OBJECT-BASED CHANGE DETECTION – AN UNSUPERVISED APPROACH

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A variety of digital change detection techniques has been developed in the past three decades, ranging from interactive to automated procedures, from pre- to post-classification methods, from simultaneous to comparative analysis, from change extraction to change labelling, from bi-temporal to multitemporal methods, from spectral to spatial techniques and, last but not least, from pixel-based to object-based approaches. Reviews on the most commonly used techniques are given by i.e. [1-4].

For the detection of change pixels, several statistical techniques exist, calculating e.g. the spectral or texture pixel values, estimating the change of transformed pixel values or identifying the change of class memberships of the pixels. But when adopted to high-resolution imagery, the results of these pixel-based algorithms are sometimes limited. Especially if small structural changes are to be detected, object-oriented procedures seem to be more precise and meaningful.

Object-oriented change detection and analysis techniques can in addition estimate the changes of the mean object features (spectral colour, form, etc.), assess the modified relations among neighbouring, sub- and super-objects and find out changes regarding the object class memberships. Previous studies implying a combination of pixel- and object-based techniques have already demonstrated the advantages of firstly pinpointing the significant change pixels by statistical change detection and subsequently post-classifying the changes by means of a semantic model of change-related object features [5].

In the given paper, we propose a purely object-based change detection and classification approach. On account of this, the procedure starts with the segmentation of a bitemporal co-registered high-resolution satellite imagery data set. As a result, the objects in each segmentation layer consist both of simultaneous features (i.e. shape) and of features that can still be assigned to the two acquisition dates, i.e. most of the layer and texture values. The timely different object features provide therefore the basis to detect changes of and within the objects between the two dates.

For change detection, the so-called Multivariate Alteration Detection (MAD) transformation [6] is being used. The MAD procedure is based on a classical statistical transformation referred to as canonical correlation analysis to enhance the change information in the difference images. This method was originally developed for change detection within the multispectral feature space of the image pixels and will be applied here within the multidimensional, multivariate feature space of the objects. For a given number of object features N, the procedure returns N eigenvalues, N pairs of eigenvectors and N orthogonal (uncorrelated) difference images, referred to as to the MAD variates.

Processing the MAD transformation on a number of object features enhances different types of changes within the object level rather than resulting in a real classification of changes.

Unfortunately only changes signalled by at most three MAD variates can be displayed at one time. Furthermore, only two change categories (negative and positive) are modelled in each variate. Thus, the comprehensive visualisation and labelling of change objects becomes pretty difficult.

As suggested in [7], we therefore continue with the clustering of the change pixels. Clustering can be applied to any number of MAD variates simultaneously, and the number of clusters chosen determines the number of change categories. Objects holding a high change probability can be clustered in N dimensions. Finally, correlation between the MAD variates and the original object features can help in the physically/spectrally founded labelling of the change clusters.

The proposed procedure will be demonstrated and evaluated on the basis of a bitemporal, high-resolution satellite imagery featuring changes of different spatial and spectral dimensions.

For a rather spatial-driven approach, the two data sets would have to be segmented separately and the space features of the two acquisition times analysed statistically as described before.

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