OBJECT-LEVEL SEMANTIC CHANGE INTERPRETATION FOR MULTI-BAND REMOTELY SENSED IMAGERY

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1. INTRODUCTION

Automated data interpretation and change detection algorithms are useful aids in the handling of the vast arrays of data collected by remote spaceborne sensors. The automatic interpretation of detected changes between images enables meaningful semantic descriptions which can be used for applications such as ecological system monitoring and surveillance [1, 2]. Depending upon the application, specific models may be employed to interpret the observed changes. In this work, we propose an object-level change analysis system in which change is semantically described according to selected causes, including: object shape and location change, object spectral composition change, cloud or cloud shadow occlusion/disocclusion, illumination-variation, and outliers.

Previously in [3], we developed an automatic change understanding system indicated by the two left blocks of Fig. 1. This system employed a set of selected change models to explain object-based changes between two time-separated multi-band images, $I^t$ and $I^{t+1}$. The image understanding system (IUS) extracts $L^t$ multi-band objects, $O^t_l; l = 1, \ldots, L^t$, from the time $t$ reference image. In the change model selection system (CMS), it is hypothesized that one or more of the $C$ change causes explain the difference of an object at times $t$ and $t+1$. Given the set of reference image objects, the test image, $I^{t+1}$, and the $C$ selected change models, the CMS estimates change model parameters which best fit the data [3, 4]. Taken together, the previously developed IUS and CMS provide an object-based change description. For the $l$-th object the change description consists of a set of optimized change parameters $\hat{a}_{l,c}$ which with the observed test object $O^{t+1}_l$ are employed to form a predicted reference object $\hat{O}^t_{l,c}$, for each change model $c = 1, \ldots, C$.

In this work, we implement object-level change analysis. We interpret object-based change according to the change description provided by model parameters and the error between observed and predicted reference image objects. As in [3] we evaluate prediction quality through the likelihood that object $O^t_l$ is generated by change cause $c$, $p_c(O^t_l|\hat{O}^t_{l,c})$, where $\hat{O}^t_{l,c} = f_c(O^{t+1}_l, \hat{a}_{l,c})$ and $f_c$ is the $c$-th change cause model. We propose a semantic interpretation of object change via two approaches: physical description of the model parameter changes and evaluation of the error objects. Thus, interpretation of object-based change consists of both semantic change description and evaluation of the quality of that description.

Experiments are performed on multispectral ASTER data in order to analyze the proposed change interpretation mechanisms. We determine the behaviors of the semantic description provided using different sets of selected change models for change interpretation. Further, we analyze the quality of change interpretation for an ASTER dataset which exhibits multiple kinds of change phenomena.

2. SEMANTIC CHANGE INTERPRETATION

To analyze the quality of a change description we employ the change cause probabilities for each object, given as

$$P_l(c) = \frac{P(c|\theta_{l,v})p_c(O^t_l|c, \theta_{l,c})}{\sum_{c=1}^{C} P(w_{l}|\theta_{l,v}) p_c(O^t_l|r, \theta_{l,r})}$$  

This work was supported in part by Gordon-CenSSIS, the Bernard M. Gordon Center for Subsurface Sensing and Imaging Systems, under the Engineering Research Centers Program of the National Science Foundation (Award Number EEC-9986821).
where $\theta_{1:t} = \{ \Theta_l^{t+1} : \hat{a}_{l:t} \}$. The probability $P_l(c)$ measures the relative likelihood the $c$-th change cause explains the observed object $t$ given the reconstruction error of all $C$ models.

Object-based change interpretation may consist of assigning each object to its most likely change cause forming a M-ary change mask, $M$, according to the rule: $M(\Theta_t) = \arg \max_{c=1,\ldots,C} P_l(c)$, where $\Theta_t$ denotes the set of pixel locations for object $t$. However, depending on both the kinds of changes exhibited in the imagery and the set of change models employed some object changes may share causes, i.e., the change may be due to multiple observed causes. In this case, $M$ may fail to convey important change information; thus, we also employ change cause probability images given as $\hat{X} = \hat{X}_c$, $c = 1, \ldots, C$, where $\hat{X}_c(\Theta_t) = P_l(c)$ to interpret the data.

3. CHANGE INTERPRETATION RESULTS

We present semantic change interpretation results between two multi-band ASTER images of the same geographic location taken at different times; selected single band images from times $t$ and $t+1$ are displayed in Fig.’s 2(a)-(f). The imaged region is composed of multiple crop patterns some of which exhibit spectral variation, shape change, and disocclusion by clouds. In Fig.’s 2(g)-(l) we display change cause probability images $\hat{X}$ for selected change causes.

Large-scale changed regions dominant across the bands are mainly due to occlusion by clouds in the time $t$ image. These changes are captured in the cloud and shadow change cause probability maps displayed in Fig.’s 2(j) and (k). Many objects are captured by both spectral variation and illumination change models. This is expected since the illumination model allows for multi-band spectral change while the spectral model captures single-band spectral change. As such, the illumination change model provides superior performance, despite an increased number of model parameters. As can be seen by comparing the scales of images Fig.’s 2(g)-(l), the outlier model has negligible probability; thus, the proposed change models capture observed change well.

![Fig. 2. Single-band reference and test images are displayed in (a)-(c) and (d)-(f), respectively. Selected change cause probability maps are displayed in (g)-(l). Note the different scales in the images.](image)

Changes due to causes such as occlusion/disocclusion by atmospheric phenomena, crop-type or moisture variation, and object shape change are identified according to the spectrally homogeneous objects extracted from the reference image. In this work, we interpret object-based change by labeling multi-band changes according to these causes, or other user-specified causes, and the corresponding estimated model parameters.

4. REFERENCES


