Object-Level Change Detection in Spectral Imagery

Geoffrey G. Hazel, Member, IEEE

Abstract—Multitemporal monitoring of sites using spectral imagery is addressed. A comprehensive architecture is presented for the detection of significant changes in scene composition described at the object level of spatial scale. An object-level change detection description is obtained by applying a statistical spectral anomaly detector followed by a competitive region growth object extractor. The competitive region growth algorithm is derived as the solution to an approximate maximum likelihood (ML) image segmentation problem. Gaussian spectral clustering is used to model the scene background. A digital site model is constructed that contains image segmentation maps and extracted object features. Object-level change detection (OLCD) is accomplished by comparing objects extracted from a new image to objects recorded in the site model. A restricted implementation of the architecture is described and tested on long-wave infrared hyperspectral imagery. It is demonstrated that spectral OLCD can eliminate false alarms based on their multitemporal persistence. Incorporating multiple images in the site model is observed to improve OLCD performance.

Index Terms—Change detection, competitive region growth, object-level change detection (OLCD), Spatially Enhanced Broad-Band Array Spectrograph System (SEBASS), spectral image.

I. INTRODUCTION

GEOGRAPHIC areas of particular interest or importance are often subjected to repeated or ongoing surveillance. A human image analyst (IA) viewing surveillance imagery of such a site accumulates knowledge of the site over time. The IA becomes familiar with the topography and thematic makeup of the area and maintains a memory of the nature and location of interesting objects in the scene. He has the opportunity to investigate existing imagery in detail in preparation for subsequent image acquisitions. This application of temporal context allows the IA to establish a sophisticated capacity to detect relevant changes in the scene. We refer to these processes as site monitoring.

Reproducing aspects of this complex behavior in an automated fashion on a digital computer is a worthy goal with important applications in remote sensing and surveillance. When two or more images of a site are available and the geometric relationship between the images and possibly the geographic coordinates is known or may be computed with some quantifiable accuracy a variety of automated site monitoring techniques may be devised. This paper addresses the detection of significant changes in scene composition at the object level of spatial scale. We refer to this approach as object-level change detection (OLCD) or when applied to spectral imagery, spectral OLCD (SOLCD).

Previous work in automated site monitoring has employed univariate sensing modalities such as synthetic aperture radar (SAR) and panchromatic electro-optical imaging [1]. The human visual system accomplishes site monitoring tasks using visual perception consisting of three spectral dimensions or colors. This chapter extends automated site monitoring concepts to the multivariate signals of the spectral imagery. One may hope that the higher dimensionality of this measurement space compared to human visual perception may in part compensate for the poverty of digital processing relative to the human brain.

We refer to the digital database of scene knowledge as a site model. The introduction of topographic and thematic information about the scene involves segmentation and material recognition [2]–[4]. In a multitemporal scenario, the material recognition may be accomplished automatically in each image or may be provided by an IA in one image and propagated to future images. The propagation of thematic information from the site model to a new coarsely registered image may be accomplished by using the stored scene segmentation map to initialize segmentation of the new image [3]. Adding object level information to the site model requires a cueing technique such as anomaly detection or spectral matching followed by object extraction and possibly classification and recognition.

The detection of changes in a scene involves the comparison of a newly acquired image with an established site model. Change detection can be performed over a range of spatial scale and level of detail. The type of change detection that may be performed is related to the accuracy with which image registration or geo-referencing may be attained. Pixel-level spectral change detection, such as the Chronochrome algorithm of Schaum and Stocker [5], is an example of the finest levels of scale and detail. In Chronochrome, where a general affine spectral transformation is assumed to relate measurements at two times, extremely precise image registration is required. Not only must the centers of the pixels be accurately aligned, but the patches of territory measured by each pixel must substantially overlap. This is because the physical principle underlying Chronochrome is the conservation of the relative abundances of the materials comprising each pixel. The level of detail captured by Chronochrome is also very fine. The site model for this case consists of a set of measured spectra for each imaged ground location together with the spectral transformation relating previously collected images. Change detection in spectral imagery was also suggested by Peli et al. [6]. This algorithm apparently detects changes across two spectral images by comparing statistics of fixed size and shape sliding windows. However, few details are provided.
OLCD is a technique that operates at a higher spatial scale and thus requires less registration accuracy. In OLCD, contiguous sets of pixels are identified as corresponding to objects of interest in the scene. The location and properties of such objects extracted from one or more images then compose a site model, and objects extracted from subsequent imagery may be compared to the model. The arrival of new objects, the departure of previously detected objects, and significant changes in the properties of persistent objects may then be detected and reported. The features of arriving and departing objects may also be used in spatial-spectral matching algorithms to find other similar objects in the scene that are either persistently detected or were previously undetected. Key research issues in OLCD are the selection of descriptive features to characterize the spatial and spectral properties of objects and the correct association of objects between images. Spectral transformations relating two scenes may also be derived and exploited in the context of OLCD.

Semi-autonomous site monitoring techniques may also be devised in which a human IA supervises site model construction. For example, the IA may provide positive identification of thematic regions in the scene as mentioned previously. The IA may also provide identification at the object level, designating particular objects in the site model as confirmed objects of interest or confirmed false alarms. This information allows the application of spatial-spectral matching techniques to find or reject similar objects in subsequent images. It also facilitates differentiated reporting of persistent objects according to their object truth status.

The applications of multitemporal site monitoring approaches are numerous. In particular, their relevance to military remote sensing should be evident. They may be viewed as avenues to improving upon the detection–false alarm rate performance of single-pass detection methods [7], [2], [8]. They are potentially valuable for battle damage assessment, troop and vehicle movement detection and the detection of other militarily relevant changes. Nonmilitary applications may also be envisioned in agriculture, counternarcotics operations, and scientific remote sensing.

This article first details a comprehensive software architecture for implementing SOLCD and discusses several related issues. Results of a limited proof of principle experiment are then presented. The paper concludes with a discussion of the implications of these results and of the most promising future research directions in this field.

II. SOLCD SOFTWARE ARCHITECTURE

Fig. 1 is a block diagram of a software architecture for implementing OLCD. The center point of the architecture is the site model. It is a database of information representing knowledge of the scene derived from some number of previously collected images. Once initialized, the site model is used to detect changes in the scene based on evidence in subsequent images. When a new image is presented to the system, it must first be registered or referenced to the common coordinate system used by the site model. Objects of potential interest must be extracted from the new image and spatial and spectral features representing the objects’ properties must be computed. The system may then present the computed features to an automatic classification subsystem [3], although OLCD can proceed without object classification. With these tasks accomplished, the system then executes the association block. In this block, the system attempts to match each object in the new image with a corresponding object in the site model. At this stage, a report of significant changes observed in the new image can be presented to the user and the information gleaned from the new image can be incorporated into the site model. In addition, if a human IA is available to verify information in the new image and change report, the IA supplied information can also be incorporated into the site model.

A. Registration and Geo-Referencing

In order to accomplish SOLCD between multiple images one must establish the relationship between the pixel coordinates in each image and the pixel coordinates in all other images. This may be accomplished by performing image to image spatial registration. Alternatively, the pixel coordinates of all images may be referenced to an independent spatial coordinate system such as geographic coordinates.

The development of registration and geo-referencing techniques is a topic of active research throughout the computer vision community, but will not be addressed further in this article. Rather the SOLCD concept will be developed and demonstrated assuming registered imagery is available.

B. Object Extraction

When an image is presented to the SOLCD system, it must be processed by an object extraction algorithm. This process represents a transition from the pixel level scene description provided
by the raw image to a larger spatial scale description consisting of objects. The object extraction approach employed in this article uses a competitive region growth (CRG) method. The first application of CRG for object extraction in spectral imagery was due to Ashton [9].

A CRG algorithm attempts to discover a spatially connected group of pixels, the region, by starting with an initial seed region, often a single pixel, and then progressively considering the pixels at the region boundary for inclusion in the region based on some similarity measure. This procedure can be formalized as a statistical scene segmentation problem. Specifically, we wish to assign each pixel in an image to one of two classes: class 0, the background, or class 1, the region. Represent this by the hidden binary-valued random field \( I \). The conditional probability distributions of the measured image data \( x \), under each class label are \( p(x_i|I_i) \) where \( x_i \) and \( I_i \) are the values of the corresponding fields at the particular lattice site indexed by \( i \). For concreteness, assume that the background pixels are distributed according to a multimodal Gaussian mixture, the region pixels are multivariate Gaussian and that the image data is conditionally spatially independent: \( p(x_i|I_i) = \prod_{j \in \Omega} p(x_i|l_i) \), where \( \Omega \) is the set of all lattice sites. The prior distribution of the field \( I \) is assumed to be an autologistic Markov random field (MRF) [10] that will be chosen to yield the desired region growing behavior.

In particular, we want to specify the MRF in such a way that if \( \mathcal{N}_I \) is the first-order neighborhood system consisting of the four nearest neighbors and \( \mathcal{I}_I = \prod_{j \in \mathcal{N}_I} I_{i+j} \) is the product of the neighborhood labels then

\[
p(I|\mathcal{I}_I) = \begin{cases} 
\epsilon, & \text{if } I_i = 0 \text{ and } l_i = 1, \\
1 - \epsilon, & \text{if } I_i = 0 \text{ and } l_i = 0, \\
\tau, & \text{if } I_i = 1 \text{ and } l_i = 1, \\
1 - \tau, & \text{if } I_i = 1 \text{ and } l_i = 0.
\end{cases}
\]

Since \( \epsilon \) is the probability that a pixel that does not border a region belongs to the region, we will want to choose \( \epsilon \) small to ensure region growing behavior. However, choosing \( \epsilon = 0 \) presents technical difficulties with the specification of the MRF [10]. One way of achieving the conditional density in (1) is by defining the MRF on a third-order neighborhood system, \( \mathcal{N}_3 \) that contains 12 pixels. Let \( \mathcal{C}_k \) be the set of \( k \)th order cliques and \( \mathcal{V}_k \) the associated clique potentials. Divide \( \mathcal{C}_3 \) into two sets: \( \mathcal{C}_{5,4} \), which contains the five site clique composed of the center pixel and its four nearest neighbors, and \( \mathcal{C}_{5,2} \), which contains all other five site cliques. Then choose \( V_1 = V_2 = V_3 = V_4 = V_{3,2} = 0 \) and \( V_k = 0, k > 5 \) and

\[
V_{5,4}(l_i, f_i) = l_i[(f_i - 1)\tau - f_i\tau]
\]

where \( \tau = \ln(\epsilon/1 - \epsilon) \) and \( \tau = \ln(\tau/1 - \tau) \). The conditional probability is then given by

\[
p(I_i|\mathcal{I}_I) = \frac{e^{-V_{5,4}(l_i, f_i)}}{\sum_{\lambda \in \{0,1\}} e^{-V_{5,4}(\lambda, f_i)}}
\]

which simplifies to (1).

Consider the following statistical problem using the previous model. The conditional distributions of the measured data \( x \) are known, and the label field is measured at a single lattice site \( m \) and found to be \( I_m = 1 \). Estimate the field \( I \). The standard approach to this problem is to employ the approximate maximum a posteriori estimate provided by the iterated conditional modes (ICM) procedure [11], and the most natural initialization for ICM is the field with \( I_m = 1 \) and \( I_j = 0 \), \( j \neq m \). At the \((n+1)\)th iteration ICM visits each lattice site in lexicographic order and approximates the maximum conditional a posteriori estimate of \( I \) as

\[
I_{i}^{(n+1)} = \arg\max_{I_i} p(x_i|I_i^{(n)}, \{I_{i+j}\}_{j \in \mathcal{N}_I}) p(I_i|\{I_{i+j}\}_{j \in \mathcal{N}_I})
\]

where \( \{I_{i+j}\}_{j \in \mathcal{N}_I} \) is the set of estimated label values of the neighbors to site \( i \) from the previous ICM iteration.

If we choose \( \epsilon \) such that no pixel that does not border the region is assigned to the region, then ICM clearly yields region-growing behavior. This is because in each ICM iteration, (4) can change only pixels at the boundary of the region. No new regions can form and no region pixel can be reassigned to the background. If the parameters to the conditional data distributions are not known a priori, they can be estimated at each ICM iteration as suggested by Besag [11].

In the CRG technique employed in this paper the parameters of the background Gaussian mixture distribution are first estimated by Gaussian spectral clustering (GSC) [2] and then taken as known during the CRG procedure. The mean and covariance of the region pixels are estimated iteratively. The smallness of the \( \epsilon \) requirement is enforced by visiting only region boundary pixels during each iteration. This also eliminates the undesirable possibility of interior region pixels being reassigned to the background due to changes in the region distribution parameter estimates.

Estimation of the covariance matrix of a region poses a difficulty when the region contains too few pixels to obtain reliable results from the standard sample average. An approximate strategy is employed for such regions in which the covariance matrix from each element of the GSC background model is used successively as an estimate for the region covariance. The maximum likelihood (ML) assignment test is then applied for each background element. The pixel is assigned to the region only if it is more likely than all the background elements. The physical justification for this approximation lies in the assumption that the spread of points described by the background covariance matrix is mostly due to sensor noise. In this case, the background and potential target region would have similar covariance matrices. In reality, the covariance matrix is often dominated by intensity variations. However, intensity suppression transformations can reduce this variation making the approximation more nearly valid. In particular, we use an apparent emissivity transformation to reduce temperature induced intensity variability in emissive data and a hyperspherical projection to remove illumination variation in reflective data. Once the region contains enough pixels to obtain reliable estimates of the covariance matrix, those estimates are used. The reliability of the covariance estimates are assessed by comparing the condition number of the covariance matrix to a threshold. A threshold on the order of the largest condition number of the covariance matrices in the background model has been found to be suitable.
To summarize, the feature extraction algorithm used in this paper comprises four stages of processing. First, an intensity suppression technique is applied to the spectral data to reduce the effect of illumination or temperature variation across the scene. Next, a GSC background model is constructed for the data. A statistical anomaly detector is applied to choose pixels to seed a region growth algorithm. Finally, the CRG algorithm is applied to each anomalous seed pixel. The result is the assignment of each scene pixel to either the background or one of some number of extracted objects.

The processing technique described previously is a sensitive detector of spectral edges and has been demonstrated to effectively extract salient spatial features from spectral imagery. The technique can accurately discriminate camouflage from surrounding vegetation and has been used to extract distinct objects beneath camouflage netting [3]. Fig. 2 shows the application of the region growth algorithm to a desert scene taken with the Daedalus Sensor on the Western Rainbow data collection experiment. Daedalus is a line scan multispectral camera with 716 cross-track pixels and 12 spectral band from 0.4 μm to 10.5 μm. A five band subset consisting of bands centered at 0.60, 0.65, 0.78, 1.69, and 2.25 μm with an approximately 19 cm ground pixel size was processed to obtain the result shown in Fig. 2. The top image is a three-color composite image of the scene containing several man-made objects. The center image shows the thresholded RX [7] detection statistic used to seed the CRG procedure. The bottom image illustrates the CRG result with each extracted object depicted in a different color. This example demonstrates the ability of CRG to accurately locate boundaries of detected man-made and natural objects and distinguish them from their surroundings. It contains several instances of adjacent and overlapping objects that were separated due to spectral differences. The joining of the rotor blade shadow with the helicopter-shaped object in the center left of the image is an instance of a rare artifact in which apparently spectrally distinct objects are joined.

C. Feature Extraction and Object Classification

The spatial and spectral properties of the extracted pixel sets must be characterized by an efficient set of features [3]. Following this feature extraction step, it may be beneficial to pre-filter the detected pixel sets. For example, spatial features may be used to remove sets that are too small, too large, or too elongated to be objects of interest, or spectral features might be used to eliminate known false alarms based on spectral matching. Alternately, spatial contextual information derived from the segmentation map surrounding the extracted object may be used to eliminate likely false alarms [1].

Once the feature set has been extracted, the objects may be classified by an automatic classification subsystem [3]. If classification is performed the result and its classification confidence measure may be included as additional object features for use in OLCD.

D. Spectral Normalization Options

The remotely measured spectrum of a material on the ground can vary dramatically over time due to variations in atmospheric effects, image formation geometry, illumination, and temperature. For spectral features to be useful in OLCD, some mechanism must be implemented to compensate for this variability. Two nonmutually exclusive approaches are possible. The first
approach is to derive spectral transformations that relate spectra measured at two different times. The second is to derive spectral features that are invariant to these effects.

There are a variety of alternatives available for the derivation of spectral transformations to relate spectra in two images. The transformations here all assume that the atmospheric effects may be modeled by an affine transformation. Specifically, if the spectra in image one and image two are \( x_1 \) and \( x_2 \), respectively, then

\[
x_2 = Ax_1 + b
\]

where \( A \) is a symmetric positive definite matrix.

If the two images are registered with excellent accuracy, the Chronochrome \([5]\) algorithm is available for computing the transformation from pixel-level correspondences. If \( A \) is restricted to being diagonal, a transformation may be derived with less stringent requirements on registration accuracy. For example, pixel level correspondences may be used to compute a “Diagonal Chronochrome” transformation. Once scene segmentation has been performed, a transformation may be derived from corresponding segment statistics. The transformation methods discussed above have the advantage that they may be derived and applied prior to execution of the association step in Fig. 1. This allows spectral features to be used in resolving association ambiguities. If instead, object association is performed first, object correspondences may be used for the calculation of a spectral transformation. An intermediate alternative also exists, if during the association step, an adequate number of unambiguous object correspondences are discovered, a transformation may be derived from their statistics thus allowing the use of spectral features for resolution of remaining ambiguous associations. The meaning of ambiguous and unambiguous associations will be clarified below in the discussion of the association step.

\[E. \text{ Site Model}\]

The site model itself is a digital database of information about the site derived from the imagery. The site models considered for this work contain two sets of information: segmentation maps and an object database. The segmentation maps are generated by segmentation algorithms such as GSC or multivariate GMRF texture modeling \([2]\). These maps represent knowledge of the thematic makeup of the scene. The object database contains entries for each set of pixels extracted by the object extraction step for each image represented in the site model. Each entry contains a variety of fields to store information about the object. These fields include the centroid location, a list of the pixels in the object, a set of spatial features, and a set of spectral features. An observation history is stored for each object that documents the presence or absence of the object in each image. If an IA is available to verify and identify observed objects, then the IA report will be stored in the site model entry for each object. Each object in the site model that has been observed in more than one image will have stored a measure of the confidence with which the object in the most recently acquired image was associated with the object in the site model. The extracted objects may also be examined by an automatic classification subsystem in which case the classification result and confidence will also be stored in the site model. In addition some description of the spatial context from which the object was extracted may be derived from the segmentation map and included in the site model entry for that object.

\[F. \text{ Site Model Initialization}\]

The first image presented to the OLCD system is processed by a scene segmentation algorithm, and an object extraction procedure. Feature extraction and automatic classification are performed. The segmentation map and object list resulting from these processes forms the initialization of the site model.

\[G. \text{ Object Association}\]

The function of the object association block in Fig. 1 is to attempt to associate each object extracted from a newly presented image with a corresponding object in the site model. Any potential association can be ascribed a confidence score that measures the likelihood that the two extracted objects both correspond to the same physical object in the scene. Factors that may be included in computation of the association confidence include the spatial distance between the object centroids, the degree of spatial overlap, a distance between spatial and spectral feature vectors, and differences in assigned classification and classification confidence. The optimal combination of these factors into a numerical association confidence is unknown and will be a topic of future research. A simple choice will be made without further justification for the experimental demonstration in Section III.

Once the association confidence is defined, the association problem may be posed as the discovery of the set of object associations between the image and the site model that maximizes the RMS association confidence. Solution of this problem by exhaustive search is a problem of great computational complexity. For example, if both the image and the site model contain \( N \) objects, the search must cover \( N! \) possible combinations. Solution of this problem would be intractable in practice. However, in OLCD, the object centroids are referenced to a common coordinate system, and we have some knowledge of the accuracy of the image registration that accomplished this referencing. It is therefore reasonable to impose the constraint that all associated objects be located within some fixed spatial distance of each other. This has the consequence that the system will not track an object that moves between two image acquisitions. Such a moving target will instead be viewed as a departure from one location and an arrival at a different location. However, if the extracted object density is sufficiently low and the registration sufficiently accurate, this constraint can dramatically reduce the complexity of the association problem.

A procedure to solve the association problem subject to the registration accuracy constraint consists of the following steps: Compute the distance between the centroids of all pairs of objects selected one from the new image and one from the site model. This calculation has complexity \( \binom{N}{2} = \frac{1}{2}N(N - 1) \) when both image and model contain \( N \) objects. Eliminate all potential pairings whose centroid distance exceeds the constraint. Identify all objects for whom no potential matches satisfy the constraint. Such objects are designated arrivals if they are in the new image and departures if they are in the site model.
Identify all object pairs for which there exists only one potential association that satisfies the constraint. These unambiguous matches are persistent objects that may be used at this point to compute a spectral normalization transformation. At this point, all remaining objects have multiple potential matches that satisfy the registration accuracy constraint. However, they may be separated into families of possibly connected objects, none of whose members have potential matches with any object outside the family that satisfy the constraint. It is clear that the global association problem may be solved by solving the local association problem at each family independently. If the largest such family contains $M$ objects in both the new image and the site model then the local association problem is of order $M!$ and if the object density is sufficiently low and the registration accuracy constraint sufficiently tight we will have $M \ll N$. In this way, we reduce a computationally intractable problem to a tractable one.

### H. Change Reporting and Model Update

Once the association problem has been solved the SOLCD system can compile a report for presentation to an operator. Arrivals, departures, and persistent objects can be reported as such. Departure and persistence reports may include the IA annotation for the object if one is available. Intermittently appearing objects may also be encountered and reported, possibly with an IA annotation. Finally, it may be desirable to report persistent objects that have undergone significant changes in their spatial or spectral properties as measured by the computed features. For example, in a military application, military vehicles that have undergone militarily significant changes in their configuration may be of interest to report. The operator or IA may respond to this report by indicating whether particular objects are or are not of interest or by supplying a confirmed classification or identification for the object. In addition, the system may at this point search for other objects in the scene that are similar to those deemed interesting by the IA. This could be accomplished by searching the list of extracted objects from the image for objects with similar features. In addition, the original spectral image may be searched for previously undetected similar objects using a matched filter derived from the properties of the indicated object in the report.

Finally, the site model must be updated to reflect the information derived from the new image. Arrivals are added to the site model, the appearance histories of departed objects are updated and the appearance histories and feature records are updated for persistent and intermittent objects present in the new image. At this point the system is prepared for presentation of the next new image.

### III. SOLCD Demonstration

This section presents an experimental demonstration of a simplified version of the SOLCD system described in the preceding section. The data used in these experiments consist of four spectral images from the November 1998 HYDRA data collection with the Spatially Enhanced Broad-Band Array Spectrograph System (SEBASS) infrared hyperspectral instrument. SEBASS is a push-broom nadir-looking dispersive imaging spectrograph operating concurrently in the MWIR and LWIR spectral regions with broad-band spectral coverages of 2.5–5.3 $\mu$m and 7.8–13.4 $\mu$m, respectively. The field data used in this study were collected at altitudes between 850 and 870 m and at relative ground speeds between 110 and 120 m/s. With these flight parameters, the sensor’s 1 mrad instantaneous field of view yielded a ground pixel size of approximately 1 $m^2$. For this study, the 128 SEBASS LWIR bands were reduced to 30 bands by deleting bands with uncorrected sensor artifacts and by binning the remaining 90 bands three to one. The MWIR bands were omitted. An apparent emissivity conversion was then applied to convert to a 29 band emissivity spectrum.

This data set allows a limited demonstration of the techniques described in the preceding sections. A more thorough evaluation of the performance of these techniques must await the availability of high-quality multitemporal spectral imagery of sites subject to well documented changes in militarily significant objects. In addition, the extent data does not support the assessment of effects such as overlapping objects, object obscuration, or other viewing angle effects that would be most pronounced in oblique viewing geometries. The data also lacks examples of imagery collected over an interval of more than two days.

The four images shown in Fig. 3 were collected on three different days with the top right and bottom left images in the figure collected at different times on the same day. The scene background is composed of vegetation, roads and disturbed soil. There were eleven military vehicles in the scene. The three circled in red were absent in the top left image. These will be the three true changes in the experiments. The scene also contains a regular array of man-made material samples and several other man-made objects none of which changed over the four images.

The four images were all registered together using local phase correlation on the first principle component remaining after a linear temperature removal projection. The resulting local shift estimates were interpolated onto the image lattice using two-dimensional (2-D) thin plate cubic spline interpolation. The spectral images were then resampled onto common lattice coordinates using a four-point DFT interpolation kernel separately in each spectral band. This accomplished the registration block of the diagram in Fig. 1 for the purposes of the experiment.

The object extraction step was implemented using CRG with sliding-window adaptive RX providing the object seeds. Three spectral clusters were used in the GSC-based background model. The 5% of the pixels with the highest RX statistic were eliminated from the estimation of the cluster statistics to prevent their corrupting these statistics. The RX statistic was thresholded at a level to guarantee that all military vehicles in the images were extracted as objects. This choice of threshold was made to facilitate the present demonstration. In practice, the selection of a threshold would be automated. An optimal method for choosing this threshold is not currently available and will not be addressed further here.

GSC segmentation maps were generated from the images for the site model but were not exploited in this demonstration. The features stored in the object database were the centroid coordinates, the area, and the spectral mean and covariance matrix. Also stored in each object entry were the complete list of object
Fig. 3. Three color composites of four SEBASS LWIR images of the HYDRA site 4 scene.

Fig. 4 shows the change report image for the two image arrival test. In this figure, objects in red were detected as arrivals, that is, they were present in the new image but not the site model. Objects in green were detected as departures, and objects in white were persistent objects that were present in both the site model and the new image. For this test, the site model consisted of the objects detected in the top left image in Fig. 3 in which the three true change objects were absent. The new image is the top right image from that figure where the three change objects are present.

The left image in Fig. 4 clearly shows the correct detection of the three true arrivals. The other eight military vehicles are correctly detected as persistent objects, as are many of the material array objects. A variety of false arrivals and departures are also visible as are several persistent false alarms. Examining the left image in the figure, we see that many of the false changes occur at the edges of persistent objects. This is caused by the fact that the CRG algorithm in the object extraction step distinguishes the spectral difference between pixels on an object and the mixed pixels around its boundary. This tends to fragment ground objects into multiple parts. Strategies for grouping CRG generated pixel sets to reassemble whole ground objects is a potentially fruitful area for future research. However, for the purposes of this demonstration, the false changes at object edges and the several very small false changes can be eliminated from the change report image by the application of a simple size filter.

The result of discarding objects with area smaller than nine pixels, the minimum size for objects of interest at this resolution, is shown in the right image in Fig. 4. Here we see the correct detection of the three true changes with only one false arrival and one false departure. In addition, there remain two persistent false alarms. This result confirms the principle that false alarms can be eliminated by OLCD based on their multitemporal persistence.

Fig. 5 shows the size-filtered OLCD change report images for the four image departure experiment compared to a two image departure test. The two image departure test uses the same two images as the two image arrival test discussed above. The association procedure is completely symmetric with respect to time reversal, so the two image result on the left in Fig. 5 is the same as the two image result on the right. In the case of the four image test, there are three true change events: the two departures of the two true changes that occurred in the two image test and the single addition of the material array to the site model. The new image is the right image in the top row of Fig. 3. Here we see the correct detection of the three true changes with no false arrivals and departures. In addition, there remain two persistent false alarms. This result confirms the principle that false alarms can be eliminated by OLCD based on their multitemporal persistence.

Automatic classification was not incorporated into these experiments so the classification results and confidences were omitted from the site model.

Each association confidence was computed as the sum of the squared centroid distance and the squared difference in area. Many other spatial and spectral features could be included in this calculation. Such features may enhance the performance of the association procedure especially in scenes with high object density. However, a simple confidence computation is adequate to demonstrate the core principles of SOLCD. The association problem was solved with an implementation of the procedure detailed in the preceding section.

Change reports were presented as color-coded images, and the site model update was implemented as discussed above. The present experiments were conducted in an unsupervised fashion, therefore the IA verification component of Fig. 1 was not implemented.

Two specific experiments will be described here. First, a two image arrival test will be considered to address the question of whether false alarms can be eliminated based on their multitemporal persistence. Second, a four image departure test will be described to ascertain whether the performance of the SOLCD system can be improved by including information from multiple images of a site in the site model.
as that on the right of Fig. 4 except that red objects became green and green objects became red and some objects had somewhat different shapes between the two times. All four images in Fig. 3 were presented to the OLCD system for the four image test proceeding sequentially from the bottom right to the top left. The change image from the two image test was the last of the three images to be incorporated into the site model in the four image test before the change image was presented.

The four image change report contains blue regions, which represent intermittently appearing objects. In particular, the one false arrival in the two image report is reported as an intermittent object in the four image report. There are two possible interpretations of intermittent objects. They may in fact be objects that were present, departed, and then returned to the same position in the scene. Another, arguably more likely interpretation is that they are stationary objects that are only intermittently detected in the object extraction stage at the particular chosen threshold. Adopting the second interpretation, which is in fact correct in this case, we may regard the blue objects in the right image in Fig. 5 as persistent objects and thereby dismiss the object that caused the false arrival in the two image test as a persistent false alarm. This demonstrates the principle that including multiple images in the site model can improve OLCD performance.

**IV. CONCLUSIONS**

The two experiments described above demonstrate the application of SOLCD and exhibit, at least anecdotally, the operation of the principle that real scene changes can be detected and false alarms rejected based on their persistence. It was also demonstrated that site models that accumulate scene information from multiple observations can yield improved OLCD performance over site models built from a single image. Quantifying the performance of SOLCD will require the execution of many more experiments using much more registrable change containing spectral imagery than is currently readily available.

Questions that remain to be addressed include the extent to which performance continues to improve with accumulated data and the manner in which the site model should be pruned of long departed objects. The impact of overlapping objects, obscuration, and other oblique viewing angle effects and long time interval collections also remain to be investigated. In addition, there are several clear avenues to the improvement of SOLCD, including improvements to competitive region growth, selection of a spectral normalization technique, and inclusion of spectral features in the association confidence calculation. The incorporation of IA input and automatic classification results are also
likely fruitful enhancements. These will all remain as topics for future research.

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Geoffrey G. Hazel (M’88) received the B.S. degree in 1990, the M.S. degree in 1992, and the Ph.D. degree in 2000, all from the Electrical Engineering Department, University of Maryland, College Park. He currently works in hyperspectral image exploitation algorithm development and flight test system integration for the Naval Research Laboratory, Washington, DC. He has worked previously in fiber optic chemical sensors and GPS attitude determining systems.