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Gradual land cover change detection based on multitemporal fraction images

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ABSTRACT

This study proposes a new approach to change detection in remote sensing multi-temporal image data. Rather than allocating pixels to one of two disjoint classes (change, no-change) which is the approach most commonly found in the literature, we propose in this study to define change in terms of degrees of membership to the class change. The methodology aims to model images depicting the natural environment more realistically, taking into account that changes tend to occur in a continuum rather than being sharply distinguished. To this end, a sub-pixel approach is implemented to help detect degrees of change in every pixel. Three experiments employing the proposed approach using synthetic and real image data are reported and their results discussed.

1. Introduction

Change detection in sets of image data covering the same scene but acquired at different times is of major interest in areas that include remote sensing, medical diagnosis, urban planning, and video surveillance. In remote sensing, change detection techniques based on multitemporal multispectral image data have been extensively applied to monitor agricultural fields, forests, and urban areas, among many other applications. Broadly speaking, the different approaches to change detection can be grouped into two categories: supervised and unsupervised methods [1–6]. In the supervised approach, the change map is basically obtained by comparing classified images produced from multispectral image data acquired at two different dates. The drawback related to this application is the necessity of ground truth data for both dates whereas unsupervised approach is based on the analysis of the multispectral image data itself, requiring no additional information. The supervised approach has some advantages over the unsupervised approach, such as the understanding of the changes in terms of the actual land-cover classes. In addition, it does not require image radiometric normalization to take account of different conditions at the two acquisition dates [7,8]. The multitemporal ground truth data required by the supervised approach gives rise to a problem however, since its acquisition is usually expensive and time consuming, rendering the supervised approach impractical in many real-world applications.

The unsupervised approaches to change detection are generally based on difference images. These are produced by subtracting, pixel by pixel, images acquired at two different times [9]. The differences can be computed either from the original features or from features extracted from the original data, such as principal components or vegetation indices. In either case, an image of differences is produced and a threshold is applied to distinguish pixels where change has occurred from pixels that remain unchanged. Many approaches proposed in the literature attempt to model the distributions for changed and unchanged classes in order to estimate an adequate value for a threshold separating both classes [2,10,11]. The change detection process can be performed using a single spectral band, which captures the changes of interest in the scene, or using a set of p spectral bands. One widely used technique to analyze the differences when more than one spectral band is used is Change Vector Analysis (CVA) [1,12,13]. In the CVA method applied to multispectral image data, differences are calculated at every spectral band and the total change is represented by a vector $\mathbf{X}$ in the p-dimensional space [12]:

$$\mathbf{X} = \sum_{j=1}^{p} (\mathbf{Y}_{2,j} - \mathbf{Y}_{1,j}), \quad (1)$$

where $\mathbf{Y}_{1,j}$ and $\mathbf{Y}_{2,j}$ are the feature vectors in spectral band j associated with corresponding pixels in two images acquired at

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the two dates, and p the number of spectral bands. Regardless of the change detection technique employed, spatial-context information can be also used to improve the accuracy in the final change-detection map [14].

Broadly speaking, the methodologies reported above seek to classify pixels into two classes, denoted by 'change' and 'no-change' classes. In some cases, however, this approach may not be the most satisfactory one. Frequently, the changes occurring in natural scenes over a given period of time show a gradual transition from a clear no-change to an unambiguous change. This might render a rigid partition of the data into two disjoint classes (change, no-change) somewhat arbitrary, unable to represent adequately the transitions that have actually occurred during a period of time. This paper proposes a different approach to this problem by considering degrees of membership to the change and no-change classes.

Several approaches to image data classification in terms of degrees of membership have been reported in the literature [15–18]. They allow pixels to belong partly to more than one class, and have proved to be more appropriate in some situations, such as when an image has a large proportion of mixed pixels, or when the land-cover classes lack a well-specified criterion to distinguish between them. A membership function based on the Gaussian maximum likelihood decision function was proposed in [15]. In [19], a supervised approach employed fuzzy classification based on decision trees, with degrees of membership estimated by the proportion of samples on the leaves of the trees. Another approach consists in applying the Linear Mixture Model to classify image pixels in terms of proportions of the component classes [20]. In that study the authors implement the concept of spectral mixture to estimate more accurately the degrees of change in vegetation cover (percentages of woody vegetation, herbaceous vegetation and bare ground) on a multi-year Advanced Very High Resolution Radiometer (AVHRR) image data set.

In this paper we investigate a Bayesian approach to estimate degrees of membership to the classes change and no-change based on the differences in the fraction images calculated for two different dates. Fraction images show the fraction of a pixel's area covered by each class present in the scene. In this context the classes present in the scene are frequently referred to as "endmembers" or "components" [21,22]. The degrees of membership are estimated in a way similar to that proposed in [15], but based on the fractions of endmembers rather than directly on the multispectral bands, allowing changes assessment at the sub-pixel level [23]. This approach may become convenient in the monitoring of natural scenes. The "hard" approach of classifying a pixel in either class based on a given threshold may obscure subtle changes in land-cover. As an example, deforestation, land degradation and loss of vegetation cover due to poor land-use practices may go undetected until the vegetation cover is sufficiently sparse to cross the adopted threshold [20]. Moreover, another advantage of a change detection approach based on fraction images rather than directly on the spectral bands lies in the fact that, in this case, there is no need to adjust the image data acquired at different dates to a common radiometric response [7], provided that the spectral signature of each endmember is extracted from each image data (e.g., by means of "pure pixels" in each one). In a second step of this work, the estimated degrees of membership are further adjusted by implementing spatial contextual information in a relaxation approach.

2. Methodology

2.1. The proposed approach to change detection

The initial step consists of producing fraction images for the images concerning the two dates we are interested to detect changes. Several approaches to the mixture problem have been proposed in the literature [24]. Here we use the well-known Linear Mixture Model (LMM) which can be expressed as a set of p linear equations representing each band, and m the number of fraction components [22]:

$$\mathbf{R} = \mathbf{SF}+\mathbf{V}, \tag{2}$$

where $\mathbf{R}$ is a $(p \times 1)$ vector whose entries are the pixel's response in each of the p spectral bands, $\mathbf{S}$ is $(p \times m)$ matrix whose entries $s_{i,j}$ represent the spectral response of endmember j in spectral band i, $\mathbf{F}$ is an $(m \times 1)$ vector with the unknown fractions (f_j), and $\mathbf{V}$ a $(p \times 1)$ vector of residuals. In practice $p > m$, and the system in Eq. (2) can be solved for the unknown fractions (f_j) by least squares subject to the constraints:

$$0 \le f_j \le 1 \quad \forall j \quad \sum_{j=1}^{m} f_j = 1. \tag{3}$$

An important task consists of extracting the endmembers to be used in Eq. (2), i.e., identifying pure source signals from the mixture. The most commonly used approach to this problem consists of assuming the existence of pure pixels in the image scene, i.e., pixels that include a single endmember [25].

We consider the pixel-by-pixel differences in the fractions ($\mathbf{X}$) as the problem variables, i.e., as the feature space. We also assume that, in the space of $\mathbf{X}$, both classes can be modeled by a multivariate normal distribution. It is well known that the normal distribution is a satisfactory model concerning many natural processes including spectral responses in natural scenes, a fact explained by virtue of the Central Limit Theorem [26]. Following this approach, a pixel is represented by an m-dimensional vector $\mathbf{X}$ of the differences in the fractions of the endmembers from date 1 to date 2. As mentioned, two classes are used in this study: change (c) and no-change (nc). The degree of membership $\Phi_i(\mathbf{X})$ (i=c, nc) of pixel $\mathbf{X}$ to each of the two classes can be estimated by the *a posteriori* probabilities:

$$\Phi_i = p(\omega_i/\mathbf{X}), \tag{4}$$

with i=c, nc.

From Bayes theorem:

$$p(\omega_i/X) = \frac{p(X/\omega_i)P(\omega_i)}{p(X)} = \frac{p(X/\omega_i)P(\omega_i)}{\sum_{j=c,nc} p(X/\omega_j)P(\omega_j)}. \tag{5}$$

Assuming a multivariate normal distribution:

$$p(X/\omega_i) = \frac{1}{(2\pi)^{p/2}} \frac{1}{|\boldsymbol{\Sigma}_i|^{1/2}} \exp\left[-\frac{1}{2}(\mathbf{X}-\boldsymbol{\mu}_i)^t \sum\nolimits_i^{-1} (\mathbf{X}-\boldsymbol{\mu}_i)\right] P(\omega_i), \tag{6}$$

where $\boldsymbol{\mu}_i$, $\boldsymbol{\Sigma}_i$, and $P(\omega_i)$ represent, respectively, the mean vector, the covariance matrix, and the *a priori* probability for class ω_i, and p the data dimensionality, which in this case is equal to the number of fraction components (m). The degrees of membership Eq. (4) can thus be expressed by:

$$\Phi_c(\mathbf{X}) = \frac{|\boldsymbol{\Sigma}_c|^{-(1/2)} \exp[-(1/2)(\mathbf{X}-\boldsymbol{\mu}_c)^t \boldsymbol{\Sigma}_c^{-1}(\mathbf{X}-\boldsymbol{\mu}_c)]P(\omega_c)}{(|\boldsymbol{\Sigma}_c|^{-(1/2)} \exp[-(1/2)(\mathbf{X}-\boldsymbol{\mu}_c)^t \boldsymbol{\Sigma}_c^{-1}(\mathbf{X}-\boldsymbol{\mu}_c)]P(\omega_c)) + (|\boldsymbol{\Sigma}_{nc}|^{-(1/2)} \exp[-(1/2)(\mathbf{X}-\boldsymbol{\mu}_{nc})^t \boldsymbol{\Sigma}_{nc}^{-1}(\mathbf{X}-\boldsymbol{\mu}_{nc})]P(\omega_{nc}))} \tag{7}$$

$$\Phi_{nc}(\mathbf{X}) = \frac{|\boldsymbol{\Sigma}_{nc}|^{-(1/2)} \exp[-(1/2)(\mathbf{X}-\boldsymbol{\mu}_{nc})^t \boldsymbol{\Sigma}_{nc}^{-1}(\mathbf{X}-\boldsymbol{\mu}_{nc})]P(\omega_{nc})}{(|\boldsymbol{\Sigma}_c|^{-(1/2)} \exp[-(1/2)(\mathbf{X}-\boldsymbol{\mu}_c)^t \Sigma_c^{-1}(\mathbf{X}-\boldsymbol{\mu}_c)]P(\omega_c)) + (|\boldsymbol{\Sigma}_{nc}|^{-(1/2)} \exp[-(1/2)(\mathbf{X}-\boldsymbol{\mu}_{nc})^t \boldsymbol{\Sigma}_{nc}^{-1}(\mathbf{X}-\boldsymbol{\mu}_{nc})]P(\omega_{nc}))} \tag{8}$$