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DETECTION OF CHANGES IN EARTH SURFACE USING SATELLITE IMAGE

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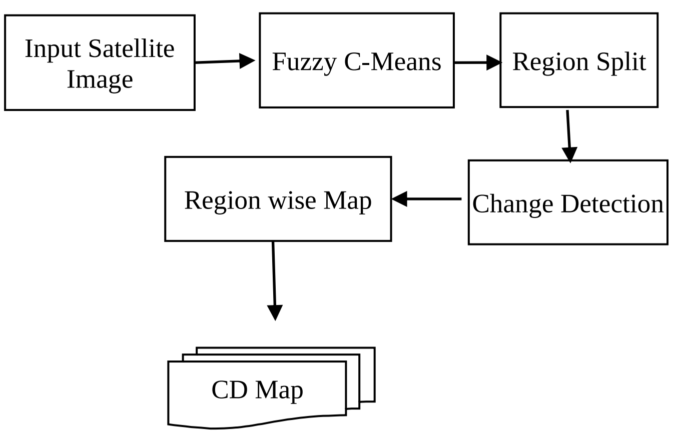
Abstract: The change detection in remote sensing images remains an important and open problem for damage assessment. A new change detection method for LANSAT-8 images based on Homogeneous Pixel Transformation (HPT) is proposed. Homogeneous Pixel Transformation transfers one image from its original feature space (e.g., gray space) to another feature space (e.g., spectral space) in pixel-level to make the pre-event images and post-event images to be represented in a common space or projection space for the convenience of change detection. A multi-value estimation method with the noise tolerance is produced to determine the mapping pixel using K-nearest neighbours technique. Once the mapping pixels of pre-event image are identified, the difference values between the mapping image and the post-event image can be directly generated. Then the similar work is done for backward transformation to combine the post-event image with the first space, and one more difference value for each pixel will be generated. Then, the two difference values are taken and combined to improve the robustness of detection with respect to the noise and heterogeneousness of images. (FRFCM) Fast and Robust Fuzzy C-means clustering algorithm is employed to divide the integrated difference values into two clusters- changed pixels and unchanged pixels. This detection results may contain few noisy regions as small error detections, and a spatial-neighbor based noise filter is developed to reduce the false alarms and missing detections. The experiments for change detection with real images of LANSAT-8 in Tamilnadu are given to validate the percentage of the changed regions in the proposedmethod.

1. INTRODUCTION

Using computer algorithms to perform image processing on digital images is referred as digital image processing i.e. processing digital images by means of a digital computer. It allows a wide range of algorithms to be applied to the input data.Also It avoids noise and signal distortion problems The information about the particular land area is defined through Remote Sensing. It is done by rapid monitoring of the land area. The classification of an image is based on the Temporal Correlation by Change detection methods. Every object has its own Spectral Characteristics This work presents a statistical approach to the change detection (CD) problem in remote sensing imagery. The main novelty of the proposed work is to find the CD based on the Homogeneous pixel transform First rely on a preliminary iterative estimation technique that takes into account the variety of regions. Once this estimation step is completed, then Homogeneous pixel transform based change detection map is derived based on the previously estimated regions, Experimental results and comparisons involving a mixture of different time images confirm the robustness of the proposed approach.

2.BLOCK DIAGRAM



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3 OVERVIEW ON ALGORITHMS USED

3.1 FAST ROBUST FUZZY C-MEANS CLUSTERING ALGORITHM:-

The homogeneous pixel transformation is used for separating the original image pixels into post event and pre event pixels. After the separation of respective pixels they are being represented in the projection plane based on their pixel value. Based on their pixel value in the projection plane the two LANSAT 8 images are compared and the changed regions are being detected for every region.

FRFCM is used for dividing the pixel into two clusters whereas the changed pixel and the unchanged pixels according to their difference pixel values. The output pixel will be belonging to the each cluster. Fuzzy *c*-means (FCM) algorithms with spatial constraints (FCMS) have been used for effective image segmentation. They have the following disadvantages: (1) The introduction of local spatial information which is corresponding to the objective functions improves their insensitiveness to noise to some extent, where they still lack enough in robustness to noise and outliers in the absence of prior knowledge of the noise; (2) The objective functions, exists a crucial parameter $\boldsymbol{\alpha}$ used to balance between robustness to noise and effectiveness of preserving the details of the particular image and it is selected generally through experience (3) the time taken for segmenting an image is based on the size of the image, hence the larger the size of the image takes the more time in segmentation. Because of the complex variety of the heterogeneous images, the change detection results directly generated by FCM may still contain some noisy regions whereas small regions of false alarms and miss detections in the classification. The proper modification of the clustering results needs to improve the detection performance In the heterogeneous images, the noisy influence obtained and their difference of modalities in the images are large for some pixels in some case. Then the K selected pixels with close values to $\mathbf{x}_i$in the pre-event image could be far away from $\mathbf{y}_i$which is corresponding to $\mathbf{x}_i$ in the post-event image and if there is no change occurred. In such situation, it is important to make false detection based on the pixel transformation from one direction which is froward transformation. In this case if we do the opposite transformation which is backward transformation it is associated to $\mathbf{y}_i$ with the feature space X of the pre-event image and some pixels with close values to $\mathbf{y}_i$in the post-event image may be also with their close values to the $\mathbf{x}_i$in the pre-event image. Therefore, the fusion of forward and backward pixel transformation will improve the robustness of change detection. The change detected areas are represented by taking the common pixels from each image and clustered together.

REGIN SEPERATION:

The LANSAT 8 images are given as input images and the comparison is done for images between May 2013 and May 2018. Based on the comparison results the percentages of change detected areas are calculated. The input images are represented in projection space and the pixel values are taken for detecting the changes in the input images. The common changes between two different time series are detected and represented in same image. The images are represented in separate regions as land, water, soil and vegetation based on their pixel value for May 2013 and May 2018 based on this the changes are detected separately for every region. After applying the Homogeneous Pixel Transformation technique and Fast Robust Fuzzy C-Means Clustering algorithm the changes are being detected for every region and are represented. The amount of change detected regions based on land, water, soil and vegetation are identified and they are compared with two time series images and their percentages are calculated.

HOMOGENEOUS PIXEL TRANSFORMATION

Heterogenous images uses before (pre-) and after (post-) of an event which are denoted by **X** (1st image) and **Y** (2ndimage). Because the images **X** and **Y** reflect the different object characteristics which are represented in different feature spaces X and Y, it is almost impossible to directly compare their pixels values for change detection. In this we want to transfer the image **X** from the original feature space X to another space Y considering that it is not affected by any of the event. Then the transferred image ˆ**Y** is called the mapping image and it will be described in the same feature space as the post-event image **Y**. So the images ˆ**Y** and **Y** are homogeneous, and they can be directly compared for the change detection process. In this determining the mapping of an image plays a crucial role in the change detection method. A new homogeneous pixel transformation (HPT) method is generated here to take out the estimation of mapping image. Some unchanged regions in the pair of images **X** and **Y** are selected at first for the prior knowledge for HPT, and they areselected as unchanged pixel pairs and are denoted **by** $\boldsymbol{T = \{(X_n, Y_n), n = 1, \ldots, N\}}$. It is denoted that the selected pixels are not affected by the event, but there is no idea for the content of each pixel. So they have weak prior knowledge about the pixel, and it cannot be further used for training the supervised classifier for the image classification. The unchanged regions easy to obtain, and it is convenient for their applications. The other pixels in the image can be transferred from one feature space to another space based on the selected unchanged pixel pairs. In HPT,

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the forward transformation to transfer the pre-event image **X** to the feature space ***Y***in which the post-event image **Y** is represented, and do the backward transformation to associate the post-event image **Y** with the space *X* corresponding to the pre-event image **X** in the same way. Now consider the forward transformation first, and it is assumed that the image is with accurate registration. Each pixel $\mathbf{x}_i$in the image **X**, and its actual respective pixel that are located at the same position as $\mathbf{x}_i$in the post-event image **Y** is given by $\mathbf{y}_i$**,** and then the estimation of its mapping pixel are described in the space of *Y* is denoted by $\hat{\mathbf{y}}_i$**.**
In this proposed work, a multi-value estimation strategy using *K*- nearest neighbors (K-NN) technique is estimated to deal with uncertainty of pixel transformation. The K-NN of $\mathbf{x}_i$from the prior knowledge of the unchanged pixels in the pre event image as $\dot{\mathbf{x}}_i$, $i = 1, \ldots, K$ with the corresponding pixels in the post-event image as $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$. Each of $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$ can be considered as a potential estimation of the mapping pixel $\hat{y}_i$. Thus, the *K* pixels $\dot{\mathbf{y}}_k$, $b_k = 1, \ldots, K$ provide multiple estimations (i.e. potential range) for $\hat{y}_i$. Hence, the value of mapping pixel $\hat{y}_i$can be approximated by the weighted sum of $\dot{\mathbf{y}}_i$, $i = 1, \ldots, K$, and it is given by eq. **(1).**

$$\hat{Y}_i = \sum_{k=1}^{k} w^k y^k$$

The determination of the weighting factors w_k , $k = 1, \ldots, K$ in **(1)** is a main key in the calculation of the mapping pixel $\hat{y}_i$.Where exists some related methods which are used to calculate the weightingfactors w_k , $k = 1, \ldots, K$ in the field of pattern classification.In the incomplete pattern classification problem,the missing attributes values are given based on theknown attribute values using the K-NN technique. This isconsidered that if their known attribute value from one patternis quite close to another pattern that is training data and their missingpart should be also very close to their corresponding part of their training pattern. So that the K-NN of the incomplete pattern are detected respective to their known

attributes, and the missing attributes of their pattern will be filled by the weight average of their selected *K* neighbors. The weighted factors are usually calculated according to the distance between the pattern and their selected neighbors in the known attributes. The bigger distance in them leads to the smaller weighting factor. The change detection of heterogeneous images in the realistic situation is very complicated. Some pixels are found closer to $\mathbf{x}_i$than other pixels in pre-event image, but their corresponding pixels are not so close to $\mathbf{y}_i$as these other pixels in post-event image because of their noisy factor and their detection of heterogeneousness. Let us consider a pair of real image LANSAT 8 from MAY 2013, MAY 2018 and are acquired for Tuticorin region and the changes for being detected for every regions.

(a) (b)

FIG 3.2:INPUT IMAGES (A) MAY 2013, (B) MAY 2018

In the estimation of the mapping pixel value $\hat{y}_i$by eq. (1), the exponential function often used in the weighted K-NN classifier is employed here to calculate the weighting factor of each selected pixel $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$.

$$W^K = e^{-\gamma \overset{x}{d}_k}$$

where $\boldsymbol{\gamma}$is a tuning parameter to control the distance influence in the calculation of weighting factor, and determination of the parameter will be explained later. For convenience of applications, $\overset{x}{d}_k$is defined by the normalized distance measure.

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$$\tilde{d}_k = \frac{\|\mathbf{y}_i - \dot{\mathbf{y}}_k\|}{\max_k \|\mathbf{y}_i - \dot{\mathbf{y}}_k\|}$$

where $\|\cdot\|$ represents the normal Euclidean distance. The estimated mapping pixel value $\hat{\mathbf{y}}_i$will be found close to the selected pixels and thay are very near to $\mathbf{y}_i$. If the pixel $\mathbf{y}_i$is seriously affected by the event, the actual pixel $\mathbf{y}_i$generally will become far away from all the K selected pixels $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$. Because the mapping pixel $\hat{y}_i$ defined by the weighted sum of $\dot{\mathbf{y}}_k$, $k = 1, \ldots, K$ as eq. (1) and (2) always lies around these K selected pixels, the distance between $\hat{y}_i$and $\mathbf{y}_i$will be also very large.
For the remaining pixels in the pre event image, the difference values of the mapping pixels and the actual pixels in the post event image can be calculated. The difference image (DI) between $\hat{\mathbf{Y}}$ and $\mathbf{Y}$ is obtained.

PERCENTAGE CALCULATION

The percentages are being calculated for every regions based on their changed pixel value. From this the Soil area is found with the 57.3656 percent of changes detected from May 2013-2018. This is found to be the highest change detected based on HPT. Then the Vegetation area is found with 56.0658 detected changes and Building is with 48.5636 and Water with 7.3016 percent respectively. These percent of change detected regions are generated accurately eliminating the noise factors to improve the performance levels.

CONCLUSION

A new change detection method for the heterogeneous remote sensing images has been proposed via homogeneous pixel transformation (HPT). HPT consisting of the forward and backward operations is to associate one image with the feature space of another image based on the prior known unchanged pixel pairs. By doing this, the pre-event and post event images are represented in a common feature space for the convenience of change detection. In heterogeneous images, the pixels with close values in one feature space may have more or less different values in another space due to noisy influence and modality difference, and such uncertainty often causes false detections. A new multi-value estimation method is introduced using K-nearest neighbors (K-NN) technique to Scope with the uncertainty in pixel transformation. The two difference values are combined in order to further improve the robustness of the detection method against noise and heterogeneousness of images. FCM algorithm is employed for clustering the integrated difference values of all pixels, and the changes are recognized by the clustering results. The experimental results show that HPT can efficiently improve the detection accuracy and reduce the false alarms with respect to other related methods. In the future work, we will extend the applications of HPT in more kinds of remote sensing images.

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