Local linear statistical modeling as a framework for change detection

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ABSTRACT

Within the context of remote sensing, change detection refers to the characterization of changes in a scene or on the earth's surface with respect to a target or targets. Many fields, including agriculture, urban planning, and national security, use satellite imagery to detect changes. However, current approaches have two major limitations: 1) the methods are effective in identifying scene changes only if changes (i.e., angle, illumination, atmospheric conditions) due to viewing the scene are negligible or corrected for, and 2) the results are typically a binary response, i.e., *change* or *no change*.

We introduce a method that applies linear statistical modeling locally to estimate scene changes while accounting for image viewing changes. In this method, we explicitly describe the quantitative variation at a pixel in terms of its pixel neighbors, spatial and temporal, with a linear probability model. We then estimate the model parameters with least squares, calculate modeling diagnostics for each neighborhood, and display these results as images in order to assess scene changes, viewing effects, and modeling effectiveness on a neighborhood scale. By focusing on image neighborhoods, this method can effectively separate scene changes from changes due to viewing the scene. Furthermore, the flexibility of the local linear model and the ease of calculation of parameter estimates and diagnostics allow the researcher to emphasize and efficiently quantify specific types of scene or viewing changes.

Keywords: Change detection, linear statistical model

1. INTRODUCTION

Within the context of remote sensing, change detection refers to the characterization of changes in the earth's surface with respect to some target or targets of interest. Examples include identification of changes in vegetation, characterization of earthquake damage, identification of change in medical applications, tracking of targets, and measurement of urban growth. Detecting change in images has received a large amount of attention in the last 20 years. The techniques in change detection vary; they include methods that use the original images (differencing, ratioing), methods that use mathematical transformations of the original images (principal component analysis [PCA]), methods that create thematic maps and identify changes from the different thematic classifications through time, and combinations of these techniques. Most change detection techniques apply these methods either to the entire image with global parameters or to an image on a pixel-by-pixel basis, leaving the important neighboring pixel information untapped.
The challenge in change detection is to identify changes of interest, among a host of noninteresting changes, such as identifying new urban growth in an agricultural area across seasons. Many of the noninteresting changes are due to the action of viewing the

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scene as opposed to actual changes in the scene. These include natural factors such as sun angle and atmospheric conditions (clouds, moisture levels, particulates). Additionally, a variety of manmade sensor-related items, including changes in the sensor, sensor calibration, and sensor physical characteristics, can result in differences in the resulting images. We classify changes in viewing the scene two ways—origin of change (natural versus manmade) and the scale of impact (global, regional, local, or pixel). Table 1 lists examples of some of the changes in viewing the scene that must be accounted for in identifying changes in the scene.

Table 1: Examples of changes in viewing the scene.

Impact Scale	Examples	
	Natural	Manmade
Global	Sun angle	Sensor angle
Regional	Atmosphere	CCD layout
Local	Shade	Pixel blending
Pixel		Dark Current/Shot noise

Accounting for changes in viewing the scene, including changes in illumination, atmospheric conditions, and other changes not of interest, is a difficult problem. Registration and normalization methods are available for correcting images for global-scale differences in sensor (manmade differences) and natural conditions (Morisette, 1997). Most of these techniques do not account for differences on regional or neighborhood scales.

In this paper, we describe many of the traditional automatic change detection techniques, focusing on methods that rely on statistical analysis. We introduce a method that addresses some of the challenges seen in change detection through the explicit modeling of image neighborhoods, accounting for scene changes and viewing effects at local level. The method produces a variety of images (i.e., images of statistics) that can assist in change identification and modeling diagnosis.

2. BACKGROUND: METHODS FOR CHANGE DETECTION

Traditional change detection techniques that use spectral information directly include image mathematics, principal component analysis (PCA), and generalized linear models (GLM). Other change detection techniques first create thematic maps from the spectral information and then assess changes. The choice of which technique is best in a given situation is a difficult problem. Deer (1995) states that "there is no universally "optimal" change detection technique: the choice is dependent upon the application." We will discuss some of the most common methods for change detection. For further information, Deer (1995) and Morisette (1997) provide lists of references as well as more details about the algorithms.

Image differencing and image ratioing are two examples of image mathematics. In image differencing, each pixel in the first image is subtracted from the corresponding pixel in the second image. Then the distribution of differences is examined: values in the tails correspond to large spectral differences, while values near the median correspond to small changes between the two images. Bruzzone and Prieto (2000) expand on image differencing and develop two automatic criteria for identification of significant changes through the incorporation of multisensor information. Their method, however, is a pixel-by-pixel method that does not appear to use local spatial information or to account for noninteresting changes due to viewing effects.

Image ratioing—dividing each pixel by its temporal neighbor and then reviewing the distribution of ratios—works well when the two images of the same scene differ by a constant percentage. Values near the median value in the ratio image correspond to small changes, and values in the tails, near zero or large values, indicate potential image changes.

Both image differencing and image ratioing require the determination of thresholds that indicate when a change is significant. These methods do not discriminate between differences due to scene changes and viewing effects. They assume that viewing effects are negligible in order to make inferences about scene changes. Because these methods work on a pixel-by-pixel level, neighborhood viewing effects will appear as potential areas of scene change.

Image regression uses one image as an explanatory variable for the second image. This method is applied to the entire image; the residuals from the regression indicate areas of high change (Morisette, 1997). This method is again a pixel-by-pixel comparison, not tapping neighborhood information. Therefore, local and regional viewing effects may again be highlighted as potential areas of scene change.

A wide variety of methods extend PCA to address changes between images. PCA is a statistical method for identifying structure between variables and a technique for reducing data dimensionality. For change detection, PCA identifies the structure between images taken at different times. The first principal component corresponds to pixels that do not demonstrate change, while the second principal component identifies changed pixels. Niemeyer, Canty, and Klaus (1999) describe the implementation aspects of a variety of PCA-like techniques. These techniques all operate on a pixel-by-pixel basis.

Statistical models, specifically globally applied GLM, have been used as a framework for predicting image change area (Morisette, 1997). An example of a GLM is the logistic regression model in which the explanatory variables include functions of the spectral information as well as other covariates to create a binary change/no change image. These GLMs can be expanded to include spatial neighborhood information, resulting in auto-logistic models (Cressie, 1993; Hoeting et al., 2000). One challenge in using GLM for image analysis is that in order to estimate the parameters, training pixels where the truth about change/no change is known are needed.

In general, current change detection methods compare two or more images and provide information that can be used to assist an analyst in determining areas for future study. All of the methods described above except for GLM classify pixels as change/no change on a pixel-by-pixel basis. In general, they provide little information about the strength of the classification, although methods based on GLMs do provide an image of the probability of change.

These methods are sensitive to local and regional viewing effects. Distortions in viewing the scene, such as those generated from different atmospheric conditions, may apply to localized areas of the image, resulting in classification as an area of change. In the next section, we introduce a method based on statistical models that incorporates neighborhood information in order to account for neighborhood viewing effects and to assess small scene changes that may not be identified in other methods.

3. DESCRIPTION OF THE LOCAL LM METHOD

The primary challenge in change detection is to account for viewing effects without losing the ability to identify actual physical changes in the scene. We propose to apply standard linear models (localLM) and generalized linear models to image data, one neighborhood at a time. The models include terms for both scene changes and viewing effects. By using these models with a variety of different neighborhoods, the technique is able to identify changes at a variety of resolutions and orientations while accounting for viewing effects.

We propose to use a variety of statistical models in the identification of scene changes. First, we propose to locally model the viewing effects. In addressing how viewing effects can impact the captured view of the scene, Wiemker et al. (1997) state that the impact on the spectral information is generally multiplicative or additive. Let Y^t represent the observed image neighborhood, or the view, of the scene at time *t* and S^t represent the scene at time *t*. The resulting model for each neighborhood, $Y^t = \alpha^t + \beta^t S^t + error^t$, describes a simple relationship between the scene and the view of the scene having neighborhood-level multiplicative and additive viewing effects.

This model arises from examining the following two situations:

- the scene within the neighborhood has not changed between time 1 and time 2,
- the scene within the neighborhood has changed between the times.

If the underlying scene within the neighborhood has not changed, then the observed neighborhood image at time 2 maybe only a shift and scale of the observed neighborhood image at time 1 plus random noise. If the underlying neighborhood scene has changed, then a shift and scale model alone will not well describe the differences between the observed images within the neighborhood. By examining model diagnostics, parameter estimates, and measures of model fit, we can identify neighborhoods of potential change. The examples in the next section focus on the residual error image as an indicator of neighborhood change.

We fit the models locally for a chosen neighborhood using least squares. For each pixel, we identify a neighborhood of interest, ranging from a first-order neighborhood around each pixel (the pixels directly north, south, east, and west of the center) to neighborhoods of size *n* pixels by *m* pixels such as a 3 by 3 mask or 15 by 7 mask to more exotic shapes. By examining a variety of neighborhood results, we can identify change on a variety of scales, enabling us to focus on scene changes of a specified size in terms of pixel resolution.

4. EXAMPLES

To demonstrate the use of local linear models, we used IKONOS™ imagery collected at two different times over Richland, Washington. Both IKONOS images were registered to a common map-based coordinate system. The images also were normalized—the first image was used as a reference, and the second was rescaled using global image regression. The original images are shown in Figure 1 along with a goodness-of-fit image. The first image corresponds to immediately after the 24 Command wildland fire on the Hanford Reach in June 2000. Effects from the fire can be seen in the upper left corner of the first image. The second image corresponds to approximately one year after the fire.

The goal of localLM is to identify small areas of change, not to identify large regional or global changes. Therefore, this technique should not identify areas of the fire in the upper left corner of Figure 1a. Instead, by using a variety of mask sizes, we are able to identify small changes corresponding to a few pixels in size. Figure 1c plots the residual error from the model using a 9 by 9 neighborhood. Areas highlighted in red and yellow correspond to sections in which the residual variability is moderate to high, indicating that in these sections the model does not fit well and therefore there is high potential for scene change.

Figure 2 magnifies a subregion of the image that corresponds to known new construction; the area in red contains the new construction. Changing the neighborhood size to 3 by 3 pixels, Figure 3 identifies the new construction area but also identifies other changes in the image. These other areas correspond to subpixel registration problems; pixel boundaries for the two images do not match exactly. Figure 4 provides another magnified area of Figure 1. In these two images, the 9 by 9 neighborhood identifies the agricultural change, while the change is too large to be observed well in the 3 by 3 neighborhood. By varying the neighborhood size, we are able to identify changes on a variety of sizes.

For a second example, we used SPOT™ images of the U.S. Army Yakima Training Center in Washington State. The images were from July 15, 2000, and July 20, 1998. Both images were registered, and global image regression was used to standardize the spectral information. Figure 5 displays the original information along with model results. Figure 5a is the image from July 20, 1998, and Figure 5b is the image from July 15, 2000. Figure 5c is the residual error image from fitting a 3 by 3 neighborhood. Note the large number of areas that indicate lack of fit, and therefore potential areas of scene change. Figure 5d is the corresponding residual error image from fitting a 15 by 15 neighborhood. In comparing the two neighborhood images, we found that both identify many of the same areas for potential change. Comparing the results from localLM(Figures 5c and 5d) to the ratio (5f) and difference (5e) images, both standard techniques identify potential agricultural areas. They also identify large areas of change not identified by the local linear models; however, these areas of change are larger than we want to identify. In contrast, the localLM are able to ignore the larger areas of change, indicating they may be areas of viewing effects. These examples demonstrate the potential in the local linear model framework to be able to focus on smaller changes as opposed to the larger viewing effect changes that may dominate traditional methods.

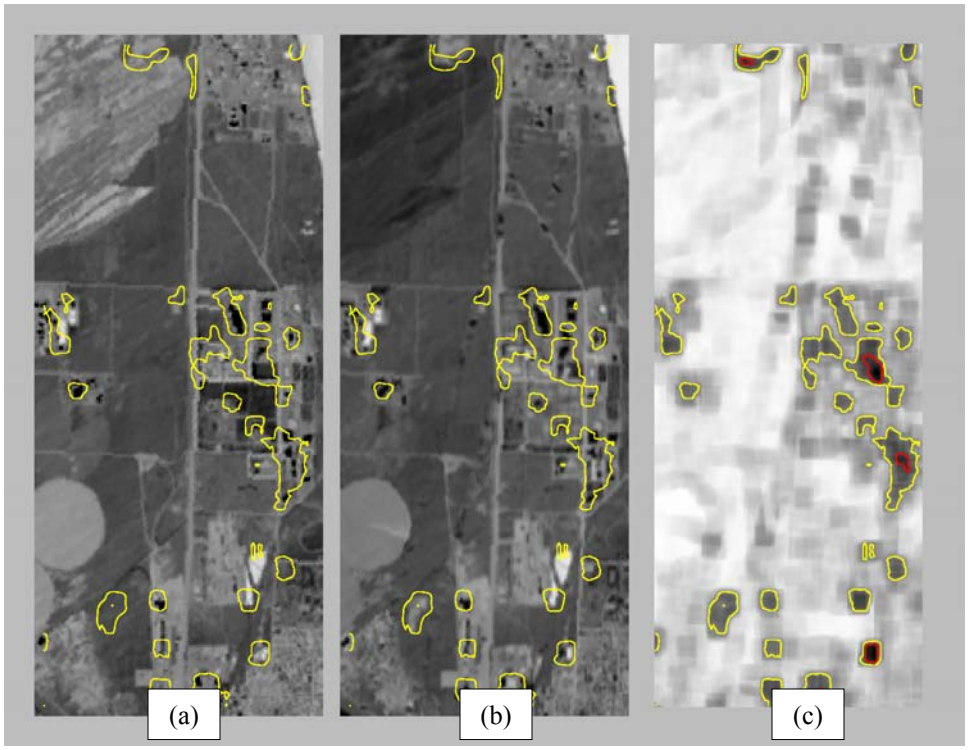

Figure 1: Sample images: a) immediately after the fire, b) one year after the fire, and c) residual error image for the 9 by 9 neighborhood. Areas of moderate variability are highlighted in yellow. Areas of high variability are highlighted in red. Copyright 2000 CNES.

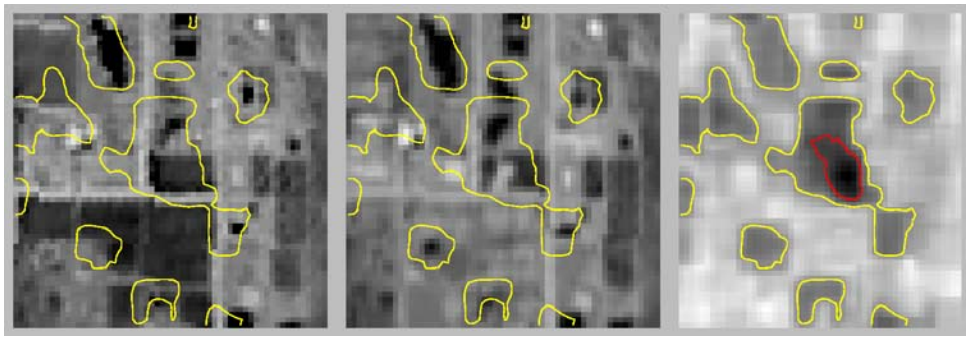

Figure 2: Close-up of known new construction area along with residual error image for the 9 by 9 neighborhood. Copyright 2000 CNES.

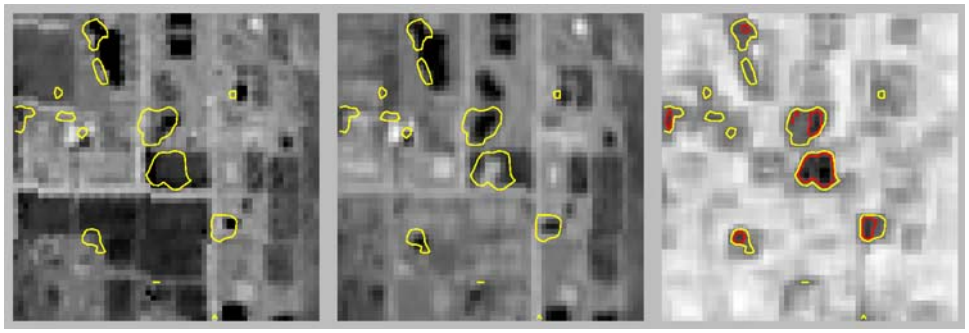

Figure 3: Close-up of known new construction area along with residual error image for the 3 by 3 neighborhood. Copyright 2000 CNES.

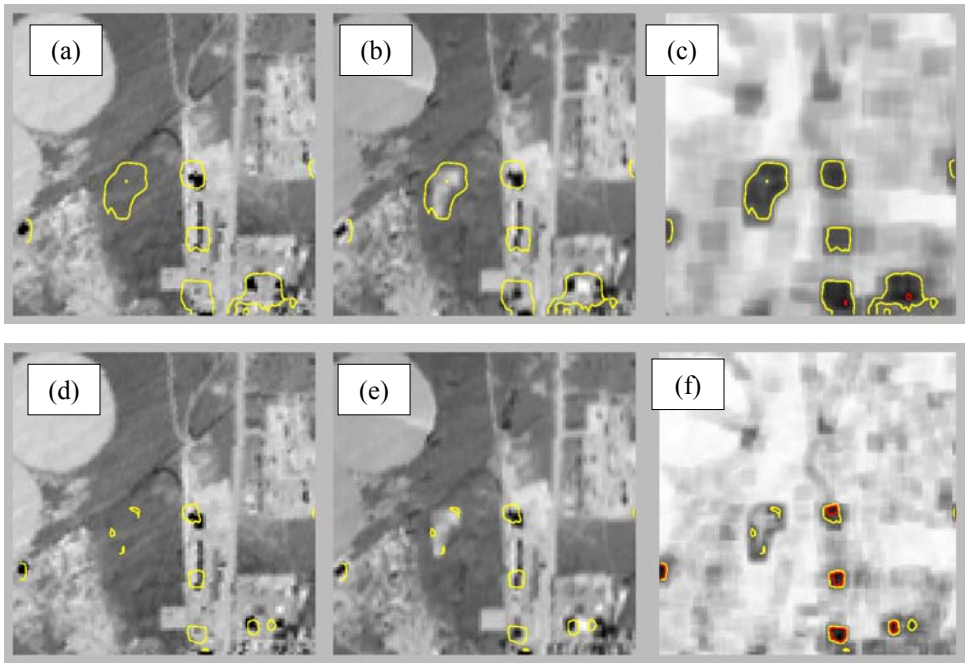

Figure 4: Close-up of agricultural change visible in the 9 by 9 neighborhood (a, b, c), but not in the 3 by 3 neighborhood (d, e, f). Figures are a) original image time 1 with moderate variability for 9 by 9 neighborhood highlighted; b) original image time 1 with moderate variability for 9 by 9 neighborhood highlighted; c) residual error from 9 by 9 neighborhood; d) original image time 1 with moderate variability for 3 by 3 neighborhood highlighted; e) original image time 1 with moderate variability for 3 by 3 neighborhood highlighted; and f) residual error from 3 by 3 neighborhood. Copyright 2000 CNES.

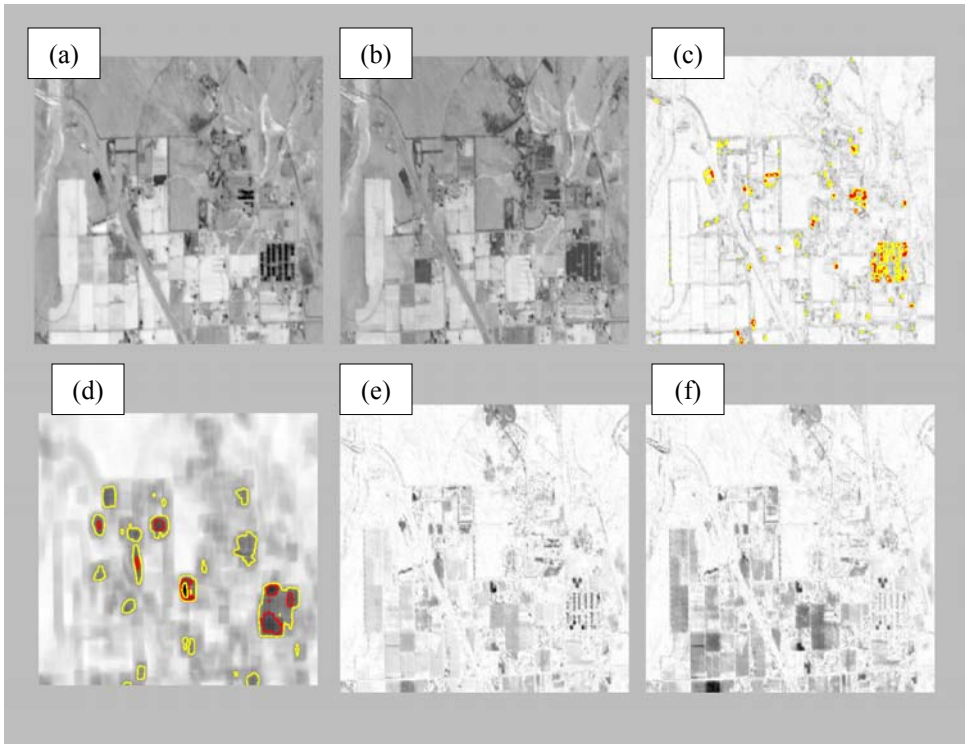

Figure 5: Images from applying the model to Yakima data. Figures are a) original image time 1, b) original image time 1, c) residual error from 3 by 3 neighborhood, d) residual error from 15 by 15 neighborhood, e) absolute value of difference image, and f) absolute value of log of ratio image. Copyright 2001 SPOT Image Corporation Reston, VA

CONCLUSION AND FUTURE WORK

Change detection techniques applied on a local basis work well in identifying small areas of change. By examining different neighborhood sizes and combining the results, we can begin to identify changes on a pixel- to small-neighborhood-level while not identifying large changes. The technique makes use of a robust statistical framework and the associated measures of model fit, parameter estimation, and diagnostics.

Extensions of this technique to image change detection include

- expanding on the set of explanatory variables – For example, we have used an analysis of variance framework to fit linear and quadratic surfaces to the images, then tested for the significance of a time effect for the surface within the local neighborhood.

- incorporating thematic classification maps into the modeling by expanding on the explanatory variables and incorporating tests of significance for the local parameter sets as opposed to the global thematic information.

- allowing for a variety of error structures in the model – In some cases, the assumption of normally distributed errors may not be appropriate. We can incorporate a variety of error distributions through the use of generalized linear models.

- combining information from multiple neighborhood sizes into single images – We can use techniques such as Bayesian model averaging to combine the results.

- developing a methodology for identifying the best neighborhood size based on the size of the target.

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