Fuzzy Based Unsupervised Change Detection using Grap Based Digital Surface Model

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Abstract: A new invention of satellite hyper spectral (HS) sensors can acquire very comprehensive shadow-like information directly related to land surface materials. Change Detection (CD) is the procedure that recognizes the changes occurred between more than two images based on the image assets. In case like tragedy management, the quick and accurate discovery of precious regions in images obtained at two different time instances that is before and after the disaster play a vital role in taking appropriate decision. In this paper proposed on adaptive change detection method based on fuzzy logic and graph representation, which is aimed at identifying all the possible change classes present between the considered images. The proposed novel fuzzification scheme is developed by considering spectral change information to identify the change classes having discriminable spectral behaviors.

Index Terms— Change detection, Fuzzy, Digital surface model, Graph.

I. INTRODUCTION

A comprehensive understanding of the global change is necessary for sustainable development of human society. As one of the most discussed topics in global change study, detection of anthropogenic and natural impacts on land surface which is essential for environmental monitoring. To enable whole monitoring and evaluating changes occurred on the ground; both long-term and short-term observations are required. We can acquire remote sensing images in a given area at different times because of the polar earth observation satellite’s revisit properties. Thus, multi-temporal remote sensing images are a major data source to find out the land surface changes in larger geographical areas, which is gradually going down the need for conventional field investigations. Change detection (CD) is the process that detects the change that has occurred between two (or more) images comparing the image properties [1].

A wide application of remote sensing images requires the image to be updated every year. In different circumstances, there are variations in the landscape features over the time between the satellite image updates. To interpret the images correctly, these changes must be identified. The word change generally refers to a transformation or modification of something over time. Changes may be occurred due to the following factors: Long period natural changes in climate condition, Ecological and Geo morphological process, Deforestation and land degradation, Green House effect.

In remote sensing usages, change detection is the process in which the differences are identified in the state of a land cover by comparing a pair of images acquired on the same geographical field at various time instances. The basic idea in using remote sensing data for change detection is that variations in the object of interest will sum up with changes in radiance value that are separable from changes caused by other factors, such as differences in conditions of atmosphere, moisture of soil, illumination and angle of viewing, etc.

Change detection can be utilized for variety of applications, such as facilities monitoring, oil spills movement and changes in ice/snow. The changed map resulting from the change identification process shows the spatial distribution of changed features within a specified area of interest. Change detection algorithms are branched into two different categories: 1) unsupervised algorithms, in which land-cover changes are detected by the comparison of spectral reflectance values of Remote Sensing images and 2) supervised algorithms, require the available labeled training samples. In most cases, unsupervised methods give us binary change detection maps, where only the information about the presence or absence of change is highlighted.

The rest of this paper is organized as follows. In Section 2 review the existing related work. The proposed models and descriptions are described in Section 3. Finally conclude the paper in Section 4.

II. LITERATURE SURVEY

In [1] authors proposed the spatio-contextual statistical model mainly used for partitioning an image into a number of regions with the constraint of Gibb’s distribution as prior probability distribution. Maximum a posteriori probability (MAP) is used to solve the change detection problem and MAP is estimated by using Hopfield type neural network. Hopfield’s network consists of a set of neurons or nodes. The output of each neuron or node is given as input to other neurons; a single
neuron is assigned to each pixel of the difference image and is assumed to be connected only to its neighbor. In [2] authors proposed a subspace-based change detection (SCD) method for hyperspectral images. SCD regards the observed pixel in the latter image as target and constructs the background subspace using the corresponding pixel in the former image, and additional information. In [3] presented the interactive segmentation methods for solving the change detection problem in multi-temporal remote sensing images. Interactive-based segmentation methods start by exploiting the user inputs. Here, the user needs to input markers in the form of lines, strokes, or curves related to change and no-change classes in difference image. Then support vector machine (SVM) classifier is applied to generate a spectral change map based on the pixels under these markers. In [4] authors discussed change detection in multi-temporal synthetic aperture radar (SAR) images based on radon transform and Jeffery divergence. In this approach the local statistics in a sliding window are compared. In each analysis window, the image is projected onto two vectors in two independent dimensions. Kullback-Leibler (KL) divergence, called Jeffery divergence used to measure the distance between the two pairs of projections. The change map is produced by comparing the probability density functions (pdf) of the projections that are generated by Radon transform. In [5] authors illustrated the Objectbased change detection techniques are a part of the object based image analysis (OBIA). OBIA is based on information from a set of similar pixels called objects. While pixel-based image analysis is based on the information in each pixel, object-based image analysis is based on information from a set of similar pixels called objects or image objects. Image objects are groups of pixels that are similar to one another based on a measure of spectral properties i.e., color, size, shape, and texture, as well as context from a neighborhood surrounding the pixels. In [6] authors proposed Multilayer perception (MLP), elliptical basis function of network (EBFNN) and fuzzy k-nearest neighbor (k-nn) techniques are used for the base classifiers. MLP has one input layer, one output layer and one or more hidden layer. Initially, the connection weight is updated by using the labeled patterns only. MLP is trained by using back propagation algorithm for updating the weight. The MLP predict the output values for both the changed and unchanged classes. To improve the performance of conventional radial basis function EBFNN uses the full covariance matrix.

III. PROPOSED METHODOLOGY

A. Image Preprocessing

In preprocessing, the hyper spectral images are in Red, Green, and Blue format. The RGB values are real absolute values so first process is convert RGB color space model into Hue, Saturation and Value (HSV) conversion. While high dynamic range intensity images are not subject to the limitations of intensity and dynamic range associated with conventional images, they share many of the same ambiguities. A remote sensing images quickly reveals that there is no consensus on what the pixel values mean in terms of real luminance values. The data is still effectively relative and often scaled arbitrarily. It is not uncommon to find an image of a nighttime scene with pixel values orders of magnitude greater than the pixel values in an image representing a sunny scene.

The image should contain enough information to determine the luminance values of that scene from the pixels in the image. In order to properly record luminance, pixel intensities must be linearly stored in absolute units of light, such as candela per meters squared (cd/m2). In order to properly record color, additional information must be included to describe the gamut in which the colors exist. This accuracy implies measuring the acquisition device to quantify its characteristics, and providing a mapping of pixel values back to the recorded luminance. This extra set of constraints is commonly termed photometric imaging, as it directly relates pixel values to the measured photons of light in the original scene.

B. Fuzzy Logic Representation

The objective function of Fuzzy is to classify Image data point, cluster centroid has to be closest to the data point of membership for estimating the centroids, and typciality is used for alleviating the undesirable effect of outliers. The function is composed of two expressions:

- The first is the fuzzy function and uses a distance exponent,
- The second is possibilistic function and uses a typical fuzziness weighting exponent; but the two coefficients in the objective function are only used as exhibitor of membership and typicality.

The fuzzy c-means assigns pixels to c partitions by using fuzzy memberships. Let \( X = \{x_1, x_2, x_3, \ldots, x_n\} \) denote an image with n pixels to be portioned into c clusters, where \( x_i \ (i = 1, 2, 3 \ldots n) \) is the pixel intensity. The objective function is to discover nonlinear relationships among data, kernel methods use embedding mappings that map features of the data to new feature spaces. The proposed technique Mean Shift with Fuzzy Clustering algorithm is an iterative clustering technique that minimizes the objective function.

Given an image dataset, \( X = \{x_1, \ldots, x_n\} \in \mathbb{R}^p \), the original KFCM algorithm partitions \( X \) into \( c \) fuzzy subsets by minimizing the following objective function as,

\[
J(w, U, V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m \|x_k - v_i\|^2 \quad (1)
\]

Where \( c \) is the number of clusters and selected as a specified value, \( n \) the number of data points, \( u_{ik} \) the membership of \( x_i \) in class i, satisfying the \( u_{ik} \geq 1, \sum_{i=1}^{c} u_{ik} = 1 \), the quantity controlling clustering fuzziness, and \( V \) the set of cluster centers or prototypes (\( \in \mathbb{R}^p \)).
To calculate the distance matrix that chooses a subset of the compound space which consists only compounds which have sufficient number of close neighbors. This is obtained based on the descriptor chosen in the earlier step. The similarity measures often used in calculation of similarity between chemical compounds are Euclidean measures. The similarity measure chosen is the Euclidean distance, which is based on the triangle inequality. Euclidean measure is chosen because it shows that it was best used in fuzzy clustering.

Euclidean distances are usually computed from raw data and the advantage of this method is that the distance between any two object is not affected if we add new objects (such as outliers) into the analysis. The similarity measures using Euclidean distance is measured based on inter-point distance \(d(x_1, x_2)\) and the equations for binary descriptor is as follows:

\[
d(x_1, x_2) = 1 - \frac{a^2 + b^2 - 2ac}{a^2 + b^2} \quad (2)
\]

**C. Digital Surface Model (DSM)**

DSM’s measure the height values of the first surface on the ground. This includes terrain features, buildings, vegetation and power lines etc. DSM’s therefore provide a topographic model of the earth’s surface. DSM’s can be used to create 3D fly-through, support location-based systems and augmented simulated environments. DSMs were checked manually for probable errors. Corresponded to ground samples, standard deviation and range of DSM pixels have been calculated.

The building extraction is focused on the detected building segments \(S\). The data \(D\) within these segments consists of points which either belong to mutually exclusive homogeneous regions \(R\), \(\{R_1, \ldots, R_k\}\), \(R_i \cap R_j = \emptyset\) or to the set \(E\) of non-homogeneous regions, thus \(D = R \cup E\). The discontinuities – borders of planar patches – are indicated either by depth changes along the surface normal’s or high curvature, which is related to changes of the surface normal’s: \(E = E_{v} \cup E_{n}\). Therefore, the first steps for building roof plane detection are the computation of surface normal’s and their filtering in order to reduce the influence of noise. The filter follows the scheme of homogeneity criterion for the selection of the mask is the variance of the surface normal’s measured by,

\[
d_{nl} = \frac{1}{|N(p)|-1} \sum_{N(p)} ||d|| with \ d = n - \bar{n} \quad (3)
\]

where \(\bar{n}\) denotes the mean surface normal and \(N\) the neighbourhood taken into account. The filtered surface normals are used to compute the strength of step edges,

\[
d_{depth} = \max(n \cdot (x_k - x_1) | P_s \in (P_i)) \quad (4)
\]

**D. Graph Based Change Detection Method**

The graph based fusion approach is to automatically extract a set of projective transformations induced by these building regions, detect the occlusion pixels over multiple consecutive frames, and segment the scene into several motion layers. First, after determining a number of seed regions using correspondences in two frames, to expand the seed regions and reject the outliers employing the graph cuts region merging method integrated with salient motion representation. Next, these initial regions are merged into several initial layers according to the motion similarity. Third, an occlusion order constraint on multiple frames is explored, which enforces that the occlusion area increases with the temporal order in a short period and effectively maintains segmentation consistency over multiple consecutive frames.

A good solution to suppress halos is to apply the scene gradients to adjust the gradient of the synthesized SDR image. The scene gradient information is adaptively captured by setting the different exposure levels, i.e., the scene gradients are captured through the local adaptation to the scene luminance for an window \(M \times M\) centered at \((x, y)\). Technically, the scene gradient of a point is reflected by the gradient that is perceivable by human eyes, called visible gradient, and that can be measured by counting the number of visible differences of luminance’s between neighboring pixels in the window.

**IV. CONCLUSION AND FUTURE WORK**

In this paper proposed on adaptive change detection method based on fuzzy logic and graph representation, which is aimed at identifying all the possible change classes present between the considered images. The proposed novel fuzzification scheme is developed by considering spectral change information to identify the change classes having discriminable spectral behaviors.

The detection of changes is extended by the use of differential geometric properties of the surfaces to distinguish between buildings areas within the DSM. Thus, the proposed approach leads to a notable reduction of computation cost with similar performance compared with traditional solutions.

In future the automatic building portion extraction system could be an extra option for processing hyper spectral images an enhancement option for future enhancement.

**REFERENCES**


