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A MODELING-BASED THRESHOLD APPROACH TO DERIVE CHANGE/NO CHANGE INFORMATION OVER VEGETATION AREA

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Abstract

Change detection is an important application of remote sensing in environmental monitoring. A modeling-based threshold approach using the connectivity information of individual pixels (regions) was introduced and compared with the method using standard deviation as the region-based change detection give often better results. This approach was used in combination with four widely used image differencing methods to derive change and no change information over a semi-natural vegetated area in Mediterranean southern France. After comparing the results visually with the aid of a vegetation map and aerial photos, a suitable automatic change detection method was developed: the tasseled cap transformation plus change vector differencing followed by this modeling-based thresholding approach. The dataset used in this study are two Landsat TM/ETM+ scenes of (acquisition dates of the images are 2001 and 1996). A graphical tool is developed in ERDAS/Imagine using EML (Erdas Macro Language) and SML (Spatial Modeling Language) for implementing this automatic change detection algorithm. This study shows that more research is required aiming at integrating digital image processing techniques and the applied use of earth observation.

INTRODUCTION

Remote sensing has the potential to be a powerful tool to study environmental changes and this attracted a lot of efforts on this research topic. Researchers have been seeking the development of efficient and accurate procedures for detecting and labeling the changes in multi-spectral or single band image sets taken at two or more different times. Change detection may mean different things to different users depending on the details of the change required. In general, change detection is a process of identifying differences in the state of objects or phenomena by observing them at different times (Singh, 1989). The term 'change detection' often involves detection of the change, normally its location and extent, and sometimes the identification (i.e., what change occurred). Analysis (i.e., the causes and implications of the change) is normally left to a human analyst.

The most difficult issue we have to deal with while working on change detection is the sources of uncertainty in mapping the changes. Spectral radiance registered by optical RS systems is a function of surface optical properties, atmospheric optical properties, solar and sensor zenith angle, solar and sensor azimuth angles and sensor properties. And the surface optical properties of vegetation is controlled by the biophysical and structural properties of canopy such as leaf water content, leaf chlorophyll content, concentration of minor absorbers, leaf area index, leaf inclination angle distribution, leaf location in 3D, index of leaf mesophyll structure and soil reflectance. Factors such as diurnal sun angle effects, seasonal sun angle differences, spatial registration, clouds, haze, or extreme humidity conditions, soil moisture conditions, seasonal and annual phenological cycles of vegetation also need consideration. Because there is not an ideal way to extinguish all these error sources, the error will be propagated in different change detection algorithms. And change detection algorithms themselves may introduce new errors and all these errors are propagated into the final change maps.

In terms of detecting changes, automatic change detection methods share similar sequential steps: preprocessing to create a multi-temporary dataset; image differencing; thresholding to derive change/no change information. Geometric correction and relative radiometric correction are widely accepted as necessary preprocessing steps. There are many options for creating differencing image, among which (Schowengerdt, 1997) image radiance /reflectance differencing, NDVI differencing, tasseled cap transformation plus change vector differencing are widely used. However, the last step i.e. threshold used to determine whether a detected change is indeed a real change, is far more difficult and only few studies have investigated this problem. One frequently used approach is using standard deviation of the differencing image as a possible threshold. However, this approach does not account for the spatial variation of land cover change and as a result is less accurate. Hence, it is not possible to derive accurate statistical information of change versus no change. Thresholding is a crucial step and needs more attention and study.

When copying techniques from digital image processing disciplines we can investigate various approaches to solve this problem. The goal of this study is to provide with a comparative study, demonstrating the success of a modeling-based threshold approach in showing a better accuracy and higher automaticity using two TM/ETM+ images to detect changes over a vegetated area.

THRESHOLD BY MODELING

It is reasonable to assume that a good threshold for change detection should reduce the noisiness of the final output and help to highlight the changes. As the threshold increases, and the real changes are small, less changes are found. From the graph “number of regions against thresholds”, you will find when noise is present in the imagery, small changes in the threshold value can substantially alter the number of regions. Such an observation suggests that if a range of the threshold values is found that leads to a stable number of regions, then these regions are unlikely to come form noise, and so a value from this range will provide a suitable threshold. Since at low threshold values there will be many regions and holes caused primarily by the noise, and the region number will change rapidly with threshold, the shape of the graph can be modeled as a decaying exponential function. At high threshold values there will be few regions. Therefore a suitable partition point between the signal and noise is the corner of the curve, which was found as the point on the curve with maximum deviation from the straight line drawn between the end points of the curve. This approach was applied successfully to two frames, with a size of 512 pixels by 512 pixels, of an outdoor scene containing a pedestrian crossing a car park. (Rosin and Ellis, 1995)

Based on its logic background, this approach was applied to Landsat TM/ETM + images. The general algorithm of thresholding by modeling the spatial distribution of signals for change detection follows the steps below:

Step one: Calculate the number of regions for each threshold. Set one threshold, convert the value of the differencing image into 0 or 1 (0 means no-change, 1 means change), clump (or cluster) the images using connectivity information to get the regions, calculate the number of regions, go to the next threshold and so on until the last threshold; Step two: Model "number of regions against thresholds" as decaying exponential function: $y = ax^b$ (y refers to the number of regions, x refers to the threshold value, a and b are model parameters); Step three: Decide the corner of the decaying exponential curve, as the suitable threshold. The threshold is at the corner where has the maximum deviation from the line between the end points of the curve. In other words, it has the same first order derivation as the line between the end points of the curve.

Because of the consideration of the spatial information contained in the neighbourhood of each pixel, it's less sensitive to noise that may affect individual pixels (Bruzzone and Prieto, 2000). We can expect that this approach can reduce the effects of noise and hence increase change-detection accuracy.

STUDY AREA

The study area is La Peyne watershed, which is located in the Herault Province, southern France, 60-km west of Montpellier.. The Mediterranean climate is defined as an extratropical climate, characterized by a rainfall concentrated in the cold and relatively seasons, with a dry, warmer summer season. The summer dry season may last from two to six months. An annual rainfall ranges from about 100 mm to more than 2 500 mm (M'Hirit, 1999). Vegetation cover is mainly a dense forest of holm oak, often mixed with arbutus, and in some places with downy oak. Other vegetation units include chestnut woodlands, shrublands and grasslands (Caraux-Garson et al., 1999).

DATA SOURCES

A TM scene of year 1996, geocoded, and a raw Landsat 7 ETM + image, year 2001, are used for this study. The acquisition date of the TM image is September 8. ETM+ image was acquired on June 26, with path/row 197/030, centre point 43.0905 N, 3.27887 E. Both images were selected with as little cloud cover as possible and were selected in a time for a better characterization of vegetation. Besides, false colour aerial Photographs (1996), topographic maps, vegetation map, field data including descriptions of sample points in La Peyne area, are available for study area.

METHODOLOGY

Together eight methods (Table 1) were implemented and compared using the same data set. Each method consists of three steps.

Step one is preprocessing to create a multitemporary RS data set for change detection comprising firstly geometric correction and then radiometric normalization. ETM+ image is rectified to the same geo-referencing system as TM image using a geometric polynomial transformation model (first degree) and nearest neighbour resampling method. The total RMS error is around 0.5 pixel, which is suggested as acceptable for change detection. Next ETM+ image was selected as base scene (or reference scene) due to the stable radiometric performance of ETM+. The DN value of base scene, year 2001, is converted into radiance and then to reflectance by simple dark pixel subtraction. Dark pixel subtraction is perhaps the simplest yet most widely used image-based absolute atmospheric correction approach for classification and change detection applications (Jakubauskas, 1996). Then scene 1996 was converted from DN value to radiance and reflectance directly by means of histogram matching. Histogram matching is the process of determining a lookup table that will convert the histogram of one image to resemble the histogram of another. It is especially useful for change detection.

Table 1: Overview of different change detection methods applied in this study.

Methods	Step 1---preprocessing	Step 2---Image enhancement and differencing	Step 3---Threshold
1	Geometric Correction and Radiometric Normalization By histogram matching	Image Radiance Differencing	S.D
2			spatial modeling
3		Image Reflectance Differencing	S.D
4			spatial modeling
5		NDVI Differencing	S.D
6			spatial modeling
7		Tasselled Cap transformation And Vector Differencing	S.D
8			spatial modeling

Step two is image enhancement and differencing. Four widely used approaches were used: image radiance differencing, image reflectance differencing, NDVI differencing and Tasselled cap transformation followed by change vector differencing. See e.g. Mas (1999) and Hayes and Sader (2001) for details of these approaches.

Step three is to set a threshold for the differencing image and finally derive change/no change information. Thresholding by statistical value, standard deviation (abbreviated as S.D. in Table 1), and thresholding by modeling the spatial distribution of signals (changes), were used.

Finally a qualitative accuracy assessment was made by visually linking the change maps with raw images and with the aid of other data like some field data and aerial photographs. We did not do a quantitative accuracy assessment due to the fact that areas detected are only covering a very small part of the total area. To obtain an assessment with high confidence, a large number of sampling points have to be chosen which might be too much time-consuming.

All the methods were implemented in ERDAS/Imagine. ERDAS Macro Language (EML) and Spatial Modeler Language (SML) provide the ability to create a graphical interface in ERDAS/Imagine to implement the modeling-based threshold approach.

RESULTS AND DISCUSSION

Model result

Only 20 thresholds were used to model the distribution of “region vs. threshold”. One example (Figure 1) shows that 20 thresholds are enough for modeling the curve “number of regions against threshold”. The threshold started corresponding to the biggest number of regions. There is almost no fluctuation in the curve of “region vs. threshold” while applying the algorithm into satellite image. It indicates that this threshold approach could work well with satellite imagery.

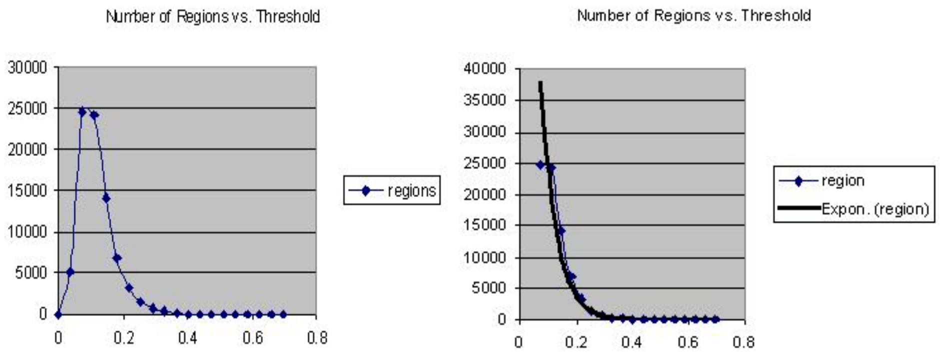

Figure 1: Modeling "number of regions vs. Threshold". The left chart shows that 20 thresholds are enough for modeling the decaying exponential curve. The right chart shows that the modeling result (bold line) fits the curve.

Compared with threshold with S.D.

Visually comparing the change maps (see Figure 2, 3, 4) created from the same image differencing method but using different threshold approaches and looking into the statistical summary of areas (Table 2) that changed, we may find that threshold by SD gives a much bigger area of changes than threshold by modeling does.

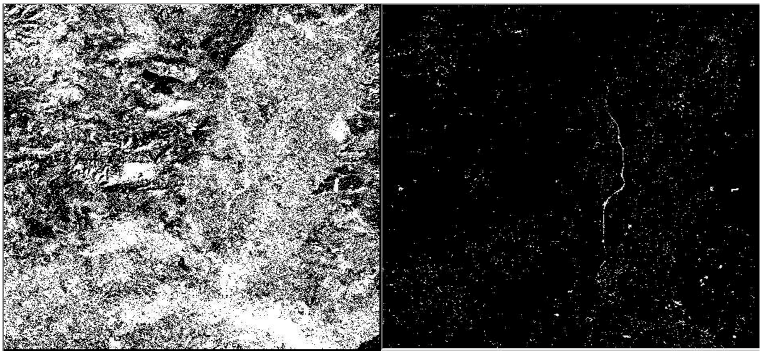

Figure 2: Change maps from image reflectance differencing with thresholding by predetermined statistic values (left) and by modeling the spatial distribution of signals (right).

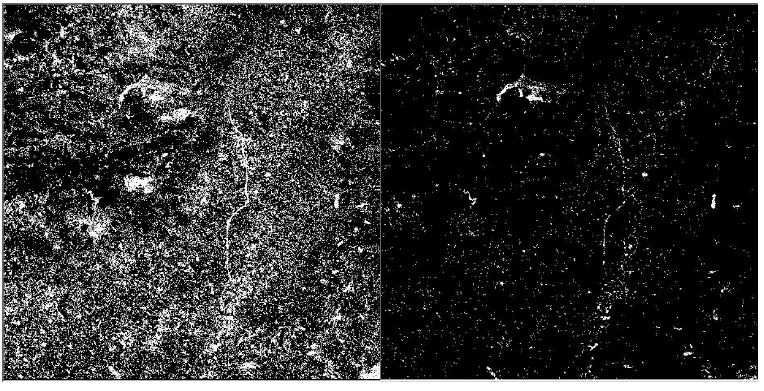

Figure 3: Change maps from NDVI differencing with thresholding by predetermined statistic values (left) and by modeling the spatial distribution of signals (right).

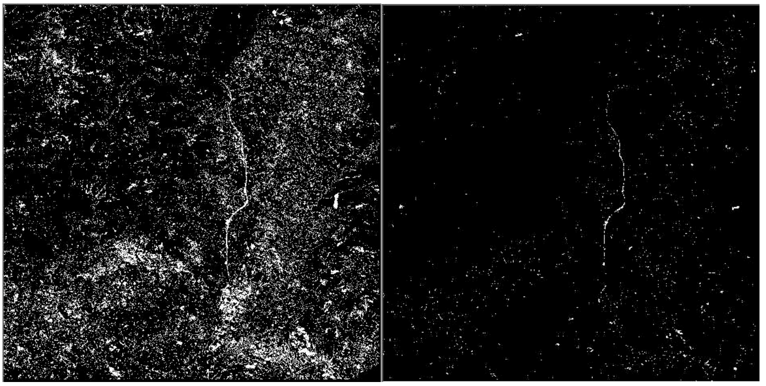

Figure 4: Change maps from change vector differencing with thresholding by predetermined statistic values (left) and by modeling the spatial distribution of signals (right).

Table 2: Statistical summary of areas that changed. SD means thresholding by Standard Deviation. (TCT refers to tasseled cap transformation).

ransformation algorithm	thresholding method	percentage of changed area (in %)
radiance difference	SD	58.0 (combination of changes from 6 bands)
	modeling	1.4
reflectance difference	SD	57.6 (combination of changes from 6 bands)
	modeling	1.4
NDVI difference	SD	27.1
	modeling	2.1
TCT + vector difference	SD	13.5
	modeling	0.7

The histogram of the differencing image produced from image differencing and NDVI differencing are approximately following normal distribution. According to normal distribution, the pre-determined statistical thresholds (standard deviation) will display roughly the same proportionate areas of change no matter what has actually happened in the area analyzed! That is to say, if you use SD as threshold, the change area will always be about 30%. In the Table 2 you can find a 27% changed area using NDVI differencing and thresholding by SD. It's the same when you examine the changes detected by image radiance (reflectance) differencing. For each band, you will get about 24% changes (Table 3). Histogram of vector difference has a different distribution so that areas of detected changes, 13.5%, are a bit far from 30%.

Table 3: The changes detected using reflectance difference for single band are around 24%.

reflectance difference (thresholding by SD)	Percentage of changes
band1	0.238
band2	0.226
band3	0.236
band4	0.267
band5	0.256
band7	0.248

Threshold by region-based spatial modeling give us much less areas of changes. It makes use of the spatial information so the noise that could affect pixels are minimized and the modeling approach itself could help to minimize noise.

The algorithm itself decided that lots of one-pixel level change couldn't be detected by this method. It means that there will be high omission error (areas where change happened are classified as non-change) if evaluated using a confusion matrix.

Comparison of the change detection methods

Since region-based thresholding is better than pixel-based thresholding as discussed above, the comparison of the change detection methods is now focused on the four image differencing methods, image radiance differencing, image reflectance differencing, NDVI differencing and vector differencing (change vector analysis), using tasseled cap components.

Looking at the four change maps (lower images in Figure 2, 3, 4, the results from image radiance difference is quite similar to that from image reflectance difference thus not presented here) using region-based thresholding method: Image Reflectance differencing detected a lot of shadows. NDVI differencing has the largest number of change pixels including a lot of wetlands or water bodies that are beyond research interests. This is due to the large difference of NDVI values over water bodies though the NDVI value in each single image is generally quite low. Other areas show a good accuracy of vegetation cover change. So, applying this method should mask the water areas first. Tasselled cap transformation with change vector differencing gave less area of changes. Visual interpretation indicates that almost all the regions of change are accurate.

The fourth one is the best method by visually evaluating the accuracy among these four methods. To see if some vegetation cover changes were treated as noises, sensitive analysis was performed to evaluate this method. Decreasing the threshold by 5%, more changes are detected but some of them are difficult to confirm by visual interpretation and most of the changes detected are one-pixel level changes.

CONCLUSIONS

Our prime goal of this study is to present a modeling-based threshold approach which is better than a conventional one using standard deviation as a threshold in detecting changes over a vegetated area. As we know it is impossible to eliminate the effects from error sources, we can minimize them in each change detection procedure from selecting of images, preprocessing the images to processing the images. Noises (false changes) can easily affect single pixel but not a region of potential real changes. Among all the eight change detection methods, thresholding change vector by spatial modeling is the best one. Visual inspection shows that it has the best global accuracy, though the omission error could be high. The method is highly automatic except the geo-referencing step. It has the potential to be used for a large multi-temporary dataset. As for other methods, NDVI differencing has potential to be good preprocessing method for change detection if water bodies or wetland can be masked beforehand.

Besides, we may conclude that TM/ETM+ images are useful datasets to derive change/no change information over such heterogeneous area as the Mediterranean area. With the created change maps we may quickly pinpoint the changed regions. The modeling-based threshold approach can also be used for detecting changes of other land cover types from time series of satellite data. This study shows that more research is required aiming at integrating digital image processing techniques and the applied use of earth observation.

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