMEWORK

The combinational framework is the combination pairwise potential. It is obtained by substituting α=0.2.

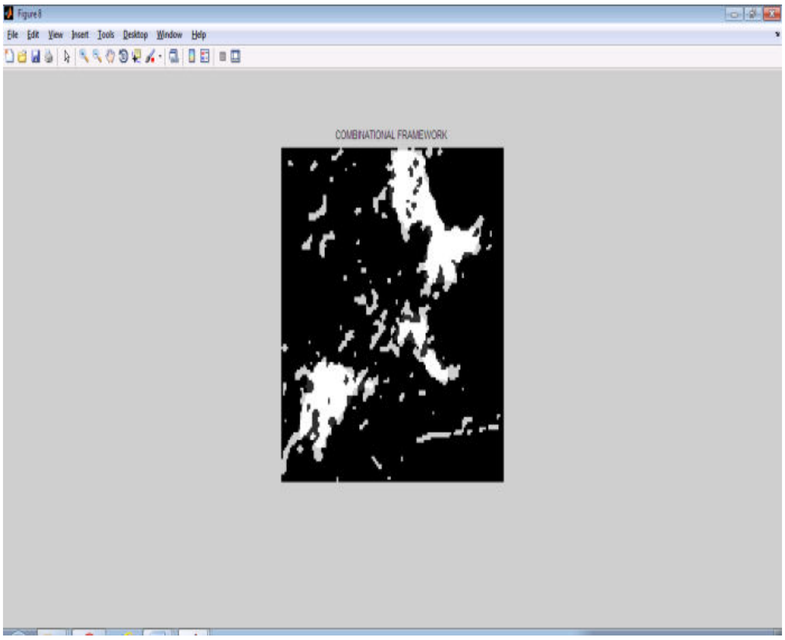

Fig 4.8 Combinational Framework

HISTOGRAM OF CHANGED AREAS

The changed areas in the two temporal SAR images are shown in histogram.

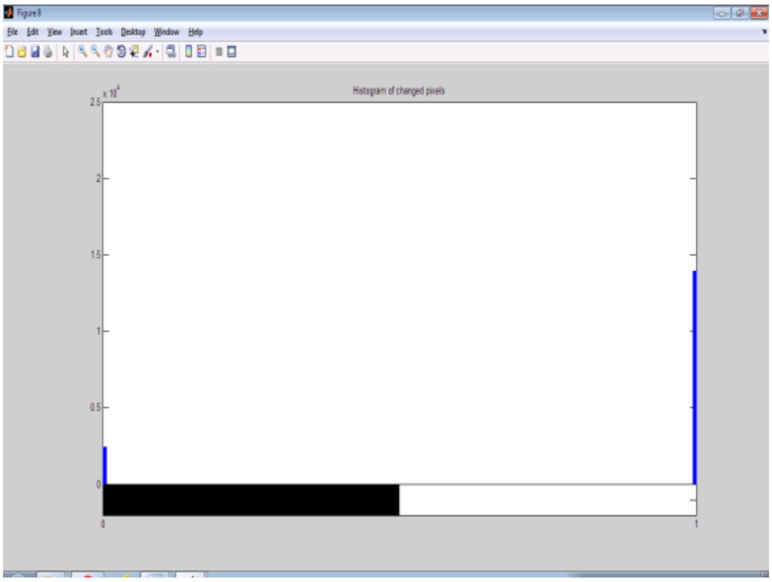

Fig 4.9 Histogram of Changed Areas

HISTOGRAM OF UNCHANGED AREAS

This histogram indicates the unchanged areas in the two temporal images.

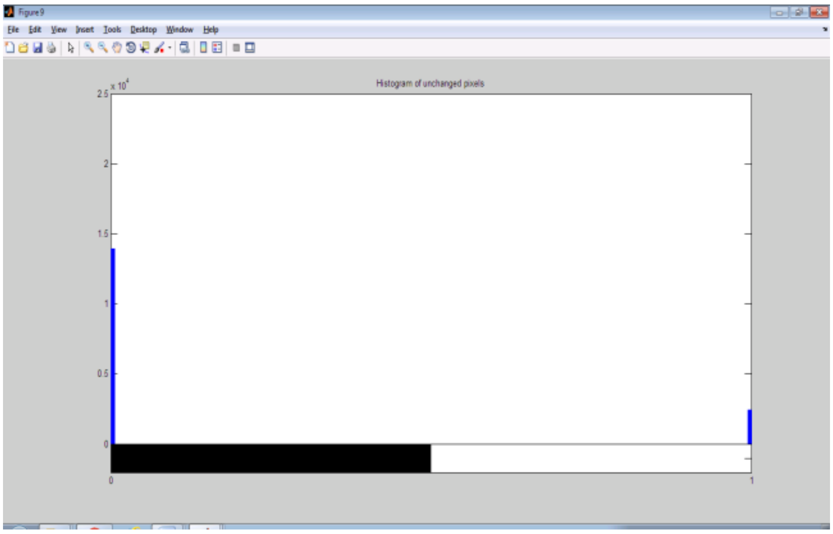

Fig 4.10 Histogram Of Unchanged Areas

PERFORMANCE CALCULATION

The performance is based on the changed and unchanged accuracy calculation. It is shown in fig.4.11.

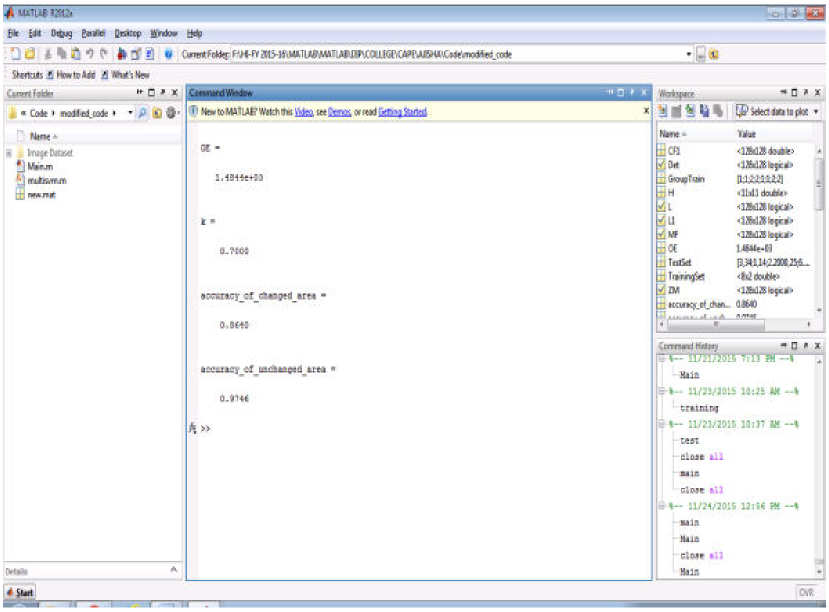

Fig 4.11 Performance Calculation

V. Conclusion

Thus, the Change detection, aimed at identified changed areas that occurred on the Earth’s surface Process of making a direct comparison of a pair of remote sensing images acquired over the same geographical area at different times. This paper proposed a hybrid conditional random field (HCRF) model for synthetic aperture radar (SAR) image change detection. The statistics of the log-ratio image derived from the two-temporal SAR images into conditional random field model. Proposed model is capable of integrating three kinds of

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