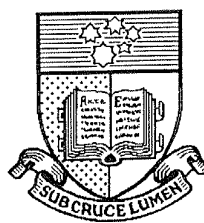




# CHANGE DETECTION IN REMOTE SENSING USING SUPERVISED FUZZY CLASSIFICATION

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# Abstract

Change detection is an important analytic function in pattern recognition and image processing. A variety of change detection approaches and techniques have been reported. Because it also identifies the nature of the change, the most appealing approach is to independently classify each image, and then compare the class labels. Unfortunately, this approach has shown relatively poor accuracy. This is, in part, because traditional classification approaches are themselves relatively inaccurate, and individual classification errors compound in the change detection process.

Traditional classification approaches seek to allocate each observation (e.g. pixel spectral values in an image) to one of a set of mutually exclusive classes, usually based on some maximum likelihood/least risk criterion. Unfortunately, classes commonly do not have distinct class 'boundaries'. Even human experts in the field will often disagree on class assignment e.g. when distinguishing between pasture and thinly wooded areas. Moreover, a single pixel in a remotely sensed image may contain a number of classes (the mixed pixel problem).

Fuzzy set theory was introduced to address issues such as class or set vagueness. Using fuzzy set theory, we can determine and reason with the grade of membership of a particular pixel in a number of classes. This provides an approach to partial class assignment in regions where there is a gradual transition from one class to another.

There is also support in the literature to its use in addressing the mixed pixel problem.

This thesis examines a fuzzy approach to Post Classification Comparison for change detection in digital remotely sensed imagery. Although this approach has wider application, the thesis focusses on its use for environmental monitoring.

A supervised fuzzy classifier was implemented by an adaptation of the unsupervised fuzzy *c*-means clustering algorithm. Class means and covariance matrices are determined from training data. Fuzzy class memberships are calculated using the normalised weighted reciprocals of the Mahalanobis Distances of each pixel from each training class mean. Two approaches to comparing fuzzy class labels are examined: an arithmetic approach, and the use of fuzzy logic operators. The fuzzy logic approach is shown to be superior. It is then compared with the Boolean logic approach of traditional Post Classification Comparison, with highly favourable results.

The Mahalanobis Distance fuzzy classifier requires the *a priori* selection of a fuzzy weighting parameter. Previous work has provided only limited guidance on this matter (usually in the context of the unsupervised fuzzy *c*-means classifier). Suitable values for the parameter are investigated, both empirically and analytically, under the requirement that the fuzzy memberships reflect the proportions of class representation in each pixel. It is concluded that it is only possible to satisfy this requirement precisely, for all mixture proportions, in a special case. For the general case, the sensitivity of the fuzzy classifier to the selection of this parameter is investigated. This work also suggests an interpretation of the physical significance of the suggested range of suitable values.

It has been suggested that fuzzy classifications should be based on class posterior probabilities. It is shown that this approach gives poor results, producing a very 'hard' classification. Variants which produce more 'fuzzy' values are examined, but

these show a close correspondence to the Mahalanobis Distance approach, and offer no apparent advantage.

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