A Review: CEST Method Based Analysis for the Detection of Damaged Buildings in Crisis Areas

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Abstract-* This paper describes new combined method that consists of a cooperative approach of several different algorithms for automated change detection. Remote sensing data are primary sources extensively used for change detection in recent decades. Many change detection techniques have been developed. This paper summarizes and reviews these techniques. Previous literature has shown that image differencing, principal component analysis and post-classification comparison are the most common methods used for change detection. In recent years, CEST method spectral mixture analysis, artificial neural networks and integration of geographical information system and remote sensing data have become important techniques for change detection applications. Different change detection algorithms have their own merits and no single approach is optimal and applicable to all cases. In practice, different algorithms are often compared to find the best change detection results for a specific application. Research of change detection techniques is still an active topic and new techniques are needed to effectively use the increasingly diverse and complex remotely sensed data available or projected to be soon available from satellite and airborne sensors. This paper is a comprehensive exploration of all the major change detection approaches implemented as found in the literature.

***Keywords-* ASTER, AVHRR, CEST, Change detection, edge detection, segmentation, TM**

I INTRODUCTION

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multitemporal data sets. One of the major applications of remotely-sensed data obtained from Earth-orbiting satellites is change detection because of repetitive coverage at short intervals and consistent image quality. Change detection is useful in such diverse applications as land use change analysis, monitoring of shifting cultivation, assessment of deforestation, study of changes in vegetation phenology, seasonal changes in pasture production, damage assessment, and crop stress detection, disaster monitoring snow-melt measurements, day/night analysis of thermal characteristics and other environmental changes. Manual handling of data for change detection using sequential imagery is a formidable task. The digital nature of most satellite data make it easily amenable for computer-aided analysis. There is a definite need for a change detector which will automatically correlate and compare two sets of imagery taken of the same area at different times and display the changes and their locations to the interpretor. The basic premise in using remote sensing data for change detection is that changes in land cover must result in changes in radiance values and changes in radiance due to land cover change must be large with respect to radiance changes caused by other factors. These 'other' factors include (1) differences in atmospheric conditions, (2) differences in Sun angle and (3) differences in soil moisture. The impact of these factors may be partially reduced by selecting the appropriate data. For example, Landsat data belonging to the same time of the year may reduce problems from Sun angle differences and vegetation phenology changes. In general, change detection involves the application of multi-temporal datasets to quantitatively analyse the temporal effects of the phenomenon. Because of the advantages of repetitive data acquisition, its synoptic view, and digital format suitable for computer processing, remotely sensed data, such as Thematic Mapper (TM), Satellite Probatoire d'Observation de la Terre (SPOT), radar and Advanced Very High Resolution Radiometer (AVHRR), have become the major data sources for different change detection applications during the past decades.

Good change detection research should provide the following information: (1) area change and change rate; (2) spatial distribution of changed types; (3) change trajectories of land-cover types; and (4) accuracy assessment of change detection results. When implementing a change detection project, three major steps are involved: (1) image preprocessing including geometrical rectification and image registration, radiometric and atmospheric correction, and topographic correction if the study area is in mountainous regions; (2) selection of suitable techniques to implement change detection analyses; and (3) accuracy assessment [1].

II. CONSIDERATIONS BEFORE IMPLEMENTING CHANGE DETECTION

MacLeod and Congalton described four important aspects of change detection for monitoring natural resources: detecting if a change has occurred, identifying the nature of the change, measuring the areal extent of the change, and assessing the spatial pattern of the change. Before implementing change detection analysis, the following conditions must be satisfied: (1) precise registration of multi-temporal images; (2) precise radiometric and atmospheric calibration or normalization between multi-temporal images; (3) similar phenological states between multi-temporal images; and (4) selection of the same spatial and spectral resolution images if possible. Many kinds of remote sensing data are available for change detection applications. Historically, Landsat Multi-Spectral Scanner (MSS), TM, SPOT, AVHRR, radar and aerial photographs are the most common data sources, but new sensors such as Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) are becoming important. When selecting remote sensing data for change detection applications, it is important to use the same sensor, same radiometric and spatial resolution data with anniversary or very near anniversary acquisition dates in order to eliminate the effects of external sources such as Sun angle, seasonal and phenological differences [2].

III. DIGITAL CHANGE DETECTION TECHNIQUES

A. *Univariate Image differencing*

A critical element of the image differencing method is deciding where to place the threshold boundaries between change and no-change pixels displayed in the histogram. Image differencing is the most widely used technique for change detection and has been used in a variety of geographical environments. From the analysis of the relevant scientific literature, univariate image differencing is the most widely applied change detection algorithm. It involves subtracting one date of original or transformed (e.g. vegetation indices, albedo, etc.) imagery from a second date that has been precisely registered to the first. With 'perfect' data, this would result in a dataset in which positive and negative values represent areas of change and zero values represent no change. A standardization of the differencing algorithm (difference divided by the sum) to minimize the occurrence of identical change values depicting different change events [3].

$$Dxkij=X^{k}_{ij}(t2)-X^{k}_{ij}(t1)+C \qquad (1)$$

Where X^{k}_{ij}; =pixel value for band k and i and j are line and pixel numbers in the image, t1=first date, t2=second date and C=a constant to produce positive digital numbers.

It is based on calculating the per-pixel gray value differences. For every pair of gray values at the same location at dates T1 and T2 the difference is calculated. If the resulting values are unchanged or do not exceed a pre-determined threshold no change has occurred. The degree of change is determined by the gray value differences [4].

B. *Image Regression*

A mathematical model that describes the fit between two multi-date images of the same area can be developed through stepwise regression. The algorithm assumes that a pixel at time-2 is linearly related to the same pixel at time-1 in all bands of the EMR spectrum acquired by the sensor. This implies that the spectral properties of a large majority of the pixels have not changed significantly during the time interval. The dimension of the residuals is an indicator of where change occurred. The regression technique accounts for differences in mean and variance between pixel values for different dates. Simultaneously, the adverse effects from divergences in atmospheric conditions and/or Sun angles are reduced. In the regression method of change detection, pixels from time t1 are assumed to be a linear function of the time t2, pixels. The difference image can be defined as follows

$$DX^{k}_{ij}=X^{\wedge k}_{ij}(t2)-X^{K}_{ij}(t1) \qquad (2)$$

The regression technique accounts for differences in the mean and variance between pixel values for different dates so that adverse effects from differences in atmospheric conditions or Sun angles are reduced. The regression procedure performed marginally better than the univariate image differencing technique in detecting urban land cover changes and tropical forest cover changes, respectively [1]. The critical part of the method is the definition of threshold values or limiting dimensions for the no-change pixel residuals. The highest change detection accuracy for tropical forest change detection with the regression method and the MSS5 band.

C. *Image Rationing*

Though not as quick and simple as image differencing, image ratioing is also one of the conceptually easier to understand change detection methods. Data are radioed on a pixel-by-pixel basis. A pixel that has not changed will yield a ratio value of one. Areas of change will have values either higher or lower than one. The image ratio method is very similar to image differencing. For every pair of gray values at the same location at dates T1 and T2 the per-pixel ratio of the two values is calculated. Both methods vary through different spectral band combinations, the choice of thresholds, or different available spectral resolutions. Especially, the choice of a suitable threshold level is a critical factor, because of a time consuming manual interpretation and the integration of a priori knowledge in the analysis process. In ratioing two registered images from different dates with one or more bands in an image are ratioed, band by band. The data are compared on a pixel by pixel basis.

D. Principal Component Analysis (PCA)

The principal component (PC) transform is a statistical method to calculate a new synthetic (uncorrelated) data space. With this approach, it is possible to strengthen wavelength dependent material specific differences. Principal component analysis (PCA) can be used in different ways for change detection.

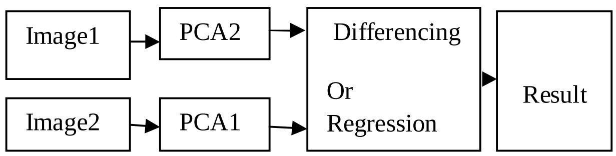

Fig.1 Principal Component analysis

Two bitemporal spectral bands of the same location are analyzed in a two dimensional feature space. As a result, all gray values are located in relation to the two principal components. Usually, the unchanged pixels show a high correlation with the first principal component in contrast to the changed pixel. As a consequence, the first principal component contains the 'unchanged' information and the second component the 'change' information [5].

E. Post-Classification Comparison

Post-classification comparison is sometimes referred to as 'delta classification'. It involves independently produced spectral classification results from each end of the time interval of interest, followed by a pixel-by-pixel or segment-by-segment comparison to detect changes in cover type.

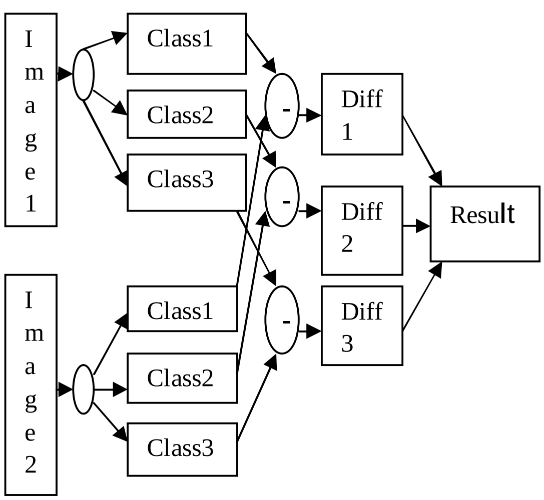

Fig. 2 Post-Classification Comparison

Post classification analysis is based on a comparison of two independent classification results for at least two dates T1 and T2. This method allows the determination of the kind of change from one class to another. For example, each input data set of T1 and T2 can be classified with the unsupervised isodata algorithm [4] using 20 classes.

F. Multivariate Alteration Detection

The multivariate alteration detection (MAD) uses canonical correlation analysis to find relationships between two datasets. The canonical analysis provides two sets of linear combinations of the original data. The first two linear combinations (canonical variates) have the largest correlation (first canonical correlation). The second canonical variates have the second largest correlation and are orthogonal to the first canonical variates. Basis for the change detection approach is the difference between these pairs of variates. The MAD transformation is defined as

$$\begin{bmatrix} X \\ Y \end{bmatrix} \rightarrow \begin{bmatrix} a_p^T X - b_p^T Y \\ \vdots \\ a_l^T X - b_l^T Y \end{bmatrix}. \quad (3)$$

Where aI and bI are the defining coefficients from standard canonical correlations analyse. X and Y are vectors with expectation values E{X} =E{Y} =0 [6].

G. Remotely sensed change detection based on artificial neural network

Usually, change detection involves two or more registered remotely sensed images acquired for the same ground area at different times. During the last two decades, there have been many new developments in remotely sensed change detection. These techniques may be characterized by their functionalities and the data transformation procedures involved. Based on these characteristics, we can classify current change-detection techniques into two broad categories: Change Mask Development (CMD) Only changes and non changes are detected and no categorical change information can be directly provided; and Categorical Change Extraction (CCE): Complete categorical changes are extracted. In the first category, changed and non-changed areas are separated by a preset threshold when comparing the spectral reflectance values of multitemporal satellite images. The amount of change is a function of the preset threshold. The threshold has to be determined by experiments. The nature of the changes is unknown directly from these techniques and needs to be identified by other pattern-recognition techniques. Therefore, these techniques are only suitable for development of a change mask. Most change-detection methods fall into the first category. For example, image Differencing, Image Ratioing, and Image Regression only lead to the development of a change mask. These techniques can be used for data of one band, two bands, three bands, or more than three bands, with decision boundaries which are two-threshold, elliptical, ellipsoidal, or hyper-ellipsoidal, respectively. The data used can be spectral data or data transformed by various linear or non-linear transformations, such as vegetation indices (e.g., Normalized Difference Vegetation Index (NDVI) [7].

IV. NEW DEVELOPMENTS

A. Combined Edge Segment Texture (CEST) Analysis for Change Detection

Because simple methods such as image difference or image ratio failed to detect reliably changes of buildings in the study images, we had to develop a different procedure for automated change detection. This procedure is based on several different principles: frequency based filtering, segmentation, and texture analysis. Four of these methods are based on filtering in the frequency domain after a Fourier transforms [8].

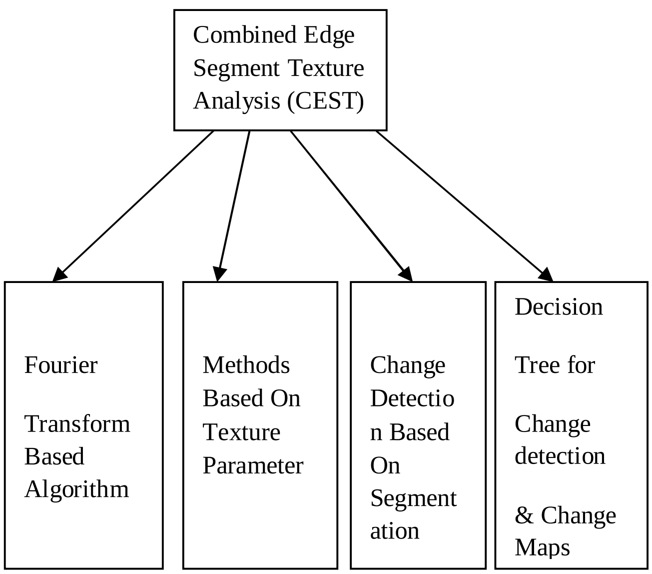

Fig. 3 CEST Method analysis

One on segmentation and the others on texture features. The frequency domain is used because it allows the direct identification of relevant features such as edges of buildings. If no features are directly visible (such as partial destruction with still standing outside walls), texture parameters are used for debris identification. A segmentation algorithm is used to extract size and shape of buildings. These methods can be combined in a decision tree for accuracy improvement. The combination of these processing steps is called Combined Edge Segment Texture (CEST) analysis. The produced change images are to a large degree abstract and hard to interpret. This holds particularly true for people not related to remote sensing such as members of official organizations or rescue forces. For planning after a crisis or a catastrophe, the interpretation of change images should be as easy as possible. An algorithm was developed to automatically produce a map which can be easily interpreted.

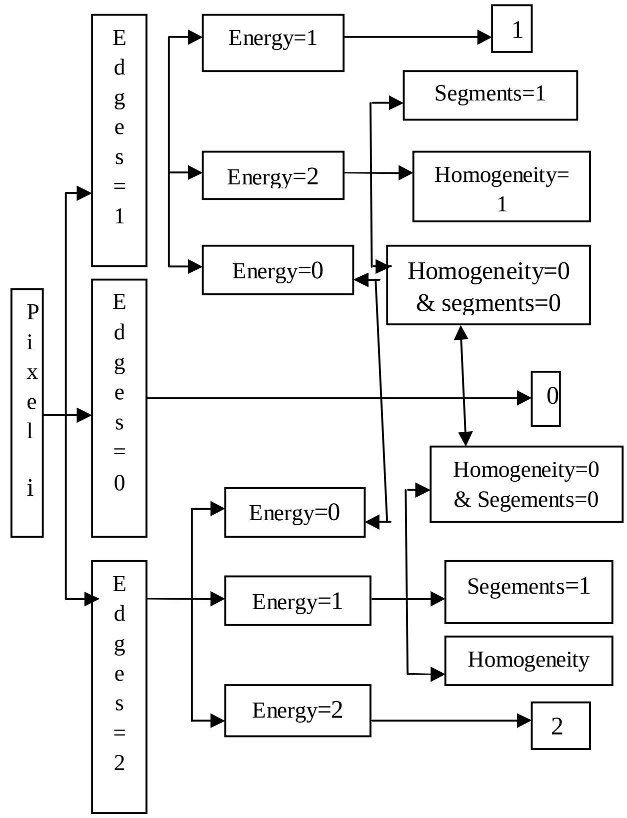

Fig. 4 Decision tree for the combination of change detection methods (CEST)

Finally, all three methods are combined in a decision-tree approach (Fig. 4). The basis for the classification is the result of the change detection algorithm using edge detection based on frequency filtering. If the edge parameter shows 'no change', the pixel in the image is classified as 'no change'. If the edge parameter shows 'new building', the pixel is classified as new, if the texture feature 'energy' is an agreement. If energy shows 'change' and one of the features 'homogeneity' or 'segmentation' shows 'change', the result is 'new'. Otherwise, it is classified as unchanged. If the edge parameter shows 'change', it is classified as 'change' if the texture feature 'energy' coincides. If energy shows 'no change', the pixel will be classified as 'no change'. If energy shows 'new' but the segment and homogeneity parameters show 'change', the pixel is assigned to 'change'. Otherwise it is classified as unchanged. The CEST procedure was tested against the standard change detection methods [9].

V. RECOMMENDATIONS

(1) For a rapid qualitative change detection analysis, visual interpretation of multi-temporal image colour composite is still a common and valuable method. (2) For digital change detection of change/non-change information, single band image differencing and PCA are the recommended methods. (3) For a detailed 'from–to' detection, post-classification comparison is a suitable method to implement when sufficient training sample data are available.(4) When multi-source data are used for change detection, GIS techniques are helpful. (5) Advanced techniques such as LSMA, ANN or a combination of different change detection methods can be useful to produce higher quality change detection results.

V. CONCLUSIONS

In this paper, a new automated change detection method (CEST) is presented. CEST combines adaptive filtering in the frequency domain with edge detection in the spatial domain, calculation of the texture features 'homogeneity' and 'energy' with a PCA change detection approach and segment based correlation.

The data-gathering capabilities of space-borne remote sensors have generated great enthusiasm over the prospect of establishing remote sensing based systems for the continuous monitoring of ecosystems. The accuracy of satellite remote sensing for monitoring forest change was not quickly or easily achieved, today it is well established that remote sensing imagery, particularly digital data, can be used to monitor and map changes in ecosystems. Although all of the possible change detection methods have not been applied to the same data for cross-evaluation, it is evident from this review that:

1. Vegetation indices are more strongly related to changes in the scene than the responses of single bands.

2. Precise registration of multi-date imagery is a critical prerequisite of accurate change detection. However, residual misregistration at the below-pixel level somewhat degrades area assessment of change events at the change/no-change boundaries.

3. Some form of image matching or radiometric calibration is recommended to eliminate exogenous differences, for example due to differing atmospheric conditions, between image acquisitions. The goal should be that following image rectification, all images should appear as if they were acquired with the same sensor, while observing through the atmospheric and illumination conditions of the reference image.

4. Image differencing and linear transformations appear to perform generally better than other bi-temporal change detection methods. Differences among the different change maps and their accuracies are undoubtedly related to the complexity and variability in the spatial patterns and spectral–radiometric responses of ecosystems, as well as to the specific attributes of the methods used.

5. Patterns of seasonal and inter-annual variations in land surface attributes, which can be driven by climatic variability (e.g. ENSO), natural disasters (e.g. fires, floods), land-use changes (e.g. deforestation) or global climate change (e.g. climate warming), can be detected using high temporal frequency data from wide field of view sensors, provided that great care has been taken to remove sensor-related artifacts in time series and that an appropriate profile-based change detection method is applied. This research area is still in its infancy compared to the more classic bi-temporal change detection techniques used with medium to fine spatial resolution remote sensing data.

6. There is a high complementarity between different change detection methods. This is certainly true when one seeks to detect a wide range of ecosystem changes at one given scale. It also applies to the design of multi-scale monitoring systems that combine methods adapted to detect changes at regional to global scales with methods better suited for landscape-scale temporal analyses. While the former can be implemented continuously over large territories, the latter could only be applied where and when a change has been detected at a broader scale.

7. The capability of using remote sensing imagery for change detection will be enhanced by improvements in satellite sensor data that will become available over the next several years, and by the integration of remote sensing and GIS techniques, along with the use of supporting methods such as expert systems and ecosystem simulation models.

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