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변화의 정량화 방법에 관한 고찰 : 픽셀값 대 분류항목별

A Discussion on the Two Alternative Methods for Quantifying Changes : by Pixel Values Versus by Thematic Categories

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要 旨

여러 분야에 있어서 원격탐사의 탐지 및 모니터링 기능과 지리정보시스템의 이성적 접근 및 분석기능을 접목함으로써 이에 의한 많은효과를 얻고 있다. 원격탐사기술 및 지리정보시스템을 접목하는 데에 있어서 핵심적인 응용분야로는 변화를 분석하는 것이 있다. 이러한 변화가 그 자체로 관심의 대상이 되거나, 또는 이로 말미암아 우리는 (지도를 개정하는 등의) 행동을 취하게 되기 때문에 원격탐사는 변화를 탐지하는 데에 있어서 훌륭한 도구가 된다. 지리정보시스템 또한 변화의 과정을 정량화하는 최상의 분석도구가 될 수 있다. 이러한 변화를 정량화하는 데에는 두 가지 방법이 있다. 개념적으로 간단한 방법으로는 각 이미지의 픽셀 값을 비교하는 것이 있다. 이 방법은 실질적인 반면, (적용이) 단순하여 복잡한 (자연) 환경에서의 다양한 변화를 분석할 수는 없다. 이에 대한 또 다른 방법으로는 기호변화탐지가 있다. 분석자는 먼저 판별하고자 하는 중요한 분류항목들을 결정한다. 이 방법은 토지리용 및 피복도가 정확하게 구분이 된 다음에야 효과적일 수가 있다. 디지탈 변화탐지를 수행하고자 하는 사람은 조사대상지역의 환경, 데이타 세트의 질, 그리고 변화탐지 알고리즘 등에 대해서 잘 알고 있어야 한다. 또한, 특정지역 및 (추진하고자하는) 과제에 적합한 변화탐지 알고리즘을 파악하는 작업을 수행 해야 한다.

ABSTRACT

In a number of areas, there are important benefits to be gained when we bring both the detection and monitoring abilities of remote sensing as well as the philosophical approach and analytic capabilities of a geographic information system to bear on a problem. A key area in the joint applications of remote sensing technology and GIS is to identify change. Whether this change is of interest for its own sake, or because the change causes us to act (for example, to update a map), remote sensing provides an excellent suite of tools for detecting change. At the same time, a GIS is perhaps the best analytic tool for quantifying the process of change. There are two alternative methods for quantifying changes. The conceptually simple approach is to compare the pixel values in each of the images. This method is practical but may be too simple to identify the variety of changes in a complex scene. The common alternative is called symbolic change detection. The analyst first decides on a set of thematic categories that are important to distinguish for the application. This approach is useful only if accurate landuse/cover classifications can be obtained. Persons conducting digital change detection must be intimately familiar with the environment under study, the quality of the data set, and the characteristics of change detection algorithms. Also, much work remains to identify optimum change detection algorithms for specific geographic areas and problems.

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1. INTRODUCTION

Remote sensing and image processing are powerful tools for many research and applications areas. Remote sensing may be defined as the process of deriving information by means of systems that are not in direct contact with the objects or phenomena of interest. Image processing specifically refers to manipulating the raw data produced by remote sensing systems. Remote sensing is a technology that has close ties to geographic information systems (GIS). For a variety of applications, remote sensing, while only one source of potential input to a GIS, can be valuable (Choung and Kim, 1992). It represents a powerful technology for providing input data for measurement, mapping, monitoring, and modeling within a GIS context. Indeed, it has been suggested that neither remote sensing of Earth resources nor GIS can reach their full potential unless the two technologies are fundamentally linked (Estes, 1984). This is very likely the case as GIS, to be most useful, must have the up-to-date information that can often be extracted from remotely sensed data.

From a philosophical point of view, applications of remote sensing are fundamentally in the realm of GIS, since the same concerns, and the same overall processing flows, are found (Star Estes, 1990). Seen this way, processing systems for remotely sensed data may, in large measure, be considered a specialized form of GIS. Remotely sensed data does, however, have certain unusual features, which may necessitate special-purpose components in the system. Furthermore, digital remote sensing systems often create immense volumes of raster data, which may stretch current computer processing and storage systems to their limits. Overall, however, we view a GIS as a generic system for manipulating spatial data, and see remote sensing and image processing as more specialized techniques of such systems.

Typically, the basis of change detection is the comparison of remotely sensed data and map data, or the comparison of remotely sensed data taken at two or more different times. When working with multi-temporal data sets, geometric registration is a fundamental concern. If we are unable to register the two images with high precision, the errors in registration will make it appear as if there has been some change in the landscape. We can consider a simple problem, such as a road running through a grassland(Star and Estes, 1990). If this area is imaged on two dates, and the imagery registered to each other imperfectly, some pixels that were originally grass will appear to be road in the later image, and some pixels originally road will appear to have changed to grass. Without critically examining the quality of the registration process in terms of accuracy and precision, we could be fooled into believing that the roadway was moved during the interval between the images. This is equally a concern when the images are each rectified to a common base map, rather than registered to each other.

Once the images are registered, there are two alternative methods to quantify change. The conceptually simple approach is to compare the pixel values in each of the images. However, while this is simple to calculate, it is exceedingly difficult to interpret. The common alternative is called symbolic change detection. The analyst first decides on a set of thematic categories that are important to distinguish for the application. The general characteristics of these two alternative methods for quantifying changes are discussed.

2. METHODS

2. 1 Quantifying Changes by Thematic Categories

Post-Classification Comparison

This is the most obvious method of change detection which requires the comparison of independently produced classification maps. An algorithm simply compares the two classification maps utilizing class pairs specified by the analyst and generates a map indicating areas of change (Jensen, 1986). By properly coding the classification results for times t_1 and t_2, change maps, which show a complete matrix of changes, can be produced. Therefore, any subset of changes which may be of interest can be identified by selective grouping of the classification results (Choung et al., 1993b).

Post-classification comparison holds promise because data from two dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates (Weismiller et al., 1977b; Howarth and Wickware, 1981; Singh, 1989). Weismiller et al. (1977a and 1977b) implied that the post-classification change detection procedure was the most suitable means of recording change among several methods tested.

However, the heterogeneity of the urban land cover frequently results in overall high classification errors on each date resulting in poor change detection performance (Jensen, 1983). That is, if the land cover classification generated from a single date of Landsat data is considered, it is not difficult to see that the change map product of two Landsat classifications is likely to exhibit accuracies similar to the product of multiplying the accuracies of each individual classification (Stow et al., 1980). Hence post-classification comparison can produce a large number of erroneous change indications since an error on either date gives a false indication of change. For example, two images classified with 80% accuracy might have only a 0.80*0.80*100 = 64% correct joint classification rate.

Gordon (1980) used the post-classification comparison method to monitor land use change in Ohio and concluded that substantial errors were associated with the use of Landsat data for land-cover and change analysis. Stow et al. (1980) found that this method produced poor results unless extremely accurate classifications of the individual dates were made. The accuracy of the method depends on the accuracy of the initial classifications, and any errors are compounded (Jensen, 1986). Toll et al. (1980) found that too much change was consistently identified and noted that the poor performance of this approach may, in part, be attributed to the "difficulty of producing comparable classifications from one date to another." The method is also more demanding in terms of computer time than the other change detection methods because it requires complete, separate classifications for each image (Singh, 1989). Choung and Ulliman (1992) evaluated this approach and compared its performance with that of image differencing to identify the patterns of wetland-cover changes in Jackson Hole, Wyoming using Landsat-5 TM images of 1985 and 1988.

2. 2 Quantifying Changes by Pixel Values

This conceptually simple approach is to compare the pixel values in each of the images. However, while this is simple to calculate, it is exceedingly difficult to interpret. This of course ignores the details of complex spectral changes. If the images can be registered with very high precision, and if the dates of the images represent identical moments in the seasonal cycle of vegetation growth and illumination, and if the viewing geometries of the two images can be taken into account, and if a host of other unlikely elements are precisely the same, then it is reasonable to compare the pixel multispectral brightness values between the two dates.

We will further discuss about this approach using two commonly used change detection algorithms, Image Differencing and Image Ratioing, as examples.

Image Differencing

In this technique, spatially registered images of times t_1 and t_2 are subtracted, pixel by pixel and band by band, to produce a further image which represents the change between the two times. The subtraction results in positive and negative values in areas of radiance change and zero values in areas of no-change. In an eight-bit (2^8) analysis with pixel values ranging from 0 to 255, the potential range of difference values is -255 to 255. Thus the results are normally transformed into ositive values by adding a constant C. Mathematically,

$$Dx^k_{ij} = x^k_{ij}(t_2) - x^k_{ij}(t_1) + C$$

where: x^k_{ij} = pixel value for band k; i and j are row and column numbers in the image; t_1 = first date; t_2 = second date; and, C = a constant, set equal to 128 for this study, to provide positive digital numbers.

The image differencing procedure yields a difference distribution for each band, approximately Gaussian in nature. In such a distribution, pixels showing radiance change are found in the tails of the distribution while pixels showing no radiance change tend to be grouped around the mean (Singh, 1986). Single-band images or combinations of different bands can be employed in this technique. The method employed in carrying out the differencing is presented schematically in Figure 1.

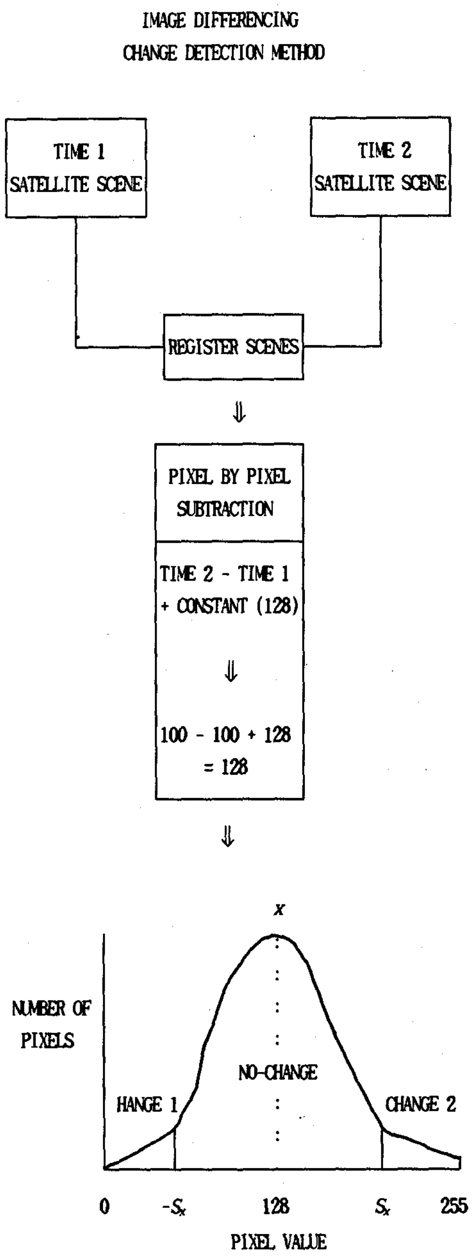

Figure 1. Image Differencing Change Detection Method.
Change 1 - Negative (Light to Dark) Change.
Change 2 - Positive (Dark to Light) Change.

Image differencing is the most widely used technique for change detection and has been used in a variety of geographical environments (Weismiller et al., 1977b; Jensen and Toll, 1982; Jensen, 1986; Singh, 1986; Griffiths, 1988; Choung, 1992). Jensen (1986) found that change detection based on the method of image differencing accurately identified land-use change between natural vegetation and partially or fully landscaped residential development in the image of Denver, Colorado using Landsat MSS band-5. LeDrew et al. (1987) also found that MSS band-5 differencing was particularly suitable for detecting changes in the urban fringe for the two study areas of Kitchener-Waterloo, Ontario, Canada and Paris, France. Singh (1986) used the technique for monitoring changes due to shifting cultivation in a tropical forest environment.

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 (Singh, 1989). Often, a standard deviation from the mean is selected and tested empirically to determine if changes were accurately monitored (Jensen, 1986). Fung and LeDrew (1988) examined the effect of using different accuracy indices in determining the optimal threshold levels for digital land-cover change detection. They found that the best threshold boundary level among five (0.8, 0.9, 1.0, 1.1, and 1.2) was 0.9 for a differenced image of MSS band-4 between 1981 and 1984 images, and 1.0 and 1.1 for the ratioed or higher-order principal component images. Singh (1986) found that standard deviation thresholds must be set at a low level, i.e., in the range of 0.5 to 1.0, in order to achieve maximum combined classification accuracy.

Varied threshold levels of this approach were examined by Choung et al. (1993a) to decide where to place the optimal threshold boundary between change and no-change pixels. The histograms of differenced change data sets were examined and the mean and standard deviation values for each data set were calculated. Threshold values of $\pm$ T standard deviations from the mean were iteratively selected to separate the change from no-change pixels. The T value was chosen as 1.0 in the first iteration. In the subsequent iterations, it was increased or decreased with an interval of 0.1 at each stage until a T value with highest accuracy for the thresholded data set was found. The thresholded images are binary theme images in which values of zero and one represent no-change and change, respectively.

Weismiller et al. (1977b) concluded that image differencing method may be too simple to deal adequately with all the factors involved in detecting change in a natural scene. Too much information may be discarded from the data in the subtraction process whereby only the four band difference data remains from the two sets of original four bands. Furthermore, Singh (1989) pointed out the mechanism for the type of information loss in image differencing. He noted that there is a potential loss of information with the use of simple differencing transformations, since two sets of different absolute values may have an identical differenced value (e.g., 180-150 = 30 and 40-10 = 30). However, this is not the case for only the image differencing technique. This kind of information loss problem is commonly applicable to most digital change detection algorithms except for the post-classification comparison method (Choung et al., 1993a).

Image Ratioing

Ratio transformations are especially useful for change detection when several dates of imagery are used in an analysis because they can reduce the effect of environmental and system multiplicative factors present such as changes in viewing conditions (e.g., shadows, seasonal reflectance differences due to sun angle, etc.) (Jensen, 1986). The better these factors are controlled, the higher the probability that accurate change detection will take place.

In ratioing, two registered images from different dates, with one or more bands, are ratioed, band by band. The data are compared on a pixel-by-pixel basis. The mathematical expression of the ratio function is:

$$Rx^k_{ij} = \frac{x^k_{ij}(t_2)}{x^k_{ij}(t_1)}$$

where, $x^k_{ij}(t_2)$ is the pixel value of band k for pixel x at row i and column j at time t^2. If the intensity of reflected energy is nearly the same in each image, then $Rx^k_{ij} = 1$, which indicates no-change. In areas of change, the ratio value would be significantly greater or less than one depending upon the nature of the reflectance changes between the two dates.

To represent the range of the function in a linear fashion and to encode the ratio values in a standard eight-bit (2^8) format (values from 0 to 255), normalizing functions are applied (Jensen, 1986). Using this normalizing function, the ratio value one is assigned the brightness value 128, while ratio values within the ranges of 1/255 to 1 and 1 to 255 are reassigned values between 1 to 128 and 128 to 255, respectively. The mathematical form for image ratioing technique is thus modified as:

$$R'x^k_{ij} = C * ARCTAN\left(\frac{x^k_{ij}(t_2)}{x^k_{ij}(t_1)}\right)$$

where C is the constant set equal to 162.34, and the ratio $R'x^k_{ij}$ can take upon itself any value from 0 to 255.

The critical element of the methodology is selecting appropriate threshold values in the lower and upper tails of the distribution representing change pixel values (Singh, 1989). The selection of threshold boundaries between change and no-change pixels is again based on empirical judgement.

The image ratioing technique for change detection was first reported by Todd (1977) for an area near Atlanta, Georgia, where 91 % of the land-use change was identified correctly using Landsat MSS band-5 data. Howarth and Boasson (1983) had good results for an area near Hamilton, Ontario, Canada, using MSS band-5 ratio data from 1974 and 1978. The band-5 ratio data were sensitive to cultural changes, while band-7 ratio data were sensitive to changes in water conditions.

Ratioing as a means of digital change detection has been criticized due to the non-Gaussian, bimodal distribution on which it is based (Singh, 1989). If the distributions are non-normal and functions of the standard deviations are used to delimit change from no-change, the areas delimited on either side of the mode are not equal. Therefore, the error rates on either side of the mode are not equal. For this, it would be beneficial to use different threshold levels in the upper and lower tails of the mode. However, using this kind of different threshold levels is not the economical approach since it requires more complicated analysis, thus, demanding more computer time. Even though the criticism on its non-Gaussian distribution, further studies of the ratioing method under a variety of conditions would be useful using simply standard deviations from the mean as the threshold boundary levels.

3. DISCUSSION and CONCLUSION

Digital change detection is a difficult task to perform accurately. The results will not be as accurate as those produced by a photointerpreter analyzing large-scale aerial photography on individual dates and transferring this information onto a base map (Jensen, 1986). Nevertheless, because manual change detection is exhausting, difficult to replicate, and incurs substantial data acquisition costs, researchers continue to seek improved digital change detection alternatives.

Spatial, spectral, and temporal constraints affect digital change detection. Assuming that the imagery can be placed in a configuration that allows digital analysis, the selection of an appropriate change detection algorithm takes on significance. There exist a variety of algorithms from which to choose. Quantifying changes by pixel values (e.g., image differencing or ratioing of spectral data) is practical but may be too simple to identify the variety of change in a complex scene. Quantifying changes by thematic categories (e.g., post-classification comparison method) is useful only if accurate land-use classifications can be obtained.

Selecting an appropriate change detection algorithm and improving levels of accuracy are based on an analysis of several important factors. First, the analyst will benefit by having a close familiarity with the cultural and physical characteristics of the study area. For any given region, there will likely be optimal anniversary dates for change detection in which differences in reflectance caused by changing seasonal vegetation, soil moisture, and sun angle are minimized. However, acquiring near-anniversary dates of imagery is sometimes not possible mainly due to the cloud cover (Jensen et al., 1987). Second, multiple-date imagery of the study area must be registered precisely to a cartographic grid. Displacement of superimposed images by one half pixel or greater will introduce unacceptable spurious change (Martin, 1989). Finally, the analyst must appreciate the strengths and weaknesses of all change detection methods available for application to a particular study area. Then, he or she must select methods that provide the highest change detection accuracies.

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