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Automatic Object-Level Change Interpretation for Multispectral Remote Sensing Imagery

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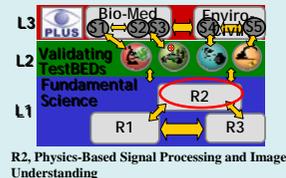
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Automatic Object-Level Change Interpretation for Multi-spectral Remote Sensing Imagery

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Abstract

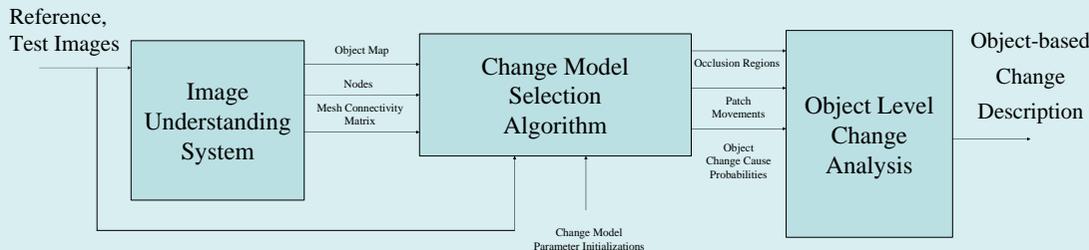
The use of satellite-based remote sensing is a cost-effective approach to documenting changes over large geographic regions. However, the large volumes of multi- or hyper-spectral data make systematic exploitation of earth observation data challenging. There is a long history of developing automated change detection (CD) systems to aid users in interpreting vast arrays of data.

Change detection is a technique that employs two or more time-separated images taken of the same geographic location and labels each spatial location according to whether there is a significant change in the images over time. Traditional CD methodologies employ a single change hypothesis, and do not interpret the causes behind the observed change. On the other hand, automatic interpretation of detected changes enables automatic labeling of images with meaningful semantic descriptions which can be used to aid in database querying, early warning systems, ecological system exploration, and defense applications.

In this work, we construct an automatic, qualitative explanation of object-level changes in multi-spectral remote sensing imagery. Our proposed object-level change interpretation system employs change models that directly reflect the nuisance effects of the data acquisition process, unimportant causes of observed object variation such as illumination variation or spectral composition variation, and important object changes like object shape or location change.

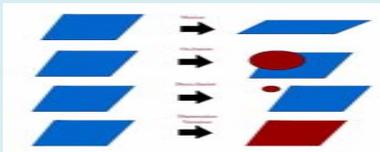
This work develops an object-level change understanding framework along with change models for multi-spectral remote sensing imagery, adding value to the R2C and R2D CenSSIS research areas.

Change Understanding System



Model-Based Change Understanding Goals

- Analysis of remote sensing imagery assists in a wide range of tasks such as crop forecasting, pollution monitoring, mineral exploration and rangeland monitoring.
- We employ a generalized approach to monitoring change via understanding what has happened to image regions according to broadly applicable descriptions of appearance change.



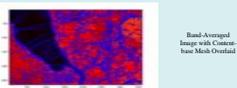
- Observed spectral signatures reflect nuisance changes due to factors such as misregistration error and illumination variation as well as changes in spectral composition due to object appearances, disappearances and motion.

Image Understanding System (IUS)

- Global image-wide spectral histogram may be employed to distinguish certain kinds of image features like clouds and cloud shadows.



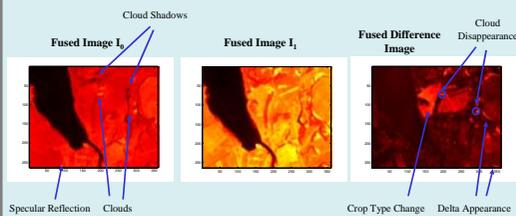
- IUS must be capable of depicting many different observed objects
- Content-based meshes are employed to describe arbitrary image features by placing nodes in areas of interest.
- Objects of variable spectral dimension may be represented by the spatial structure of a mesh with appropriately chosen image feature description.



Challenges and Significance

- Mesh-model for arbitrary multi-band object representation and object shape / location change is applicable to a diverse range of biomedical and earth-surface image understanding problems.
- We are currently exploring the viability of advanced motion models for complex image understanding problems.
- Model-based image understanding on an object-based scale is widely applicable to other change understanding problems in the geophysical and medical fields.

Change Modeling Example



Model-Selection Framework

- The probability of observing object j in image t is given as

$$p(\mathcal{O}_j^t | \{\theta_{ic}\}_{c=1}^C) = \sum_{c=1}^C P(w_c | \theta_{ic}) p_c(\mathcal{O}_j^t | w_c, \theta_{ic})$$

where $\{\theta_{ic}\}_{c=1}^C$ represent the set of change model parameters for object j in image t , w_c is the change cause and $\theta_{ic} = [a_{ic}, \mathcal{Q}_i^t, \Psi]$ where Ψ is a scale matrix and a_{ic} is the parameter set for potential change model c . This approach extends Black's [5] for multispectral remote sensing imagery on an object-based scale.

- The EM algorithm is employed to obtain the ML parameter estimates for each change hypothesis.

- A multi-band signature located at pixel index k in image t is modeled using the multivariate Student's t -distribution given by

$$p_c(x_k^t | w_c, \theta_{ic}) = W(w, B, \Psi) \left(1 + \frac{(x_k^t - \hat{x}_k^t)' \Psi^{-1} (x_k^t - \hat{x}_k^t)}{v} \right)^{-(v+B)/2}$$

Object-Level Change Models

- Object Location Change Model (\mathcal{W}_{Lj}):
 $\hat{\mathcal{O}}_{Lj}^t = \mathcal{Q}_i^t (\mathcal{E}^{t1} + \alpha (\mathcal{E}^{t1}, a_{Lj}))$
Identifies large-scale movements of rigid objects such as man-made objects.
- Object Shape Change Model (\mathcal{W}_{Sj}):
 $\hat{\mathcal{O}}_{Sj}^t = \mathcal{Q}_i^t (W(\mathcal{E}^{t1}, N', N^{t1}))$
Employed to describe shape changes of arbitrary objects.
- Spectral Composition Change Model (\mathcal{W}_{Cj}):
 $\hat{\mathcal{O}}_{Cj}^t = g(\mathcal{Q}_i^t, a_{Cj})$
Models smaller-scale spectral variations which affect limited portion of observed spectrum.
- Illumination Change Model (\mathcal{W}_{Ij}):
 $\hat{\mathcal{O}}_{Ij}^t = h(\mathcal{Q}_i^t, a_{Ij})$
Models effect of varying illumination conditions between test and reference images.
- Partial Object Occlusion Model (\mathcal{W}_{Oj}):
 $\hat{\mathcal{O}}_{Oj}^t (\mathcal{E}^{t1}, \mathcal{E}^{t0}) = \mathcal{Q}_i^t (\mathcal{E}^{t1}, \mathcal{E}^{t0})$
Captures effects of shadows, clouds, or other partially occluding objects.
- Outlier Model (\mathcal{W}_{Oj}):
Certain types of object change such as full object occlusion cannot be predicted with the use of a single reference image. We employ a constant outlier probability model.
 $p_{Oj}(\mathcal{O}_j^t | \mathcal{W}_{Oj}) = \left(\frac{1}{256} \right)^{|\mathcal{O}_j^t|}$

State of the Art

- We construct a motion model for RS imagery to incorporate into the model selection framework introduced in [5] and expand the framework for object-based description of change.
- The AMT algorithm expands the idea of neighbourhood structure introduced in [2] for content-adaptive meshes and it expands the occlusion adaptive methodology of [1].

Results on Synthetic Images



- To evaluate the model selection performance we present the change cause probabilities for each object, given as

$$o_j(w_c) = \frac{P(w_c | \theta_{ic}) p_c(\mathcal{O}_j^t | w_c, \theta_{ic})}{\sum_{c=1}^C P(w_c | \theta_{ic}) p_c(\mathcal{O}_j^t | w_c, \theta_{ic})}$$

Object Number	Change Cause Probabilities				General Truth
	no	change	no	no	
1	0.0000	0.0000	0.0000	0.0000	no
2	0.0000	0.0000	0.0000	0.0000	no
3	0.0000	0.2150	0.5700	0.0000	0.1122
4	0.0000	0.3550	0.5630	0.0000	0.2889
5	0.0000	0.1240	0.5700	0.0000	0.1258
6	0.0000	0.1155	0.2600	0.4544	0.1710
7	0.0000	0.0000	0.0000	0.0000	no
8	0.0000	0.0000	0.0000	0.0000	no
9	0.0000	0.0000	1.0000	0.0000	no
10	0.0000	1.0000	0.0000	0.0000	no

Ongoing Work

- Implement the content-adaptive mesh construction problem for multi-band RS imagery as nonlinear optimization problem.
- Implement mesh-based motion estimation as nonlinear optimization problem in place of current deterministic search-based approach.

Technology Transfer

- National Geospatial-Intelligence Agency (NGA)
- Lockheed Martin Corporation
- Analogic

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