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Survey on Change Detection in Satellite Images.

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ABSTRACT

Change detection can be defined as changes in the surface of the earth. Change detection can be computed by using several techniques such as Context-Sensitive Technique Robust to Registration Noise for Change Detection in VHR Multispectral Images, Morphological Attribute Profiles, New multivariate statistical model for change detection in images obtained by homogeneous and heterogeneous sensors, Multiple Neural-Network Models for suburban areas, of Gibbs Markov Random Field and Hopfield-Type Neural Networks for Unsupervised Change Detection**.** Using this above methods the efficiency and accuracy is poor.
Keywords: Change detection, Multiple Neural-Network Models, Morphological Attribute Profiles, VHR

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INTRODUCTION

In [1], very high resolution Synthetic Aperture Radar (SAR) sensors represent an alternative to aerial photography for delineating floods in built-up environments where flood risk is highest. However, even with currently available SAR image resolutions of 3 m and higher, signal returns from man-made structures. Here, a hybrid methodology combining backscatter thresholding, region growing, and change detection (CD) is introduced to enable the automated, objective, and reliable flood extent extraction from very high resolution urban SAR images. The calibration of a statistical distribution of "open water" backscatter values from images of floods is used in this method. Flood monitoring from space has the advantage of large area coverage and fast response services. The flood extraction algorithm uses as input Level 1 SAR data that are geocoded, co-registered, and calibrated. The first step is the estimation of the probability density function (PDF) of backscattering values associated with "open water." This calibrates a theoretical PDF that optimally fits the empirical distribution of backscatter values from "open water" showed from the SAR image. Extracting the seeds of "open water" areas from the flood image, being either individual pixels or regions is the aim of backscatter thresholding. The parameter *σ0thr* represents the maximum backscatter value. Over-detection needs to be removed by the subsequently applied CD step. CD thus aims at removing pixels from the flood extent map that do not correspond to flood water.

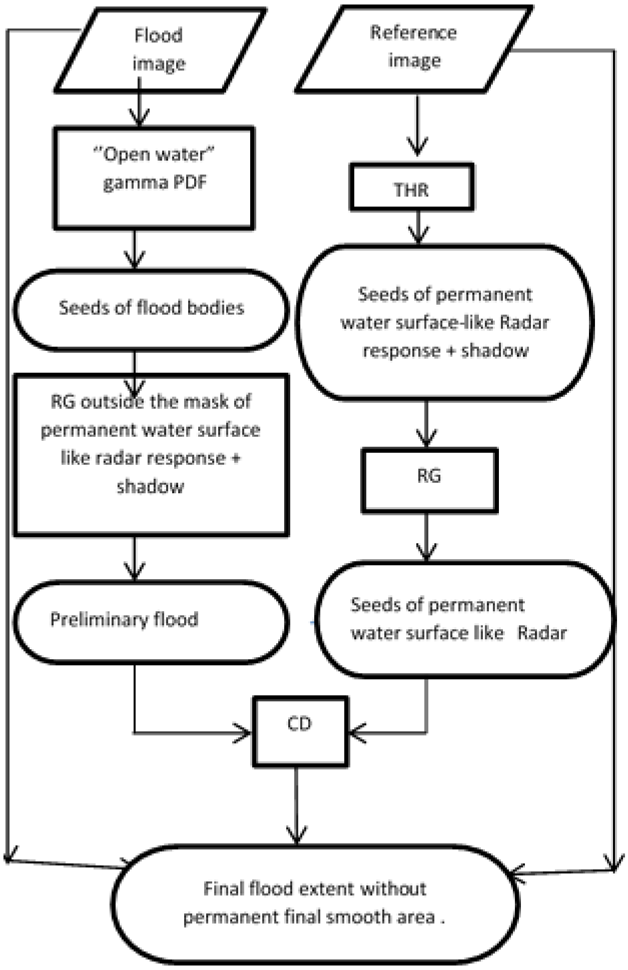


Fig.1 General scheme of the three processing steps of the flood detection Algorithm

The classification accuracy obtained with the fully automated flood detection algorithm M2b and contrasts its performance with those of the previously introducedM1 and M2a algorithms. The flood extent has been extracted from the Terra SAR-X Image using the three methods M1, M2a, and M2b.This study proposes a promising methodology that is shown to be capable of providing satisfactory results in mapping, in a completely unsupervised way, flood extent in a challenging case study, such as an urban flooding.

In [2], multi-temporal Space borne SAR Data for Urban Change Detection is to examine effective methods for urban change detection using multi-temporal space borne SAR data in two rapid expanding cities in China. To compare the SAR images from different dates, a modified ratio operator that has taken into account. Both positive and negative changes were developed to derive a change in images. A generalized version of Kittler-Illingworth minimum error thresholding algorithm was then tested. This is to automatically classify the change image into two classes that is change and no change. Detecting the temporal changes in urban areas using SAR images is very effective which is done by Kittler-Illingworth algorithm. Log normal and Nakagami density models has given the best results.

Ortho-rectification of SAR Data: To correct for relief displacement and bring the multi-temporal SAR images together, all SAR images were ortho-rectified to WGS 84 datum with UTM projection using a satellite orbital model and a SRTM DEM.

Peckle Filtering: SAR images which contain multiplicative speckle noise, affect the ability of the algorithm to separate change and no change classes. To enhance the distinction capability between change and no change classes, a pre-processing step is required to remove this noise in SAR images. In this research, the effectiveness of the minimum error thresholding algorithm in identifying urban changes in Beijing and Shanghai was evaluated.

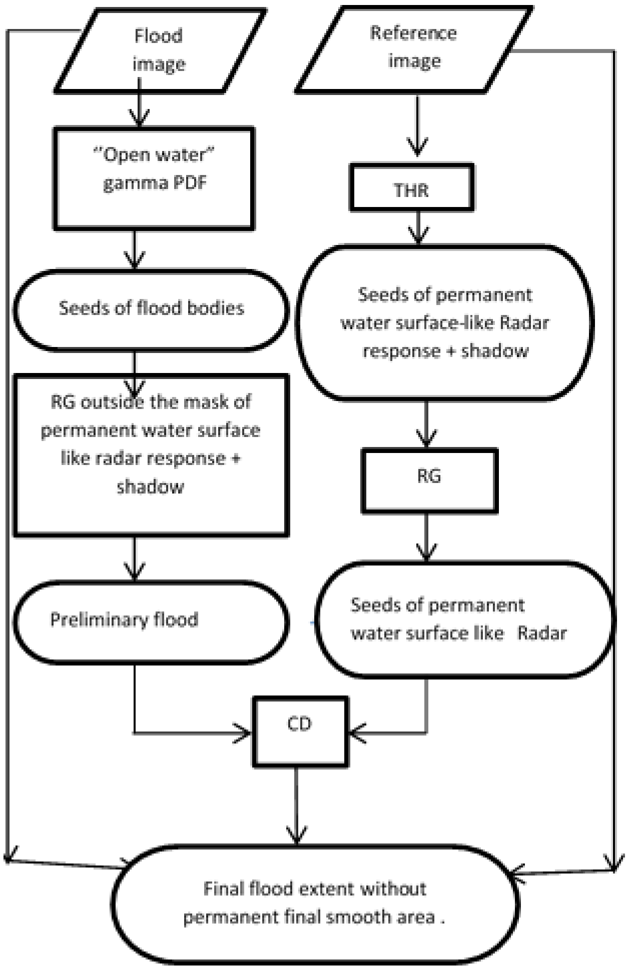


Fig.2. Methodology flowchart

For the comparison of the multi-temporal SAR images, the modified ratio operator was developed. This operator has the important property of considering both positive and negative changes simultaneously. As a result, this operator increases the size of the change class which in turn improves the accuracy of the estimation of the optimum threshold. In Image and Video Segmentation by Combining Unsupervised Generalized Gaussian Mixture Modeling and Feature Selection [3], a clustering model is proposed that efficiently mitigates image and video under/over-segmentation by connecting generalized Gaussian mixture modeling and feature selection. The model accurately specifies heavy tailed image/video histograms, while automatically discarding uninformative features. This leads to better differentiation and localization of regions in high-dimensional spaces.It is a new model which combines the GGD formulation and feature selection in robust mixture modeling for segmentation. This results demonstrate the usefulness and the effectiveness of the proposed model in reducing over/under segmentation due to heavy-tailed and high-dimensional data. The Fast Object level change detection [4] represents for change detection of very high resolution images, which is achieved by fast object level change feature extraction and progressive change feature classification. An object-level change feature is helpful for improving the discriminability between the changed class and the unchanged class. Progressive change feature classification helps improve the accuracy and the degree of automation, is implemented by dynamically adjusting the training samples and gradually tuning the separating hyper plane .For object-level change detection, the segmentation algorithm is a key issue since it affects object-specific change feature extraction and object-specific change feature classification. To take advantage of the object-level approach, we first apply the aforementioned segmentation procedure on the two co-registered images separately. To avoid the shortcoming of the post classification-based change detection approach, the multi-temporal segmentation is then applied. For a region B in one image and the corresponding region A in the other image, the final segmentation is achieved according to the following rules.

1) If A has no subregions and $A = B$, then A keeps unchanged in the final result.
2) If $A = B$ and A is composed of subregions, i.e., $A = A1 \cup \cdots \cup An$, then the final result in $A \cup B$ is split into n regions: $A1, \ldots, An$.
3) If $A \neq B$ and $A \cup B \neq \Phi$, then the region $A \cup B$ in the final result is split into three regions $A \cap B$, $A - (A \cap B)$, and $B - (A \cap B)$.

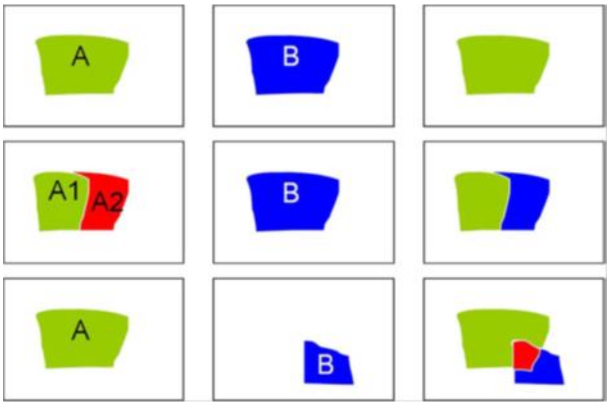


Fig.3. Illustration of multi-temporal segmentation

First row) Case (1), (Second row) Case (2), (Third row) Case (3). (First column) Segmentation result from one image. (Second column) Segmentation result from the other
Image. (Third column) Final segmentation result.

In Fast Object level change detection of VHR images, the novelties lie in the following three aspects:

1) Fast multi-temporal segmentation and object-specific change feature category make the proposed approach very fast.
2) An object-specific change feature representation and the *tSVM* form the proposed approach high in accuracy.
3) The iterative *tSVM* makes the proposed approach automated.

In [5], PCNNs (Pulse-Coupled Neural Networks) are based on the implementation of the mechanisms fundamental the visual cortex of small mammals, and, with respect to more traditional NNs architectures, that is multilayer perceptron, own interesting advantages. In particular, they are unsupervised and context sensitive. Latter property of this may be particularly useful when very high resolution images are considered as, in this case, an object analysis might be suitable than a pixel-based one. A PCNN is an NN algorithm that, when applied to image processing, provides a series of binary pulsed signals, each associated to one pixel or to a cluster of pixels. Cluster of pixel belongs to the class of unsupervised artificial NNs in the perception that it does not need to be trained. The network be formed of nodes with spiking behavior interacting each other within a predefined grid. The architecture of the net is quite simpler than most other NN implementations. PCNNs do not have multiple layers, which pass information to one another. PCNNs have only one layer of neurons, which receive input directly from the original image, and form the resulting “pulse” image. The PCNN neuron has three compartments. The feeding compartment receives both an external and local stimuli, whereas the linking compartment only receives the local stimulus. The third compartment is represented by an active threshold value. PCNNs are unsupervised and context sensitive. Moreover, they are invariant to an object scale, shift, or rotation. Once the two images are co-registered, might be quite useful, particularly for VHR images. Each image is generated by the PCNN when iteration of the algorithm creates specific signatures of the scene which can be compared for deciding about the occurrence of a change.

The schematic representation of a PCN is shown in Fig.4while, more formally, the system can be defined by the following expressions:

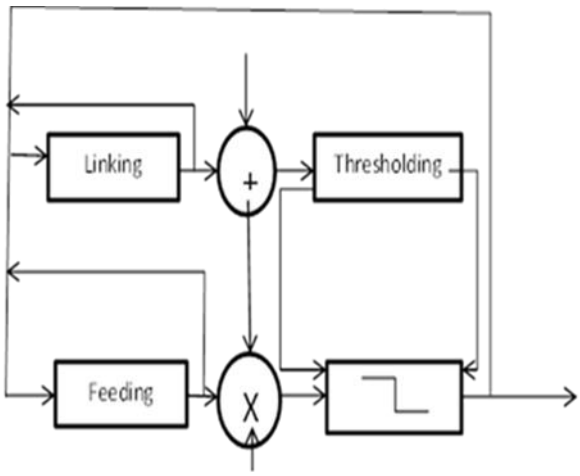


Fig.4

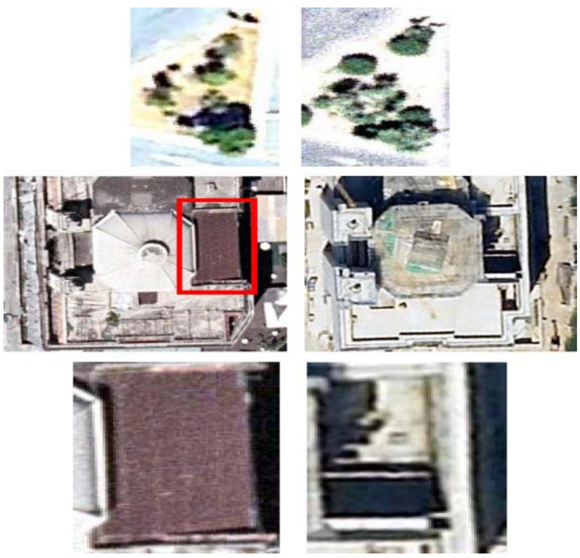


Fig.5 Test areas (up) A, (middle) B, and (bottom) C imaged at two different times (left) t1 and (right) t2.

In an automatic context-sensitive Technique robust to registration noise (RN) for change detection in multi temporal very high geometrical resolution (VHR) remote sensing images is discussed in this paper. In proposed technique analysis distribution of the spectral change vectors (SCVs) calculated with respect to the change vector analysis (CVA) in a quantized polar domain. The effects of Registration noise in the polar domain can be identified automatically by studying the spectral change vectors falling into each quantization cell at different resolution levels. In this paper change detection technique is obtained by the behavior of the distribution of SCVs in the polar domain at different scales [6].

A new method to change detection in very high resolution remote (VHR) sensing images based upon the morphological attribute profiles (APs) is presented**.** Temporal changes are made by comparing geometrical images of each day. This experiment Works on panchromatic Quick Bird images related to an urban area show the effectiveness of the proposed technique in detecting changes according to the spatial morphology by preserving geometrical details. The experiments can be performed on panchromatic Quick Bird images which related to an urban area which is related to the effectiveness of the proposed technique. Detecting the changes on the basis of the spatial morphology by preserving geometrical details is explained in [7].

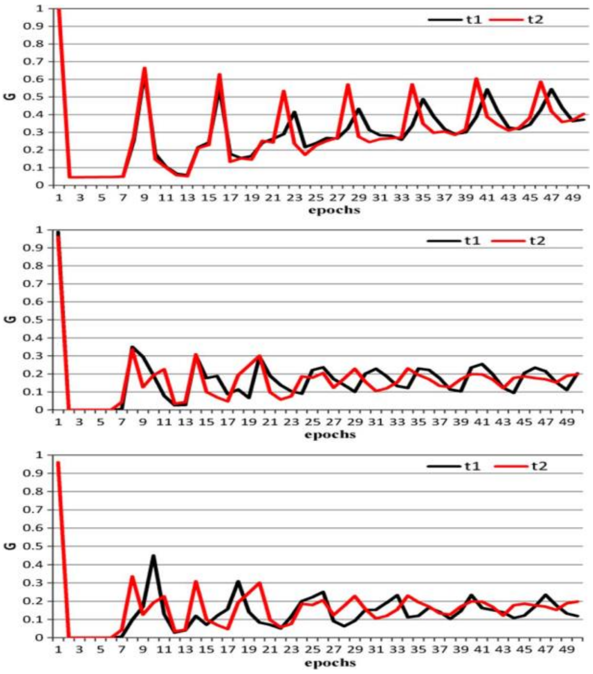
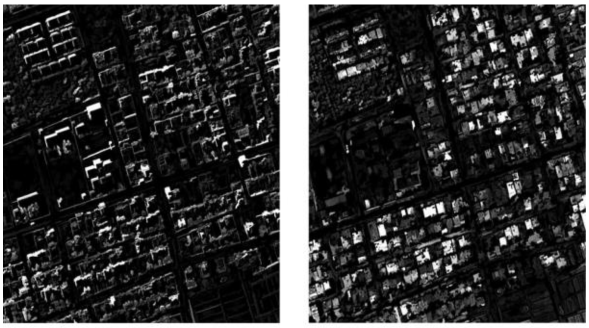


Fig.6. PCNN signals of the images taken at two different times. (Up) Test area A. (Middle) Test area B. (Bottom) Test area C.

Fig.7. Panchromatic multi-temporal images of the city of Bam (Iran) appear in (a) September 2003 and (b) March 2004



(a) (b)

Fig.8.CI maps obtained by the (a) closing and (b) opening components.

In remote sensing application, a change may be considered too as an alteration of the surface components. But temporal analysis of remote sensing image is facing several difficulties, among them the large amount of data to be processed and also the very few number of temporal observations. Despite the lack of temporal model, the natural evolution of landscape and the evolution induced by the sensors, many valuable techniques exist that perform change detection from two or more images acquired from the same or from different sensors.

EARTH observation based on aerial and satellite image series, including high-resolution remote sensing image time series (RSITS)The utilization of semi-automatic methods with user's intervention (i.e., interactive segmentation) has become familiar in the literature of Remote-Sensing image processing. Interactive-based segmentation methods start by exploiting the user inputs through a set of strokes, lines, scribbles, or curves for generating labeled pixels for object and background. Classifying segments and detecting changes in terrestrial areas are important and time-consuming efforts for remote sensing image analysis tasks, including comparison and retrieval in repositories containing multi temporal remote image samples for the same area in very different quality. RSITS, the images in the series are usually different in light, weather, season, traffic, flooding, or blooming conditions.

According to multivariate statistical model for change detection using homogeneous and heterogeneous sensor [8], the decision function is the key tool which detect change from no-change in CD algorithms. In this method, the threshold value is used to differentiate change from no change. However, it often suffers from misdetection or over-detection. Selecting a suitable threshold value to identify change is also difficult. Lower the threshold value will exclude areas of change. Higher the threshold value will include too many areas of change. Selecting an appropriate threshold is generally not clear. Especially for unsupervised algorithms it is difficult because ground truth is not available to present prior knowledge. Fusion techniques can be used select appropriate threshold decision function as it involve in improving overall performance of the decision by combining the individual opinions to derive a consensus decision. This technique is most often using improving classification results. It can be also applied to change detection when change and no-change are inferred as binary classification problem.

In this method, two different strategies are used namely, Multilayer Markov random field (M-MRF) and level-set (LS) methods. Finding clusters on the stack of image layers results in aligned cluster definition for the different layers. Fused segmentation on the stack of image layer results in multilayer labeling. Multilayer labeling is used for the unsupervised clustering of single-layer labeling; this aligned labeling makes the change detection unequivocal. A noise-tolerant cross-layer similarity measure, cluster reward algorithm (CRA), is used to better identify .Cartesian product of the separate frames of discernment used for the classification of each image can be process DSmT, Dempster–Shafer Theory (DST) Multidimensional Evidential Reasoning Multilayer MRF model is applied by contributing the term of the cross-layer CRA similarity measure calculated between each pair in a subset of three or more consecutive images.

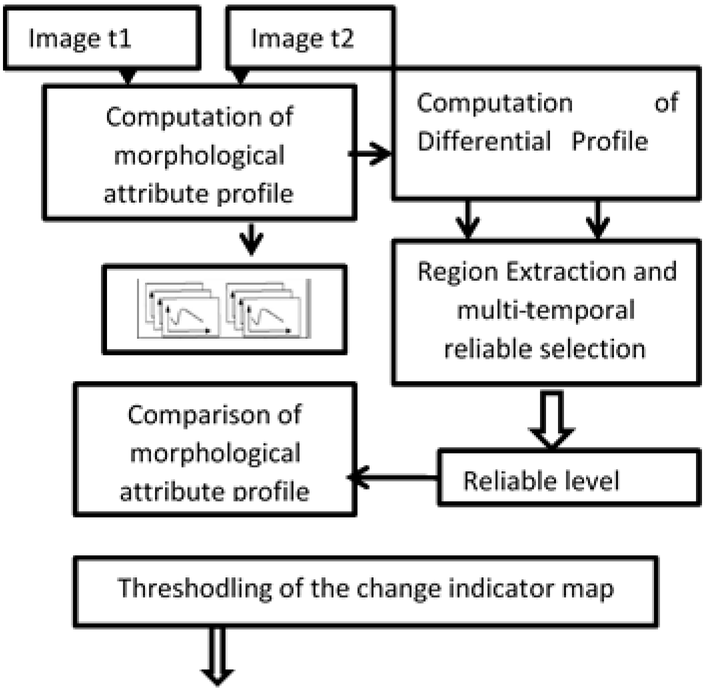


Fig.9. General block diagram of proposed technique

The advantages of this technique are it is very attractive in generating accurate Change Detection results with minimum interaction. It is robust when initial markings based on interactive Multi Segmented Random Method. Fused segmentation on the stack of image layers, resulting in multilayer labeling [8].

Fully automatic detection of changes by combining multiple neural network models in suburban areas has aimed at developing fast, automatic and accurate algorithms for detecting changes of land cover from VHR SAR X-band images. This can be provided by recent Earth Observation satellite missions. Old and present images are first Ortho-rectified, De-speckled, and Co-registered. This method has been based on two different NN architectures. The first algorithm is a supervised MLP-NN, which gives the land cover map for each acquisition.

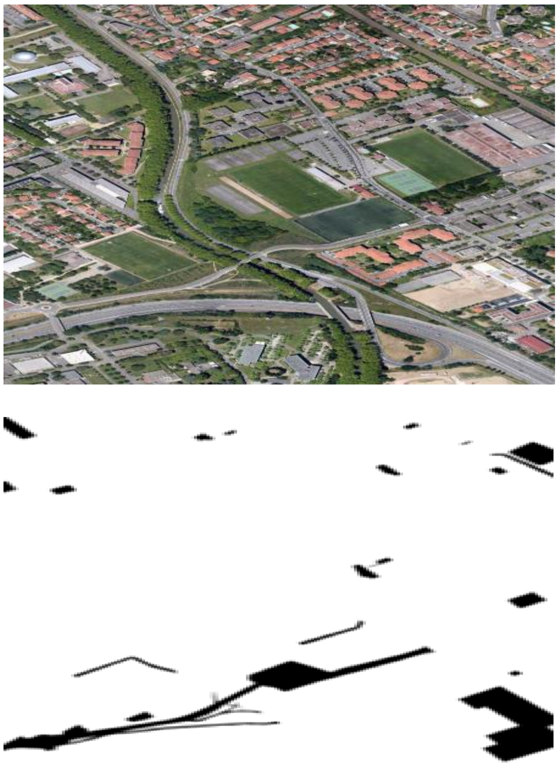


Fig.10.(a)old image (b)new image (c) change detection

The second algorithm is an unsupervised and automatic PCNN model, which allows identifying "hot spots". The hot spot can be measured by the correlation value between the pulsing signatures of the signals generated from each image. A comparison between the change map obtained by a post classification analysis and the correlation mask produced by the PCNN module yields the final change map. Further post processing is useful to improve the accuracy of the resulting product. The change detection is measured from two strip map images, while all the transitions which are into the manmade class have been identified from the Spotlight data. It is worth highlighting that the inclusion of the PCNN into the change detection processing chain resulted in improved robustness against co-registration errors. A disadvantage of this method is several changes will occurs on rainy seasons. Hence it is difficult to monitor the changes perfectly [9].

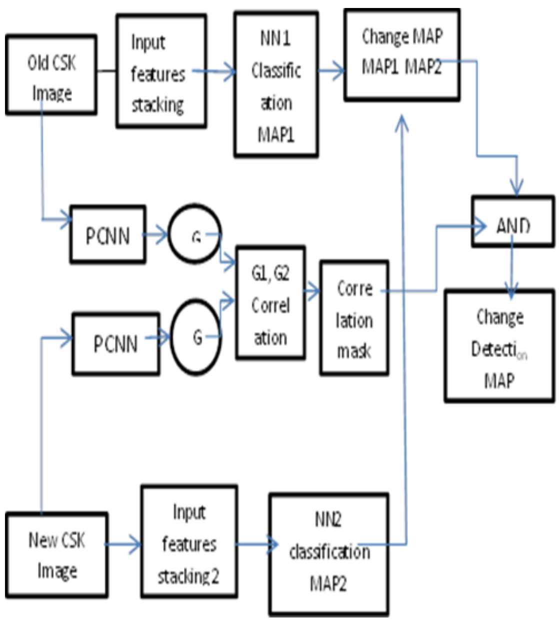


Fig.11. Block diagram of change detection algorithm.

The unsupervised change detection is a technique which is used for multi-temporal and multispectral Remote sensing images [10]. Gibbs Markov random field (GMRF) is used to model the spatial regularity between the neighboring pixels of the multi-temporal difference image, which is generated by change vector analysis applied to images acquired on the same physical area at distinct times. By using maximum *a posteriori* probability (MAP) estimation principle change detection problem is solved. Hopfield type neural network (HTNN) is used for estimating the MAP. By classifying the difference image into changed and unchanged classes it is possible to obtain the change detection map of the considered area. To classify the difference image into two classes, the use of GMRF based probabilistic modelling and HTNN is proposed as MAP estimator.

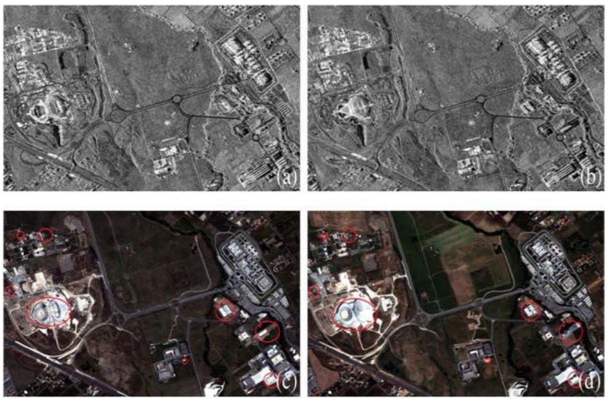


Fig.12. Second CSK Spotlight data set ASI (4319 X 2083 pixels). (Red circles) Ground truth of changed objects.

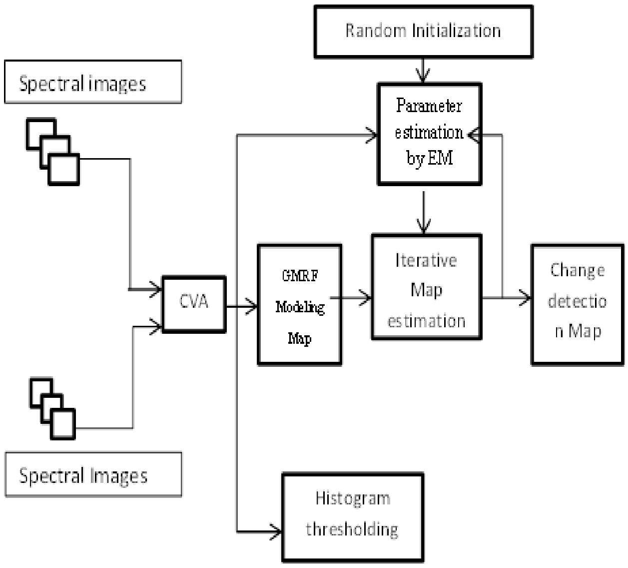


Fig. 13.Block diagram of the change detection technique.

GMRF probabilistic model gives an advantage of approximating the spatial regularities of pixels. Expectation maximization (EM) algorithm is used to evaluate the GMRF model parameters. HTNN consider only single neurons which are applied to each pixel of different images. This provides more accurate change detection maps compared to other method. Advantages of this method are more reliable change detection results when comparing with the other techniques. Satellites are ideal for monitoring changes all over the earth which are accessible. The orbit at high angles to the equator is measured in days or a couple of weeks. This helps in monitoring the crop growth and regional vegetation progression. Environmental damage and effects of flooding are effectively monitored. Particularly, now there are a number of different satellites in operation. Hence the likelihood of any area covered on a given day will be increased. Of course, daily weather changes are the mission of most of the meteorological satellites. The state of a surface that is not cloud-covered is observable.

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CONCLUSION

A new statistical method is proposed to describe the distribution of any number of joint images. Expectation-maximization algorithm is used to find the parameters of mixer of multi-dimensional distributions. Cluster Quality is poor by K-means clustering method. In [9], it is difficult to monitor changes perfectly on rainy season as it changes. In [7], even Attribute profiles is applied to the panchromatic images it can be extended which can be used with multispectral images. In [10], Multi-class segmentation problem is occurs. In [1], SAR image cannot be seen by the radar sensor because of its side looking nature. In [2], it is not suitable to describe the distribution of the change class since its distribution is Non symmetrical. In [4], Spectral changes of the unchanged regions are more complex.

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