

A Multidimensional Scaling Optimization and Fusion Approach For the **Unsupervised Change Detection Problem in Remote Sensing Images** Redha Touati & Max Mignotte Department of Computer Science and Operations Research (DIRO), University of Montreal

Introduction

- Develop a new automatic unsupervised change detection in remote sensing images.
- Process whose purpose to analyze two or several images Generated by different satellite sensors or the same sensor of the same area at different times.
- Aims to identify any changes that may have been occurred between the two images.
- In general, require three main steps:
 - Preprocessing : radiometric correction... etc. Pixel wise difference: pixel by pixel

Experiments was conduced on different real, publicly available, optical, multi-temporal, multispectral, airborne SAR or radar data sets with available ground truth, shown different kind of changes and acquired by different sensors:

Experimental Results

- X-band airborne SAR.
- Landsat-5 (TM) and Landsat-t Enhanced Thematic Mapper Plus (ETM+)
- Radar-SAT SAR
- European Remote Senisng 2 (ERS 2) satellite SAR sensor.
- Landsat Multi-Spectral Scanner.

Model Validation

- Validated using the classification rate accuracy procedure on the different data sets...
- Based on the calculation of the percentage of the correct changed and unchanged pixels.

- Classification
- Most unsupervised methods are based on the quality difference and the accuracy of classification method.
- In general, generate difference by (log)-ratio operator.
- Depend on the type of remote sensing images
- Different remote sensing data with different imaging modalities
- A new and robust model to address these issues
- More reliable than the difference by modeling each pair of pixels expressed by set of constraints.
- Does not require any pre-processing step or distortion corrections-normalization
- Model that reduce the quadratic complexity to a linear complexity.

Change Detection Model

Change detector based on two steps :

FastMap -Based Model Optimization Step



- Estimate a robust feature similarity map.
- Play the same role as so-called difference but not by pixel • wise difference.
- Specify a set of constrains. •
- The constraints are expressed for each pair of pixels existing in the multi-temporal images.
- The set of constraints satisfy :

 $\beta_{S,t} = \left| |y_s^1 - y_t^1| - |y_s^2 - y_t^2| \right|$

Our similarity map can be seen as the solution to the \bullet following cost function to be optimized :

 $\hat{y}^{D} = \arg\min_{y^{D}} \sum_{\langle s,t \rangle_{s\neq t}} \left(\beta_{s,t} - \|y^{D}_{s} - y^{D}_{t}\|_{2}\right)^{2}$

- Fast alternative to optimize the model ۲
- The optimization of the proposed model is done by the FastMap mapping technique.
- The distance between each pair of grey-level associated to pixels s and t are close of $\beta_{S,t}$ as faithfully as possible.
- Projection Based on the cosine rule.
- Poor estimation from one pivot due to its linearity
- Generate more than one pivot line

Experimental results on optical Eros center dataset : BURN, CUTS, DRALKE; From left to right; image acquired at time t1 and t2, ground truth, similarity feature map, final (changed/unchanged) binary segmentation result obtained by our approach.

Experimental results on SAR airborne dataset; From left to right; image acquired at time t1 and t2, ground truth; similarity feature map, final (changed/unchanged) binary segmentation result obtained by our approach.

Method Data set	Ours	J. Lu and .all	H. Li and .all	M. Gong and .all	J. Ma and .all	B. Xiong and .all	M. Gong and .all
Bern dataset	.993	.997	.996	.996	.996	-	-
Ottawa dataset	.943	.965	.974	.972	-	-	.988
SAR Airborne dataset	.986	-	-	-	-	.997	-
Number of images tested	17	2	3	3	2	2	5

Averaging the different estimations obtained from • different pivot lines to estimate a robust feature map.

Fusion-Based Segmentation Step

- Integration of multiple different criteria.
- Decision on histogram
- Combining the results of different automatic thresholding algorithms.
- Binary process fusion based on majority vote filter.
- Using 3D window.

Table 1. Accuracy rate of change detection obtained by different state of the art methods, on BERN, OTTAWA, and SAR Airborne datasets with the total number of images tested in each case

Conclusion

- A new and simple model for multi temporal remote sensing change detection.
- Based on modeling each pair of pixels in the multi-temporal images by a set of constraints.
- The efficiency of the proposed model on fifth data sets is *94%*.
- Pre-processing step of the multi-temporal images is not needed such as radiometric, noise or distortion corrections/normalization.
- The quadratic complexity in the number of pixels is reduced to a *linear* complexity.