A SIGNAL-SYMBOL APPROACH TO CHANGE DETECTION

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ABSTRACT

A hybrid (signal-symbol) approach for detecting significant changes in imagery uses a signal-based change detection algorithm followed by a symbol-based change interpreter. The change detection algorithm is based on a linear prediction model which uses small patches from a reference image to locally model the corresponding areas in a newly acquired image, and vice versa. Areas that cannot be accurately modelled because some form of change (signal significant) has occurred are passed on to the change interpreter. The change interpreter contains a set of "physical cause frames" which attempt to determine if the change is physically nonsignificant (e.g., due to clouds, shadowing, parallax effects, or partial occlusion). Changes due to nonsignificant changes are eliminated from further consideration. If the physical cause of the change cannot be determined, it is passed on to an image analyst for manual inspection. Preliminary results of work in progress are presented. These results indicate that the methodology is extremely effective in screening out large portions of imagery that do not contain significant change as well as cueing areas which are potentially significant.

Key Words: Change Detection, Signal-Symbol Processing, Image Understanding, Image Analysis, Knowledge-Based Systems

1. INTRODUCTION

The ability to detect changes between two or more images of the same scene is important in fields such as aerial reconnaissance, remote sensing, and cartography. The image analyst, in looking for changes between images, is confronted with substantial variation in image quality, perspective and illumination differences, and image formats covering large geographic expanses. The time-consuming and tedious nature of this process is compounded by the low rate of occurrence of significant changes. As a result of these factors, the change detection problem has received considerable attention in the literature.

Previous efforts to automate change detection have focussed on implementations in either the signal or the symbolic domain. Signal change detection techniques produce a measure of dissimilarity between images by correlation techniques or image subtraction. In an early treatise, Rosenfeld (1961) outlined the principle steps involved in change detection and reviewed several measures of statistical correlation. NASA (1978) demonstrated the effectiveness of digital subtraction of Landsat multispectral imagery for monitoring land cover changes. Global subtraction highlights areas of change but also produces a large number of false alarms due to variations in image registration, sensor calibration, illumination and atmospheric conditions. In developing a pattern recognition system for city planners, Kawamura (1971) computed statistical difference features such as correlation coefficients, average entropy change, and the change in probability of bright areas over subareas in aerial imagery. Subareas were then classified as either a "change of interest" or "no change of interest" based on these features.

Additional studies have investigated the efficacy of performing change detection in the symbol domain. Price (1977) segmented two images into regions with similar characteristics (e.g., based on radiance and texture) and represented these regions by feature-based descriptions including information such as size, location, and geometric measures. Change detection is accomplished during a matching process which computes the similarity between regions of the two images and pairs regions which are most similar. Regions which do not match represent the appearance or disappearance of a feature. While successful, the resolution of feature-based symbolic matching is limited by the granularity of the segmentation of the images into regions. Since many spurious regions are generated during image segmentation, the matching process can be computationally expensive. As a result, additional criterion such as size and average radiance should be used to organize the regions and guide the matching process (Price, 1982).

This paper outlines a hybrid change detection strategy which uses signal processing techniques to detect changes between registered images and symbolic reasoning methods to eliminate changes that are not physically significant. Our goal is to detect all local changes in the scene at the signal level and to filter out only those changes whose physical cause can be determined based on features of the changed areas. The proposed approach thus does not attempt to recognize and match objects in the two images. The advantage of this approach is that by using signal processing at the initial stage, when there is no evidence of a change at the signal level, symbolic processing is not invoked. When there are few changes, the computational efficiency of the technique is similar to pure signal-based techniques; when there are many changes, the computational efficiency of the technique is similar to pure symbol-based techniques.

The organization of the paper is as follows: Section 2 provides a framework for formulating the change detection problem. A signal-symbol architecture for change detection is outlined in Section 3. The signal change detection algorithm is detailed in Section 4 and a preliminary design for the knowledge-based change interpreter is discussed in Section 5. Initial results are presented in Section 6.

2. BASIS FOR CHANGE DETECTION

Ideally, an automatic change detection system should extract only significant changes between images. Exactly what is significant is often defined by the application. In the present application, localized man-made activities such as building construction and vehicle displacement, or large scale non-seasonal changes in surface material characteristics (e.g., forest-fire damage and changes in flood zone areas) are considered to be significant changes. Nonsignificant changes include atmospheric effects such as the presence of clouds or haze, and seasonal changes which affect vegetation and surface characteristics. In addition, nonsignificant changes may be induced by comparing images acquired at different times and perspective, and images which differ in contrast, resolution and noise level.

In order to develop a consistent framework for change detection, changes are modelled at three distinct levels: signal, physical, and semantic. In previous work in multi-band image processing (Tom, 1985), it was observed that images of the same scene acquired at different wavelengths (possibly by different sensors) at the same time tend to be locally correlated at the signal level. That is, even though images sensed at different wavelengths may be globally uncorrelated, local structure (e.g., due to changes in albedo) tends to be highly correlated across wavelength. In previous applications this local correlation property has been exploited to use higher resolution/lower noise imagery to spatially enhance lower resolution/higher noise imagery. In applying the above technique to change detection, wavelength is replaced by time. The basic assumption then is that small patches in registered images acquired at different times tend to be locally correlated if the underlying scene has not changed.

The detection of changes in imagery at the signal level is the first step in the change detection process. The second step is determining whether the changes detected at the signal level are physically significant (i.e., determining their physical cause). Changes attributed to nonsignificant physical effects such as differences in atmospheric conditions, perspective and illumination differences, and seasonal changes are eliminated. The third step is determining whether the remaining changes are significant in a semantic sense given a context for interpretation. For example, if the goal is to detect large areas of change due to forest fire damage, small isolated areas may be ignored. The overall process generates hypotheses that areas have changed using signal-based models in a bottom-up fashion, and tests the hypotheses top-down based on heuristic models of physical cause and semantic relevance.

3. CHANGE DETECTION SYSTEM ARCHITECTURE

A hybrid (signal-symbol) architecture for automatic image change detection is shown below in Fig. 1. Its primary function is to screen out imagery which does not contain significant change. The architecture is structured as a cascade of a signal-based change detector and a symbol-based change interpreter. At each level of processing, the amount of image data that needs to be processed is reduced.

The change detector uses a locally adaptive image subtraction technique to detect and localize areas of change in an input image relative to one or more (spatially preregistered) reference images. Following adaptive subtraction, prediction error images are filtered and combined to produce change cues. The output of the signal change detector is a map of cues indicating signal significant changes. For each change cue, descriptive processes build a symbolic representation of the changed area in terms of features derived from the original imagery. The change interpreter applies rules in a hypothesis-driven fashion to the change-tokens, determining the physical cause and semantic relevance of the change. Nonsignificant changes are eliminated, and the remainder are displayed to the image analyst. Currently, the change detection software is implemented on a VAX 780/FPS array processor system, and the change interpreter is implemented in Zetalisp on a Symbolics Lisp machine. Future versions of the system may factor collateral data (terrain data and maps) into the change detection process.

4. SIGNAL-BASED CHANGE DETECTION ALGORITHM

The change detection process is an outgrowth of a detection technique based on two-dimensional (2-D) linear prediction by Quatieri (1983). His technique demonstrated that

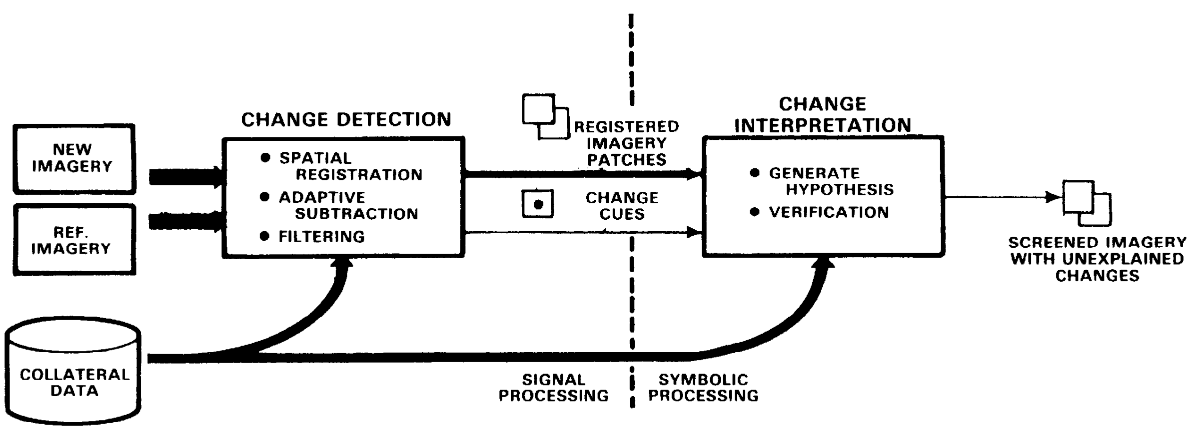

Figure 1 Overall Change Detection System Concept

image backgrounds of grass, fields, or trees (natural textures) in aerial photographs could be viewed as sample functions of a 2-D nonstationary random field and could be modeled by 2-D linear models. Manmade objects, whose statistics are generally unknown (since it is desired to detect a broad class of objects), are not modeled well by the linear approach and exhibit large modeling errors. Quatieri's major contribution was the notion of using these linear prediction error residuals to derive a significance test for detection exhibiting a constant false alarm rate (CFAR detector). In addition to the detection of manmade objects, however, detection of natural boundaries also occurred. The approach in this paper overcomes that problem by using a multi-band approach, i.e., one in which a reference image is used to locally model a newly acquired image.

The 2-D linear prediction approach involves solving for the optimal set of prediction coefficients that model a patch of a new image from a patch of a reference image using a noncausal mask. This procedure is recomputed for all patches of imagery (i.e. for a patch centered on each pixel location). In order to simplify computations, an approximation to the 2-D linear prediction method was implemented. The simplified method is appropriately termed the adaptive subtraction method. For a local patch of imagery, scale and offset coefficients are computed to optimally predict (in the minimum squared error sense) the new image from the reference and vice versa. The new image is predicted from the reference image (forward prediction), and the reference image is predicted from the new image (backward prediction).

The prediction error is the difference between the estimate and the image patch that is being estimated at the center of the prediction mask

$$\underline{e}_{forward}(n,m) = \underline{i}_{new}(n,m) - \hat{\underline{i}}_{new}(n,m)$$

$$= \underline{i}_{new}(n,m) - [\, a(n,m)\, \underline{i}_{ref}(n,m) + b(n,m)\,]$$

$$\underline{e}_{backward}(n,m) = \underline{i}_{ref}(n,m) - \hat{\underline{i}}_{ref}(n,m)$$

$$= \underline{i}_{ref}(n,m) - [\, c(n,m)\, \underline{i}_{new}(n,m) + d(n,m)\,]$$

where the scale and offset coefficients a,b,c and d are continually computed by solving sets of overdetermined equations (Tom, 1985).

Objects which appear or disappear in the imagery are evidenced by corresponding signatures in the forward or backward error images respectively. Objects which appear in the newly acquired image cannot be modeled by the reference and thus give rise to a large forward prediction error. (The backward prediction error is small since the absence of the object in the reference can be modeled in the newly acquired image by lowering the gain c and adjusting the offset d.) Where objects disappear in the newly acquired image, the situation is reversed. Objects that are spatially displaced are characterized by comparable signatures in both error images.

In the process flow of the the signal-based change detection module (Fig. 1), the new image is first registered to the reference image by an automatic registration technique. The images are first coarsely registered given the camera position, and then locked together using a statistically based technique for generating control points automatically. Next, the adaptive subtraction module generates the forward and backward prediction error images. These error images are thresholded for significant detections at a given CFAR level, combined to cancel complementary errors due to minor displacements, and then filtered to remove isolated noise peaks. The output from the signal change detector is a bit map which delimits the extent of areas which have undergone some form of signal level change (significant or not) as well as the corresponding registered imagery patches.

5. CHANGE INTERPRETATION

The output from the signal-based change detector is a map of change cues where each cue represents an assertion that something has changed over the corresponding area in the image pair. The goal of change interpretation is to reduce the number of detected changes that must be ultimately examined by the image analysis. Our approach is to eliminate those changes that are not significant based on physical causes or semantic relevance. The preliminary implementation of the change interpreter focusses on identifying three types of nonsignificant changes common to many aerial scenes: shadows, clouds, and partial occlusion of existing objects. Experience with different geographic scenarios indicates that a large majority of nonsignificant changes result from these phenomena.

Before the change cues can be interpreted, they must be converted into symbolic form. The first step in generating the symbolic description is to label connected areas in the map of change cues provided by the signal change detector. For each connected area, a change-token is created. Change-tokens contain slots for descriptive information (i.e., for features of the changed area) such as the size, shape, location, orientation and spatial context of the changed area, as well as information derived from the input and reference image (e.g., image radiance statistics and local correlation structure).

The change interpreter (Fig. 2) contains a set of "physical cause frames" for clouds, shadows, and partially occluded objects. Descriptive information is computed on an "as needed basis" as individual physical cause frames are triggered during the interpretation process. Each physical cause (cloud, shadow, partial or total occlusion) activates descriptors which extract features from the imagery in and around the corresponding change cue. Descriptors are applied in a hierarchical fashion based on the cost of computation and the degree of evidence they provide in determining a physical cause. The control strategy is designed to minimize the amount computation needed to prove that a change is not significant. Coarse level information is initially computed for all change-tokens. Change-tokens generate physical cause hypotheses which then attempt to verify that they are the cause of the change. If there is insufficient evidence to conclude the cause of a detected change, finer level descriptive processes are dispatched. If the cause of the change cannot be determined, it is brought to the attention of the image analyst.

As an example, the interpretation process begins by computing simple feature descriptions of the change-token (area and radiance statistics) and generating hypotheses that the change is due to shadow or cloud. If collateral information is available, the possibility of a shadow is eliminated entirely if the sun-angle is the same in both images. Otherwise, the shadow hypothesis records a high confidence level if the change-token has a low average radiance measurement over a small area, with little variation in the spectral variance. The cloud hypothesis is eliminated if available collateral data indicates that the image conditions were cloud-free; otherwise, the cloud ruleset operates on the radiance statistics. The cloud hypothesis is verified by a relatively high radiance measure covering a substantial area. If there is high confidence that the change is cloud or shadow, the change-token is eliminated from further consideration.

The cloud hypothesis should be either proved or eliminated within the first cycle of description/verification. If weak evidence exists for shadow, secondary features are derived to verify that the change is the result of shadow or partial occlusion. The majority of change cues resulting from shadows mirrored about an object or minor shadow variation and parallax differences are eliminated by locally averaging the difference of the prediction error residuals as described in the next section. The remaining shadow changes occur in only one image. Shadow confirmation may be obtained by using measurements such as correlations between areas on opposite sides of the shadow edge (Witkin, 1982), or by examining the shadow-making regions which have long boundaries in common with the shadow and are oriented at the appropriate sun angle (Nagao, 1980).

Because of differences in the look-angle of sensors, roads or buildings which are visible in one image may be occluded in the other image. The possibility of occlusion is explored if there is a change in camera position between acquisitions. If so, it is then necessary to decide if the occlusion is due to a significant object. As noted in Section 3, man-made objects are not modelled well by the linear approach and thus give rise to large modelling errors. Two types of changes occur; a man-made object occluded by a natural object, and a man-made object occluded by man-made objects. The former change is insignificant and is being examined because it frequently occurs as a result of natural object overlay, e.g., a tree obscuring one side of the road. In this case, partial occlusion can be identified by linear edges or regions which once extended in the changed image are similar to edges contained in the unchanged image.

As it is currently being developed, change interpretation must handle a variety of scenes from different geographic areas. Efforts are being made to structure the physical cause ruleset so that it is robust across all scenes. Senario-specific rulesets are being developed for semantic level interpretation since the relevance of a change depends on what one is looking for in the imagery.

6. EXAMPLES

For the following two examples, aerial photographs were acquired from USGS and digitized using a CCD camera. The images are cloud-free, and were acquired at about the same time of day. The pair of images in Fig. 3 are of a scene in which a building not present in the reference image (a) appears in the newly acquired image (b). The images differ both in perspective and in the amount of haze present (which is simulated). The images are registered so that features on the ground are spatially aligned. The pair of images in Fig. 5 show the prediction error obtained by predicting the image in Fig. 3a from that in Fig. 3b (5a), and the prediction error obtained in predicting the image in Fig. 3b from that in Fig. 3a (5b). (A 7x7 sliding window was used.) It is evident that prediction errors occur in the vicinity of the building which appeared in Fig. 3b as well as around buildings and other vertical structures due to parallax effects. To mitigate the effects of parallax, differences in illumination, as well as other effects due to minor misregistration and noise, the prediction error images are locally averaged. For parallax effects, the assumption is that the residual errors caused by vertical features will cancel within windows that are large compared to the feature of interest. The result of averaging the prediction error within a 33x33 Gaussian tapered window (Fig. 4) shows that the parallax effects do in fact cancel in areas that did not change; however, a net prediction error residual is evident in the vicinity of the building that appeared in the new image.

The second example in Fig. 6 is of another scene in which a vehicle in (a) is missing in (b) and a building in (b) is missing in (a). By examining the sign of the prediction error one can identify objects that either appear or disappear between images. Fig. 7a shows an area of negative error caused by the disappearance of the vehicle in Fig. 6b. Fig. 7b shows an area of positive error due caused by the appearance of the building in Fig. 6b.

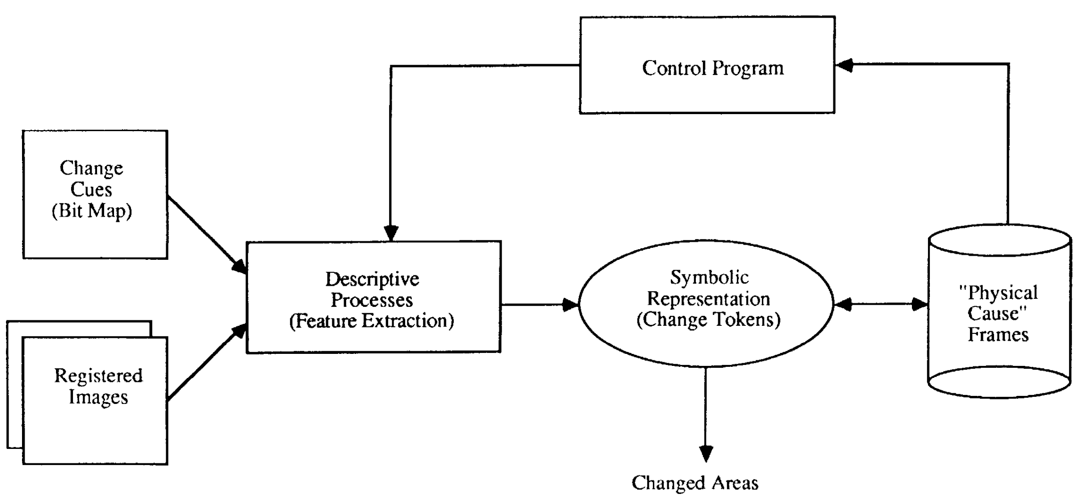

Figure 2 Symbol-Based Change Interpreter

7. SUMMARY

A hybrid approach to detecting changes in imagery was described. It consists of a signal-based change detection algorithm which identifies all areas which have changed at the signal level (significant or not), and a symbol-based change interpreter which eliminates those areas caused by changes that are not physically significant or semantically relevant. Preliminary results of the signal change detection algorithm, and a discussion of the design of the change interpreter were presented. Preliminary results indicate that the methodology is extremely effective in screening out large portions of imagery which do not contain significant change. On-going work focusses on expanding the rulebases within the change interpreter which reason about the physical cause and semantic relevance of the detected changes.

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Fig. 3 a)

Fig. 3b)
Aerial Photography taken at Different Times

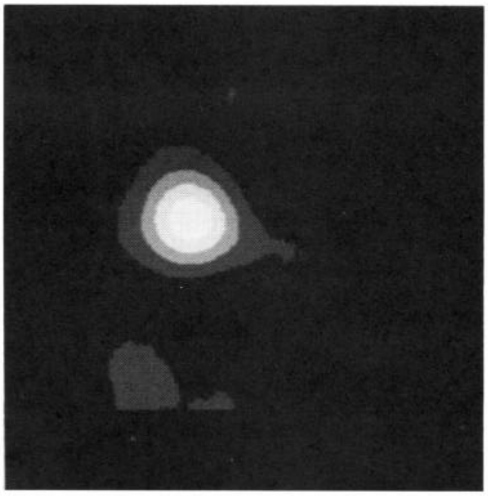

Figure 4 Combined and Filtered Error

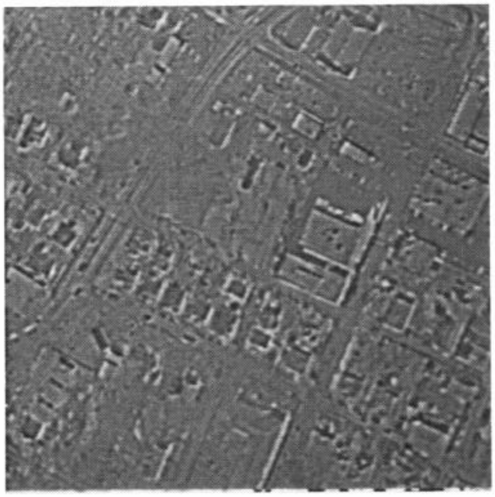

Fig. 5 a)

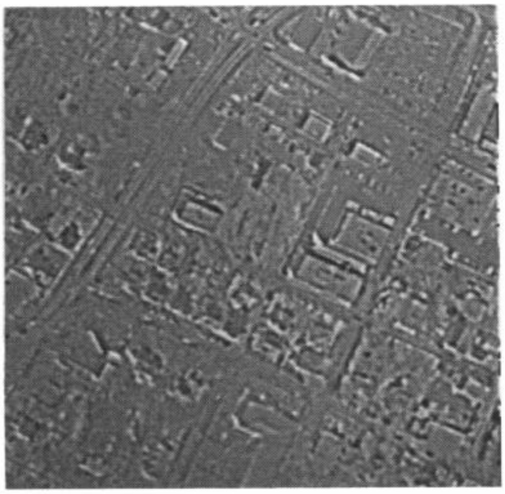

Fig. 5 b)
Forward and Backward Linear Prediction Error

Fig. 6 a)

Fig. 6 b)
Aerial Photography taken at Different Times

Fig. 7 a)

Fig. 7 b)
Detected Changes Indicated in White