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→ 4th ADVANCED TRAINING COURSE IN LAND REMOTE SENSING

CURRENT SCENARIO AND CHALLENGES IN THE ANALYSIS OF MULTITEMPORAL REMOTE SENSING IMAGES

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1–5 July 2013 | Harokopio University | Athens, Greece

Outline

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1. Current Trends and Background on Multitemporal Images

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Multitemporal Images

In the last ten years we had a significant increase in the interest on topics related to the time series and the analysis of multitemporal data:

- ✓ Sharp increase in the number of papers published on the major remote sensing journals (e.g., IEEE Transactions on Geoscience and Remote Sensing, IEEE Geoscience and Remote Sensing Letters, IEEE Journal on Selected Topics in Applied Earth Observation and Remote Sensing, Remote Sensing of Environment, International Journal of Remote Sensing).
- ✓ Increased number of related sessions in international conferences.
- ✓ Increased number of projects related to multitemporal images and data.

Multitemporal Images

The increased interest in multitemporal data analysis is due to many issues:

- ✓ Increased number of satellites with increased revisitation time that allow the acquisition of either long time series or frequent bitemporal images.
- ✓ New policy for data distribution of archive data that makes it possible a retrospective analysis on large scale (e.g. the Landsat Thematic Mapper archive).
- ✓ New policies for the distribution of new satellites data (e.g. ESA Sentinel).

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Multitemporal Images: Change Detection

- ✓ Change detection (CD): process that analyzes multitemporal remote sensing images acquired on the same geographical area for identifying changes occurred between the considered acquisition dates.
- ✓ We can define different change detection problems:
  - Binary change detection.
  - Multiclass change detection.
  - Change detection in long time series of images.

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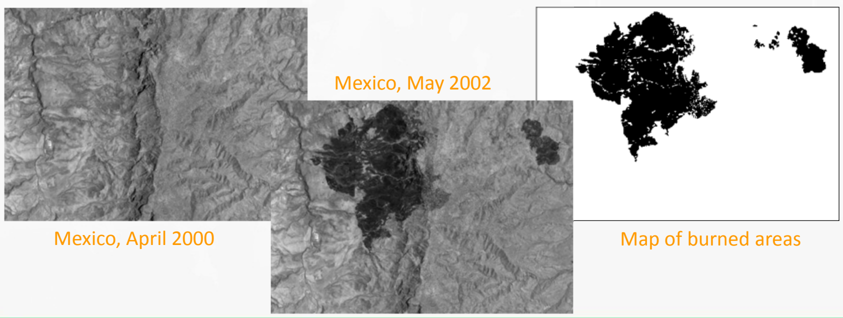
Taxonomy of CD Problems

1. Binary change detection

- ✓ Goal: production of binary maps in which changed and unchanged areas are separated;
- ✓ Number of images: 2 (or pairs of images extracted from a series);
- ✓ Application domain: detection of abrupt (step) changes.



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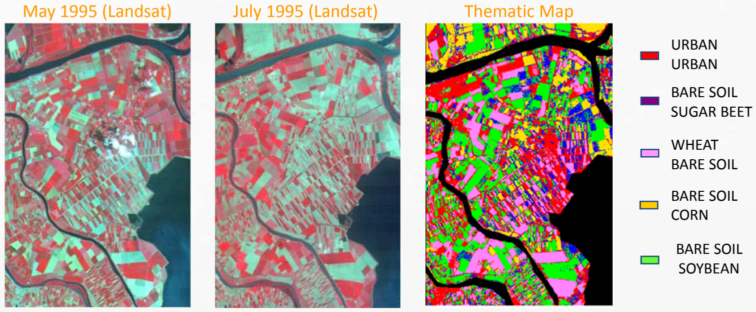
Taxonomy of CD Problems

2. Multiclass change detection

- ✓ Goal: generation of a change-detection map in which land-cover transitions are explicitly identified;
- ✓ Number of images: 2 (or pairs of images extracted from a series);
- ✓ Application domain: updating thematic maps, detection of multiple changes.



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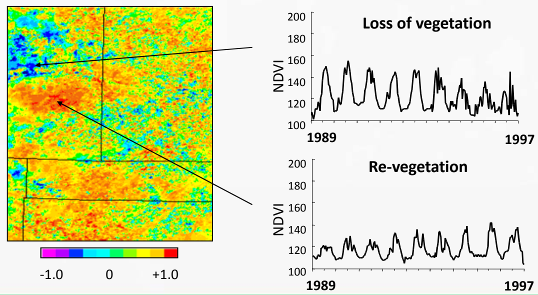
Taxonomy of CD Problems

3. Change detection in long time series of images

- ✓ Goal: detection of changes associated with modifications of the behavior of the temporal signature of a land cover between two time series (detection of long term changes);
- ✓ Number of images: 2 time series made up on n images (n>>2);
- ✓ Application domain: monitoring seasonal/annual changes.



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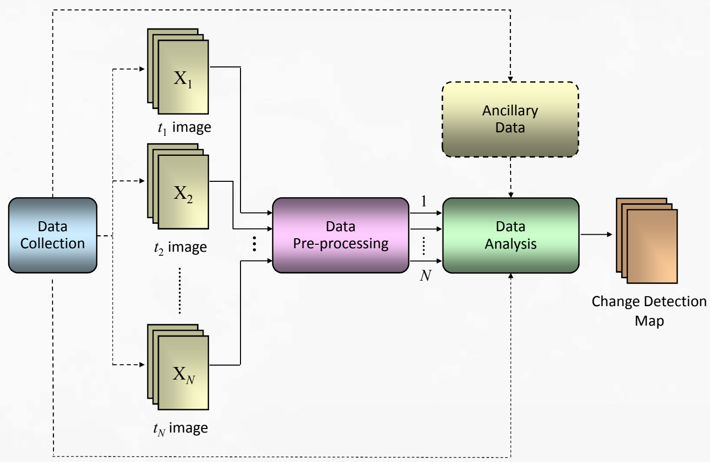
2. Change Detection in Multispectral Images

Change Detection Architecture



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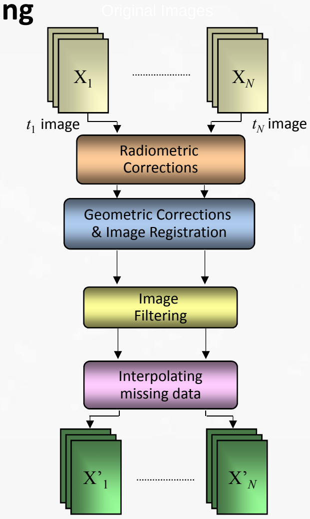
Data Pre-processing

Very important with optical images

Mandatory in all change-detection techniques

Depends on the specific sensor considered and on the quality of the considered images

Depends on the requested acquisition frequency and data availability (careful application, see information theory!)



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Data Pre-processing: Radiometric Corrections

Differences in light and atmospheric conditions between the two acquisition times can be mitigated by applying radiometric calibration to the images. Two different approaches can be applied:

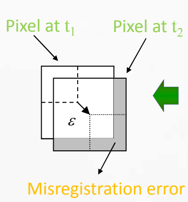
- ✓ Absolute calibration: digital numbers are transformed into the corresponding ground reflectance values (radiometric transfer models, regression algorithms applied to ground-reflectance measurements collected during the data acquisition phase).
- ✓ Relative calibration: modification of the histograms, so that the same gray-levels values in the two images can represent the same reflectance values, whatever the reflectance values on the ground may be (histogram matching).

The choice of one of the two approaches depends on the particular application considered and on the specific information available.

Data Pre-processing: Image Registration

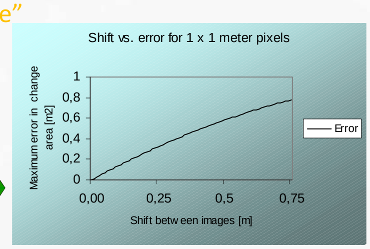
Generally it is not possible to obtain a perfect alignment between multitemporal images. This is mainly due to local defects in the geometries of the images.

Residual misregistration results in a very critical source of noise, which is called "registration noise"

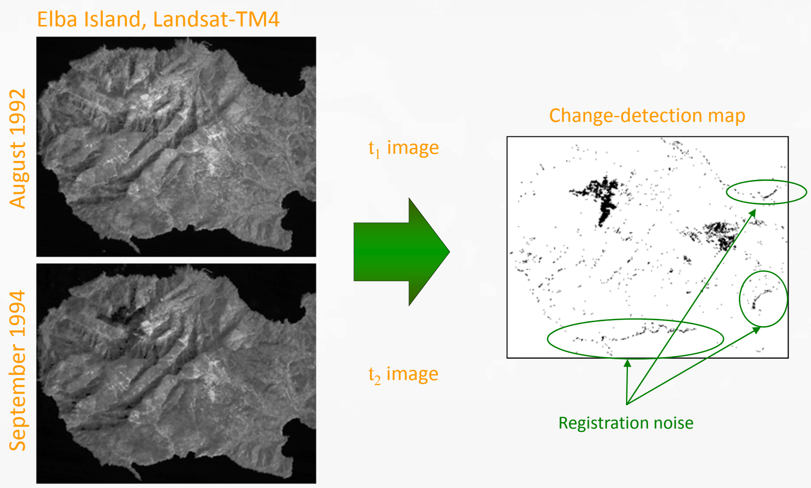


Generic effect of misregistration

Error in area as a function of the displacement in high resolution sensors



Data Pre-processing: Registration Noise Effects



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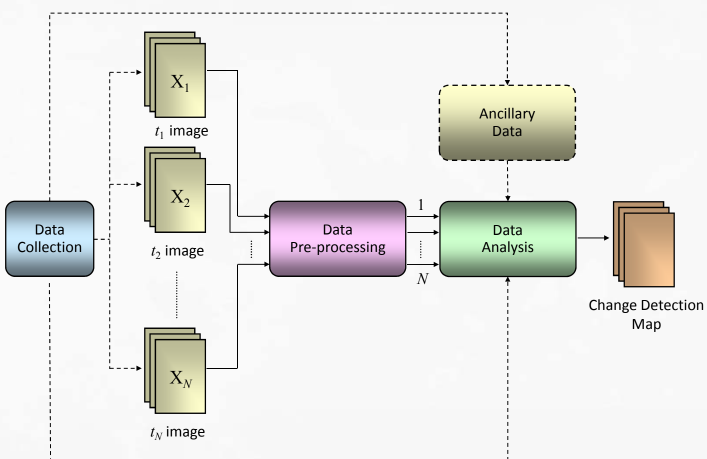
Change Detection Architecture



Binary Change Detection in Remote Sensing

Binary change detection in remote-sensing images is characterized by several peculiar factors that render ineffective some of the multitemporal image analysis techniques typically used in other application domains. Some of these factors are:

- ✓ Differences in light conditions, sensor calibration, and ground moisture at the two acquisition dates considered;
- ✓ Absence of a reference background;
- ✓ Lack of a priori information about the shapes of changed areas;
- ✓ Non-perfect alignment (registration noise) between the two considered images;
- ✓ Different acquisition conditions of multitemporal images (view angle, shadows, etc.).

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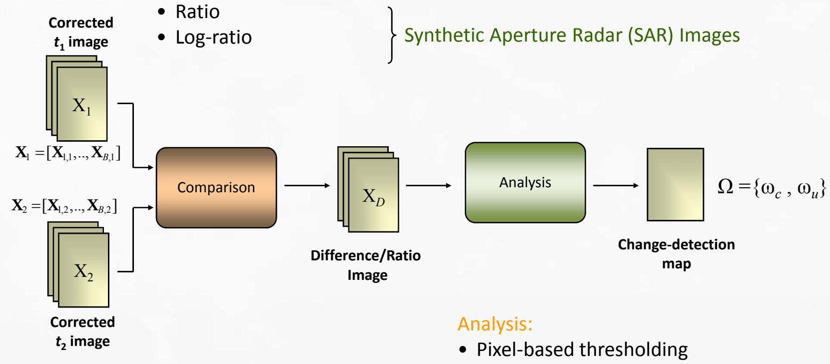
Binary CD: Typical Architecture

Comparison Operators:
- Difference
- Vector difference
- Ratio
- Log-ratio

Difference, Vector difference → Optical Images

Ratio, Log-ratio → Synthetic Aperture Radar (SAR) Images



Analysis:
- Pixel-based thresholding
- Context-based approaches

CD in Multispectral Images: Comparison Operators

Technique	Feature vector f_k at the time t_k	Computation of X_D
Univariate image differencing	$f_k = X_k^b$	$X_D = f_1 - f_2 + C$
Vegetation index differencing	$f_k = V_k$	$X_D = f_1 - f_2 + C$
Change vector analysis	$f_k = [X_k^1, .., X_k^m]$	$X_D = \lVert f_1 - f_2 \rVert$
Regression	$f_1 = X_1^b$ and $f_2 = \hat{X}_2^b$	$X_D = f_1 - f_2 + C$
Principal component Analysis	$f_k = [P_k^1, .., P_k^m]$	$X_D = \lVert f_1 - f_2 \rVert$

b: variable associated with the spectral channel
k: variable associated with the acquisition date

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CD in SAR Images: Comparison Operators

Technique	Feature vector f_k at the time t_k	Computation of X_D
Image rationing	$f_k = X_k^b$	$X_D = f_2 / f_1$
Kullback-Leibler distance (Similarity measures)	$f_k = [p(X_k)]$	$KL(X_2 \mid X_1) = \int \log(f_1/f_2) f_1$
Difference of scattering matrix element products	$f_k = [S_{HH} S_{VV}^*]$	$X_D = f_1 - f_2$
Difference of scattering matrix amplitude correlation coefficients	$f_k = \left[\frac{S_{HH} S_{VV}^*}{\sqrt{\lvert S_{HH} \rvert^2 \lvert S_{VV} \rvert^2}} \right]$	$X_D = f_1 - f_2$

k: variable associated with the acquisition date

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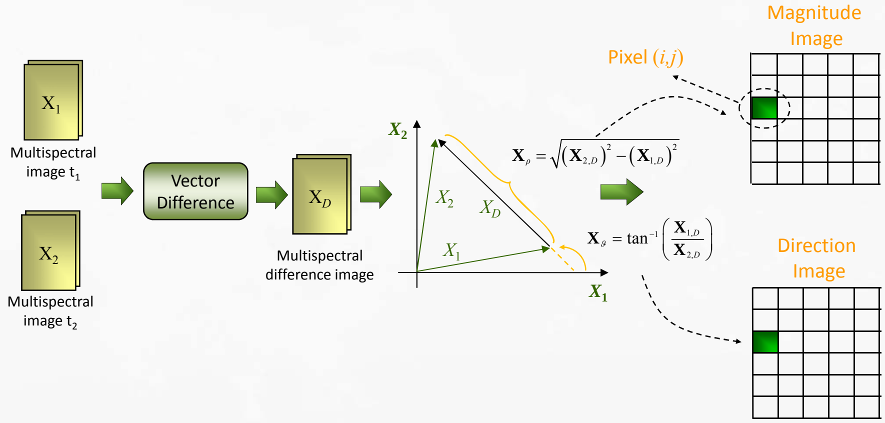
Change Vector Analysis (CVA)

Assumption: only 2 spectral channels are considered for each date.



Polar Change Vector Analysis

Polar Domain

$D = \{\rho, \vartheta : 0 \le \rho < \rho_{max} \text{ and } 0 \le \vartheta < 2\pi\}$

ρ -> Random variable associate to magnitude image X_ρ

ϑ -> Random variable associate to direction image X_ϑ

Circle of unchanged pixels

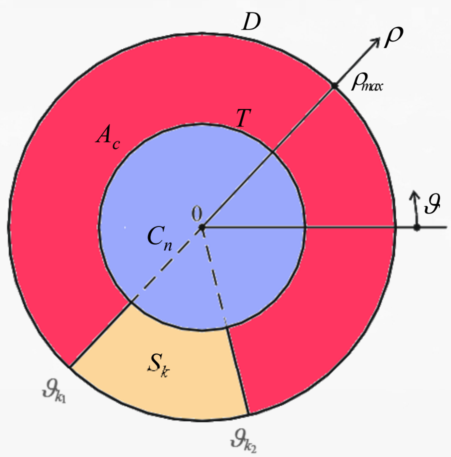
$C_n = \{\rho, \vartheta : 0 \le \rho < T \text{ and } 0 \le \vartheta < 2\pi\}$

Annulus of changed pixels

$A_c = \{\rho, \vartheta : T \le \rho \le \rho_{max} \text{ and } 0 \le \vartheta < 2\pi\}$

Sector of changed pixels

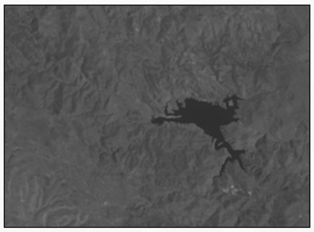
$S_k = \{\rho, \vartheta : \rho \ge T \text{ and } \vartheta_{k_1} \le \vartheta < \vartheta_{k_2},\ 0 \le \vartheta_{k_1} < \vartheta_{k_2} < 2\pi\}$



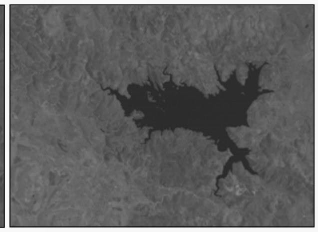
Polar Change Vector Analysis: Example

Study area: Lake Mulargia, Sardinia Island (Italy).

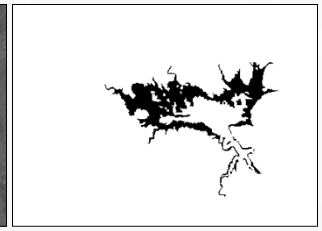
Multitemporal data set: a portion of 412×300 pixels of two images acquired by the TM sensor of Landsat-5 satellite in September 1995 and July 1996.



Before Change



After Change



Reference Map

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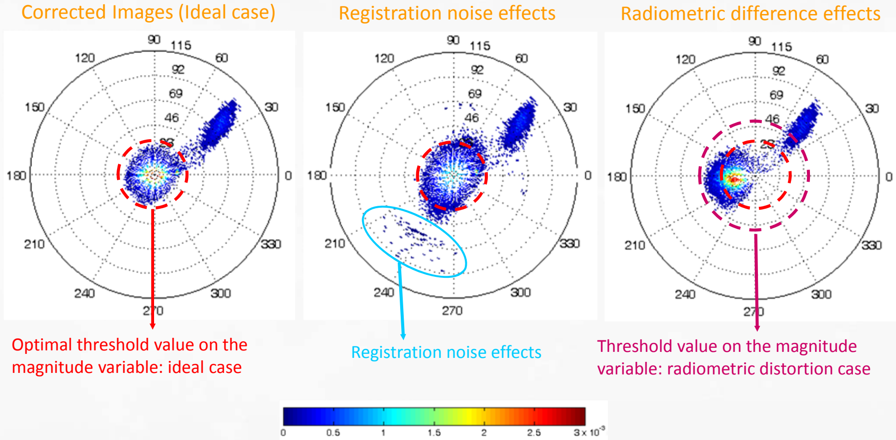
Polar Change Vector Analysis: Example

Corrected Images (Ideal case) | Registration noise effects | Radiometric difference effects



F. Bovolo, L. Bruzzone, A Theoretical Framework for Unsupervised Change Detection Based on Change Vector Analysis in Polar Domain, *IEEE Transactions on Geoscience and Remote* Sensing, Vol. 45, No.1, 2007, pp.218-236.

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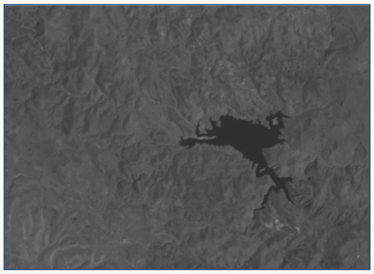
Polar Change Vector Analysis: Example

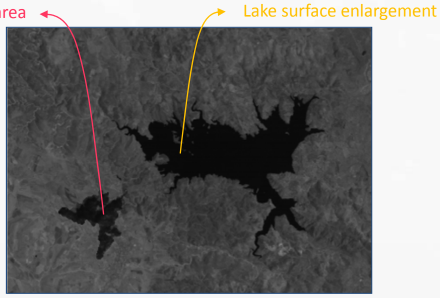
Study area: Lake Mulargia, Sardinia Island (Italy).

Multitemporal data set: a portion of 412×300 pixels of two images acquired by the TM sensor of Landsat-5 satellite in September 1995 and July 1996.

Changes: 1 natural change, 1 simulated change.



September 1995



July 1996

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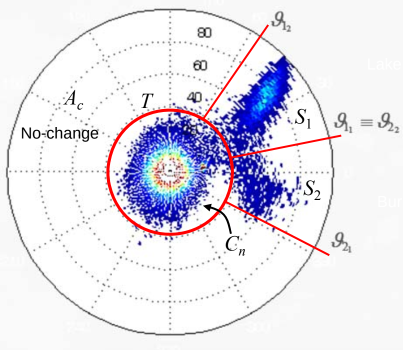
Polar Change Vector Analysis: Example



F. Bovolo, S. Marchesi, L. Bruzzone, "A Framework for automatic and unsupervised detection of multiple changes in multitemporal images," IEEE Transactions on Geoscience and Remote Sensing, Vol. 50, No. 6, pp. 2196–2212, 2012.

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3. Change Detection in Very High Resolution Multispectral Images

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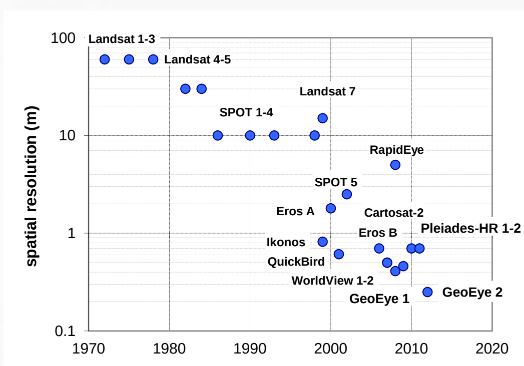
New Satellites with VHR Multispectral (MS) Sensors



CD in Multitemporal VHR MS images


July 2006


October 2005

Quickbird images of the city of Trento (Italy)

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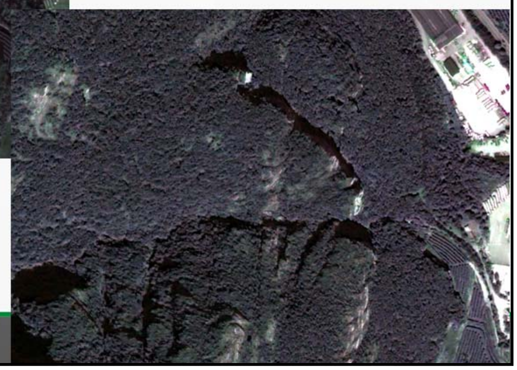
CD in Multitemporal VHR MS images


October 2005

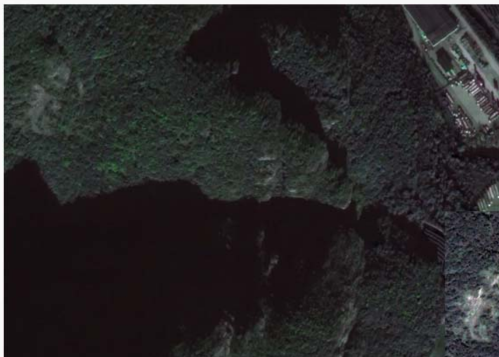

July 2006

Quickbird images of the city of Trento (Italy)

CD in Multitemporal VHR MS images



July 2006



October 2005

Quickbird images of
the city of Trento (Italy)

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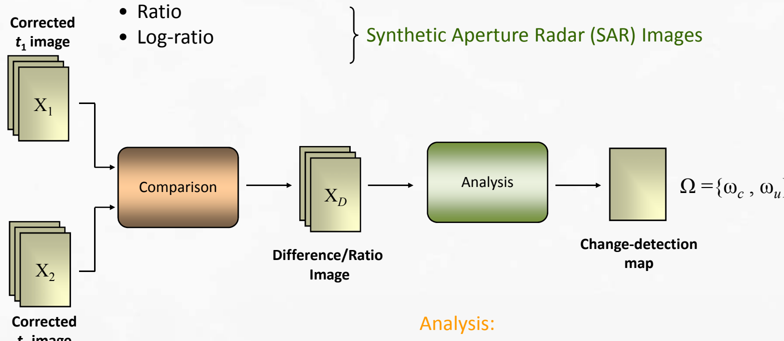
Unsupervised CD: Typical Architecture

Comparison Operators:
- Difference
- Vector difference
- Ratio
- Log-ratio

} Optical Images (Difference, Vector difference)

} Synthetic Aperture Radar (SAR) Images (Ratio, Log-ratio)



Analysis:
- Pixel-based thresholding
- Context-based approaches

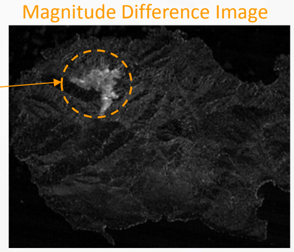
CD in Multitemporal HR Images: Example

Landsat TM, Pre-event

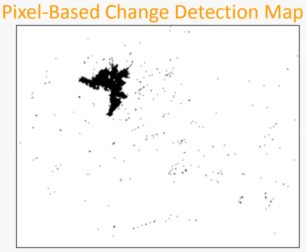
Landsat TM, Post-event

Magnitude Difference Image

Burned area



Pixel-Based Change Detection Map



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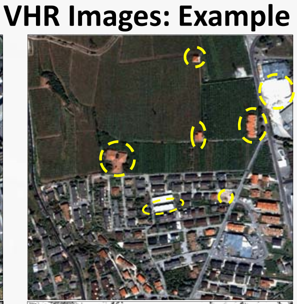
CD in Multitemporal VHR Images: Example

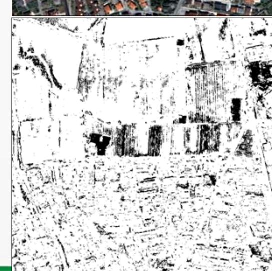
Quickbird, October 2004 (true color composition)

Quickbird, July 2006 true color composition



Magnitude Difference Image

Pixel-Based Change Detection Map



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CD in Multitemporal VHR images

Change detection in VHR Images should exploit a top-down approach to the definition of the processing architecture. This approach should:

- ✓ explicitly model the presence of different radiometric changes on the basis of the properties of the considered images;
- ✓ extract the semantic meaning of changes;
- ✓ identify changes of interest with strategies designed on the basis of the specific application;
- ✓ exploit the intrinsic multiscale properties of the objects and the high spatial correlation between pixels in a neighborhood.

L. Bruzzone, F. Bovolo, "A Conceptual Framework for Change Detection in Very High Resolution Remote Sensing Images," *Proceedings of IEEE*, March 2013.

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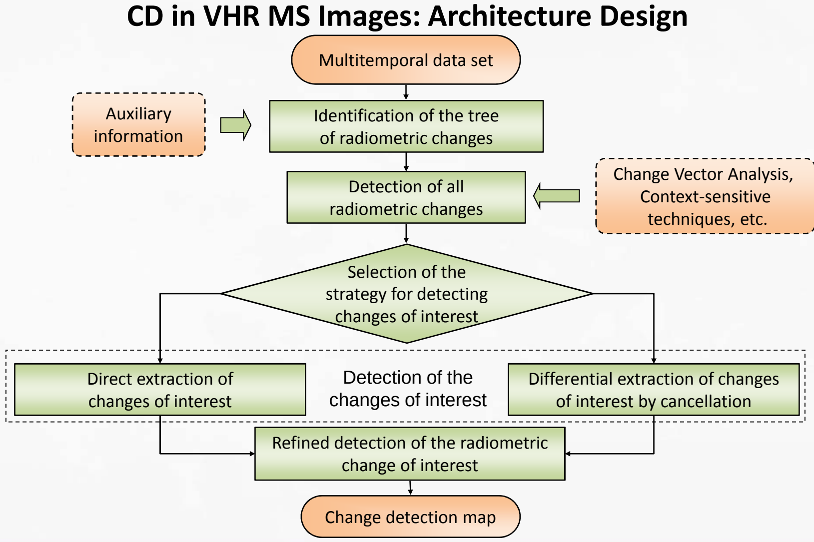
CD in VHR MS Images: Architecture Design



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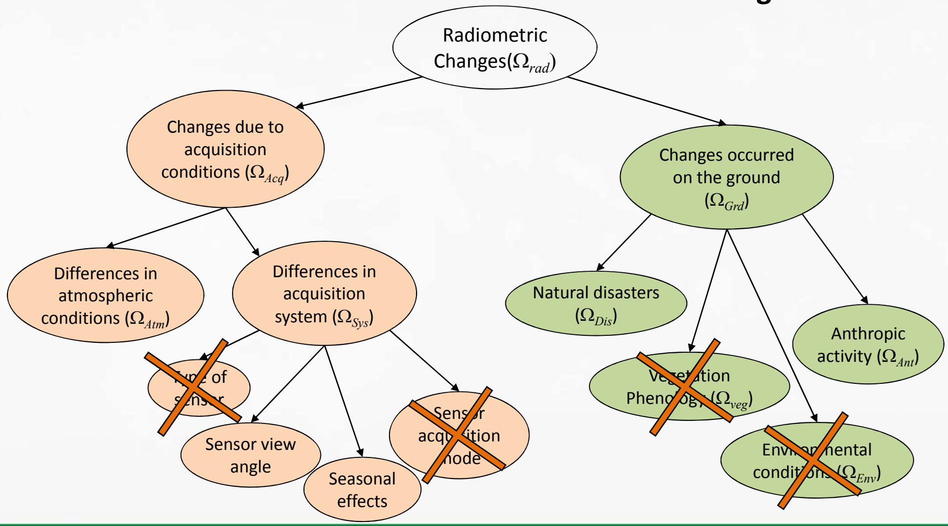
Identification of the Tree of Radiometric Changes



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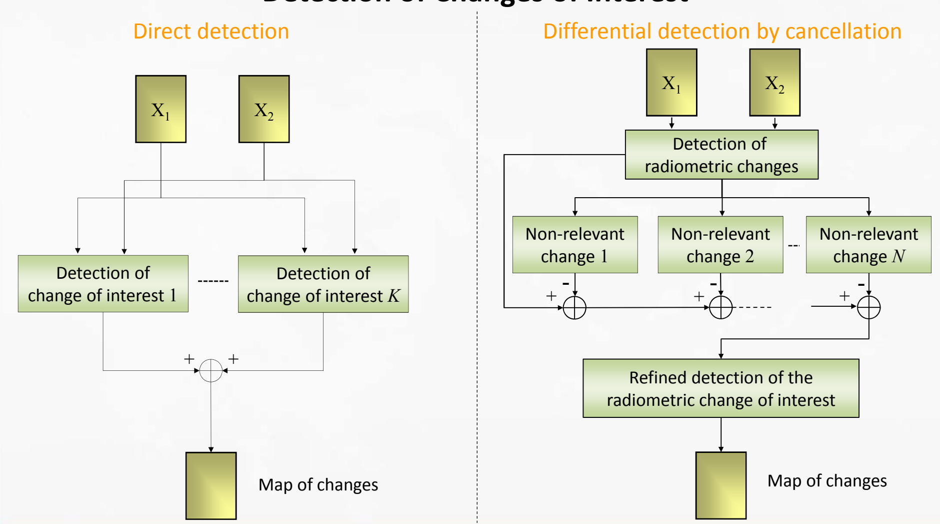
Detection of Changes of Interest



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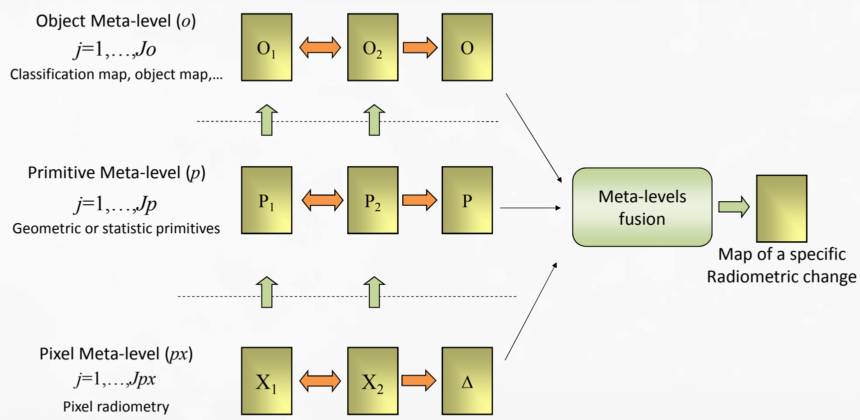
Multilevel Approach: Semantic of Changes



L. Bruzzone, F. Bovolo "A Conceptual Framework for Change Detection in Very High Resolution Remote Sensing Images," Proceedings of *IEEE*, March 2013.

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Example: CD in VHR Optical Images

Study area: South part of Trento (Italy).

Multitemporal data set: portion (380×430 pixels) of two images acquired by the Quickbird satellite in October 2004 and July 2006.

Causes of Change: changes on the ground, seasonal changes, registration noise.

October 2004 | July 2006 | Reference Map

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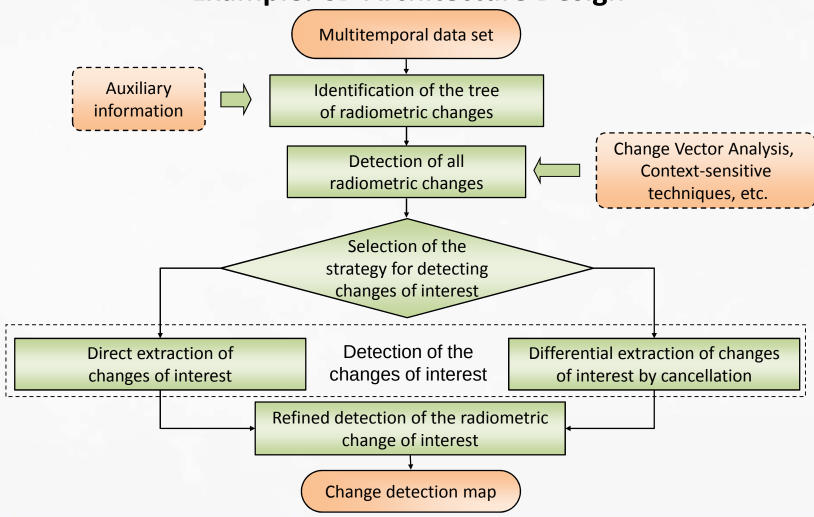
Example: CD Architecture Design



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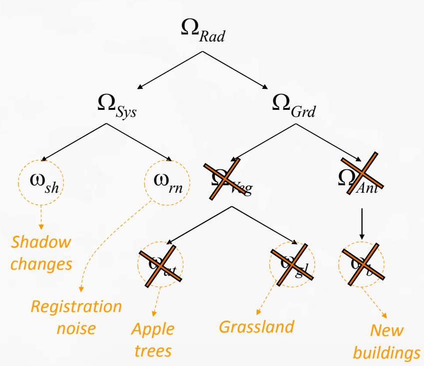
Identification of the Tree of Radiometric Changes



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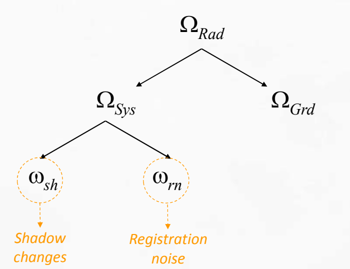
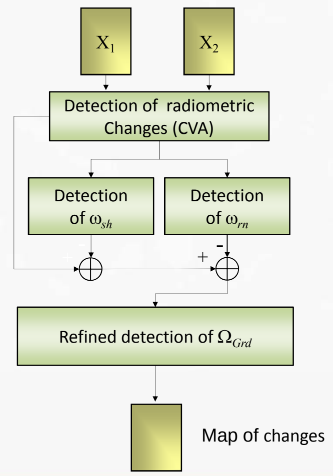
Changes Tree and Detection Strategy

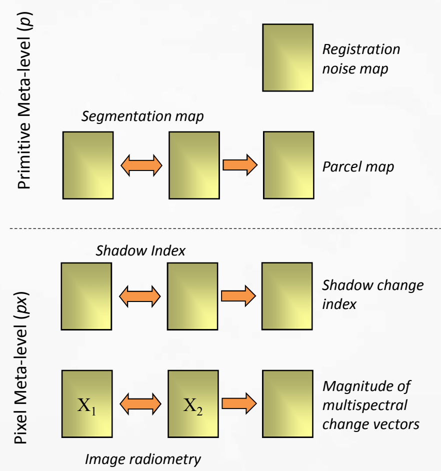
Identification of the tree of radiometric changes



Differential detection by cancellation



Multilevel Representation of Radiometric Changes



S. Marchesi, F. Bovolo, L. Bruzzone, "A Context-Sensitive Technique Robust to Registration Noise for Change Detection in VHR Multispectral Images", *IEEE Transactions on Image Processing*, Vol. 19, pp. 1877-1889, 2010.

F. Bovolo, "A Multilevel Parcel-Based Approach to Change Detection in Very High Resolution Multitemporal Images," IEEE Geoscience and Remote Sensing Letters, Vol. 6, No. 1, pp. 33-37, January 2009.

V. J. D. Tsai, "A comparative study on shadow compensation of color aerial images in invariant color models," IEEE Trans. Geosci. Remote Sens., vol. 44, pp. 1661-1671, 2006.

L. Bruzzone and D. Fernández-Prieto, "Automatic Analysis of the Difference Image for Unsupervised Change detection," IEEE Trans. Geosci. Rem. Sens., vol. 38, pp. 1170-1182, 2000.

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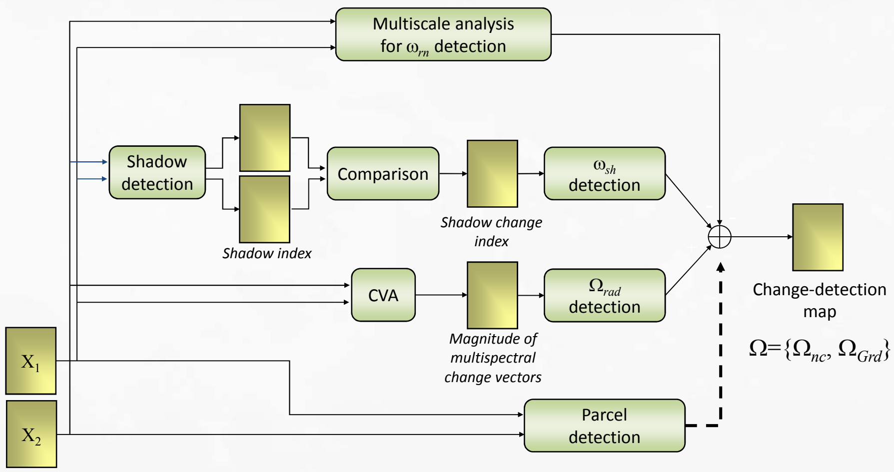
Example: CD Architecture



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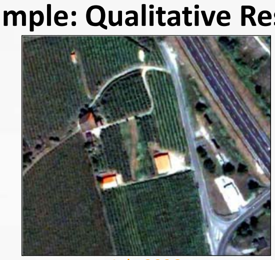
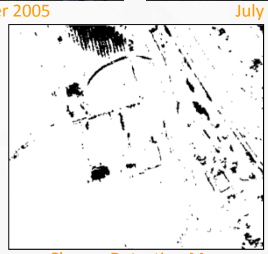
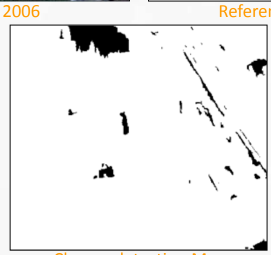
Example: Qualitative Results


October 2005

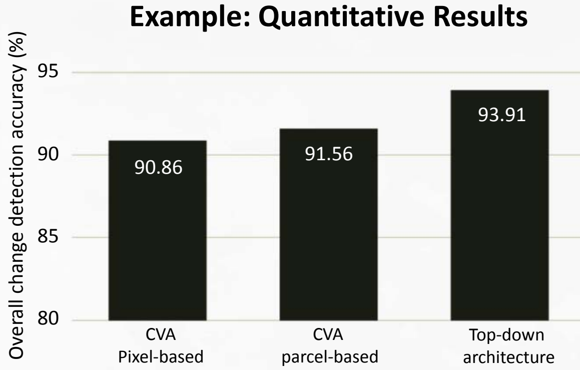

July 2006


Reference Map


Change Detection Map
CVA Parcel Based


Change detection Map
Top-down Architecture

Example: Quantitative Results

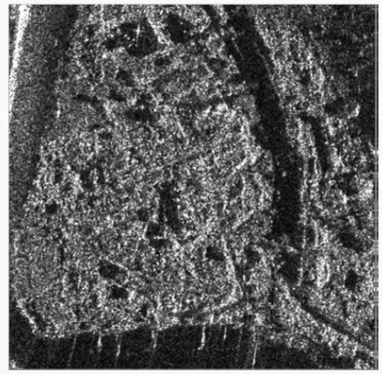


Technique	False Alarms	Missed Alarms	Total Errors	Overall accuracy (%)
CVA pixel-based	5005	9924	14929	90.86
CVA parcel-based	3537	10261	13798	91.56
Top-down architecture	1470	8480	9950	93.91

4. Change Detection in Very High Resolution Multisensor Images

New challenges: Data Fusion

Quickbird image before earthquake



COSMO-Skymed image after earthquake

Earthquake of Sichuan province, China, May, 2008

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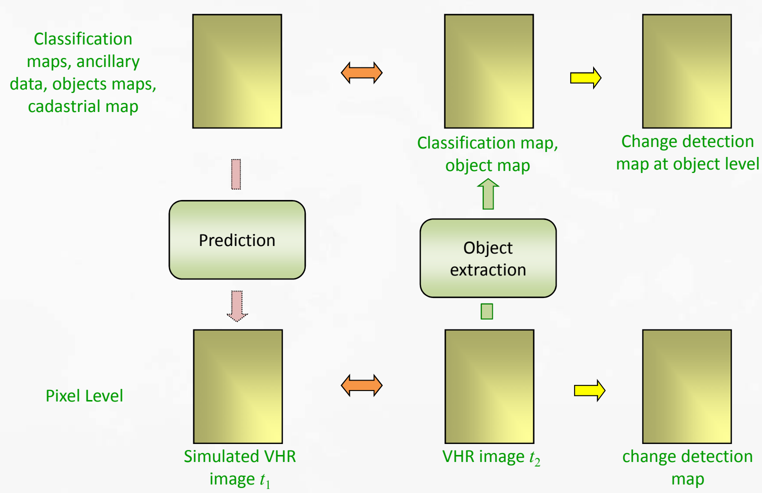
Top-Down/Bottom-Up Approaches



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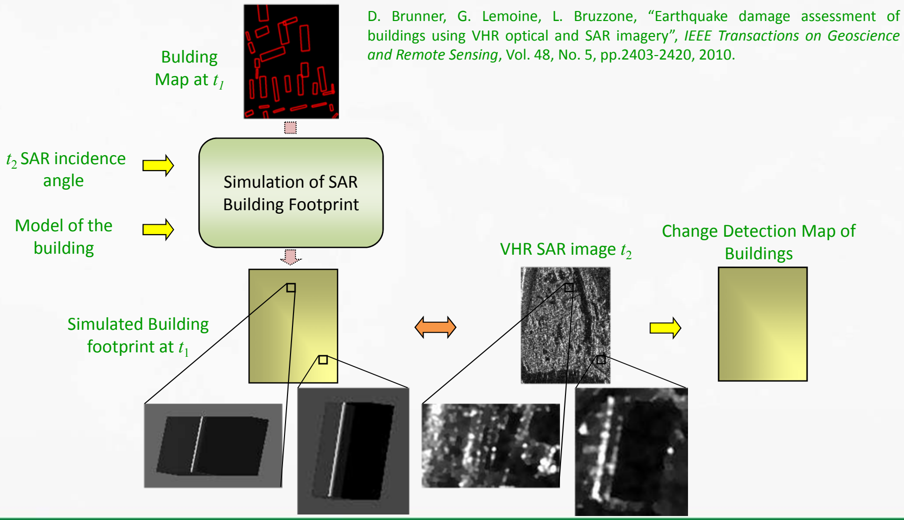
CD in Multisource Data: Example

D. Brunner, G. Lemoine, L. Bruzzone, "Earthquake damage assessment of buildings using VHR optical and SAR imagery", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 48, No. 5, pp.2403-2420, 2010.



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Conclusion

- ✓ Analysis and exploitation of time series and multitemporal images is a very important topic both from the methodological and the application perspective.

- ✓ Many methodological challenges are related to the properties of new satellite data that require the development of a new generation of processing techniques for the analysis of:
  - VHR multispectral and SAR images.
  - Hyperspectral images.
  - Long time series (data mining).

- ✓ These properties open the possibility to develop also new applications that exploit either the very high geometrical (e.g. analysis of single buildings) or spectral (e.g. detection of subtle changes) resolution and the increased revisit time (e.g. monitoring and surveillance application).

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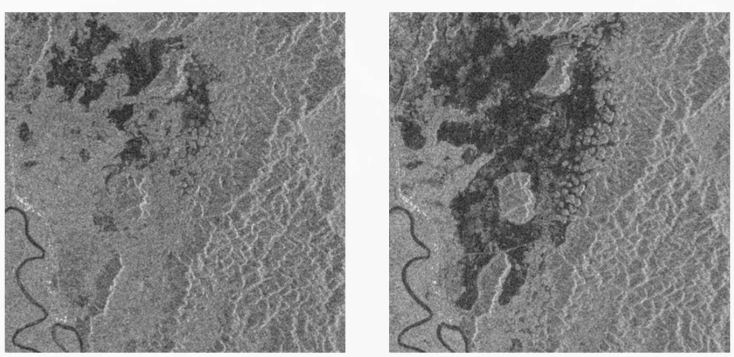
Change Detection in Very High Resolution SAR Images

Multitemporal SAR Images: 10 years ago…

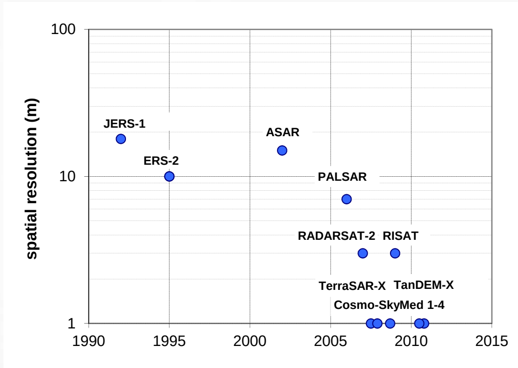
May 1999



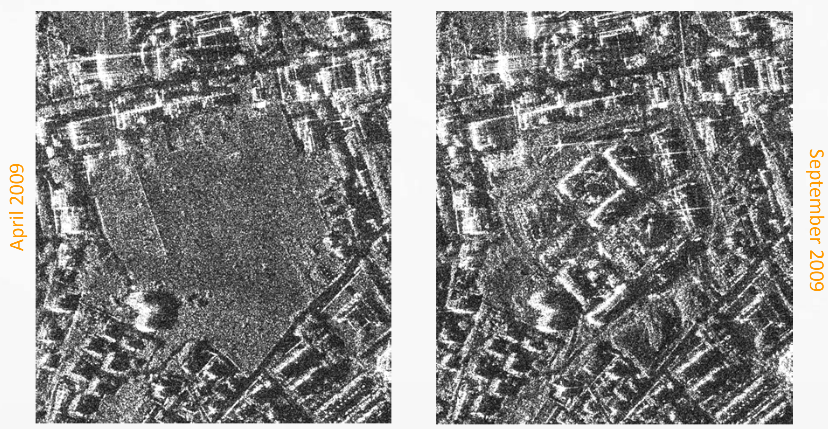
September 1999

ERS SAR images of a flood in the Cat-Tien National Park, Vietnam

New Satellites with VHR SAR Sensors



Multitemporal SAR Images: New challenges

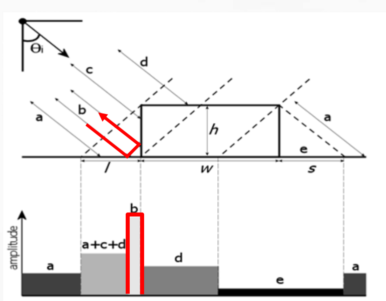


Comso-Skymed SAR Images of the Earthquake of L'Aquila, Italy

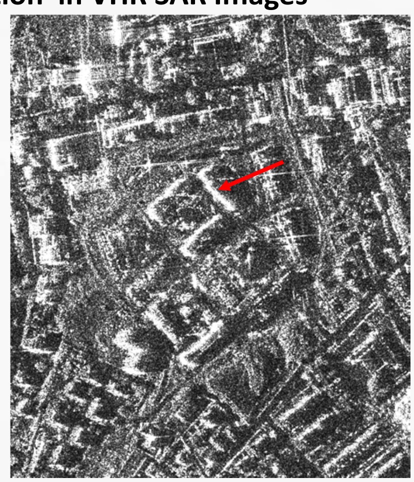
CD in VHR SAR images

- ✓ In multitemporal SAR VHR images we have many sources of backscattering changes.
- ✓ Often backscattering changes associated with different sources exhibit characteristics similar to each other. They can be separated only by explicitly modeling the EM behavior of complex objects.
- ✓ To this end it is necessary to bridge the semantic gap between low level features and semantic information:
  - Modelling the interaction between the EM waves and the imaged objects;
  - Extracting the different object components with proper detectors;
  - Combining object components for identifying the objects and the possible changes in their state.

Example: Building Detection in VHR SAR Images

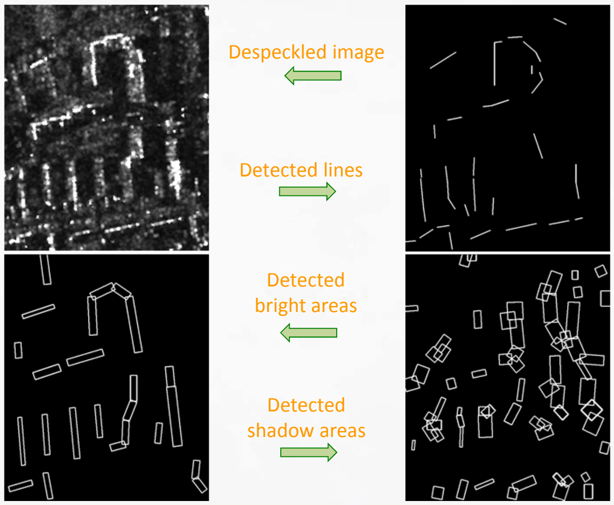


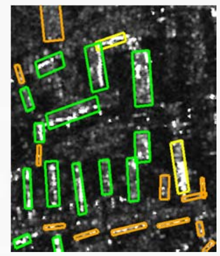
Building EM model



VHR satellite SAR image

Primitives and Semantic: Building Detection





Detected building fooprints

A. Ferro, D. Brunner, L. Bruzzone, "Automatic Detection and Reconstruction of Building Radar Footprints from Single VHR SAR Images", *IEEE Trans. on Geoscience and Remote Sensing*, 2012

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Change Detection in VHR SAR Images

✓ Moving from object detection in single images to object change detection in multitemporal images increases the complexity of the information extraction.

✓ In order to define an effective general approach to change detection for VHR SAR images we have to:

- Decompose the general complex problem in simpler hierarchical problems.
- Exploit the intrinsic multiscale nature of objects present in VHR images.
- Model the specific properties of expected changes for extracting the semantic meaning of backscattering changes.
- Exploit the available prior information on the considered scenario.

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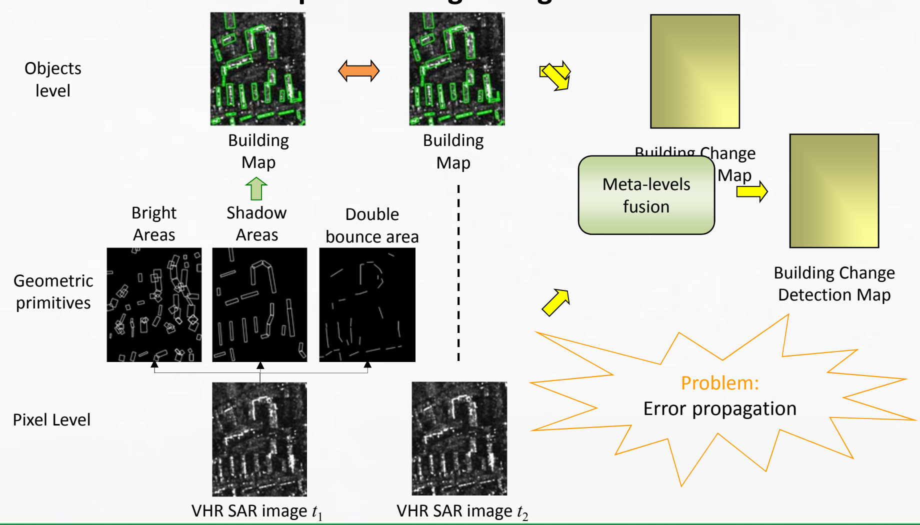
Example: Building Change Detection



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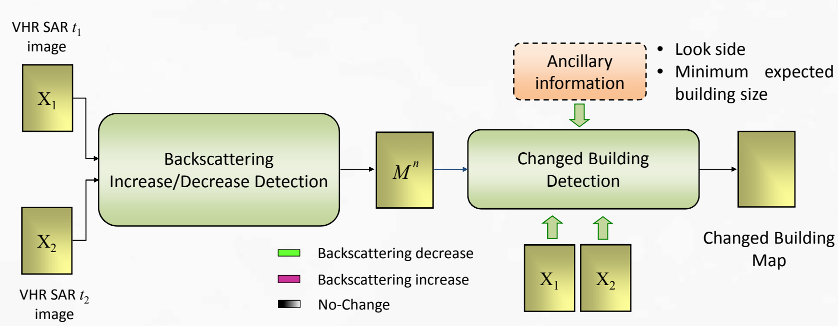
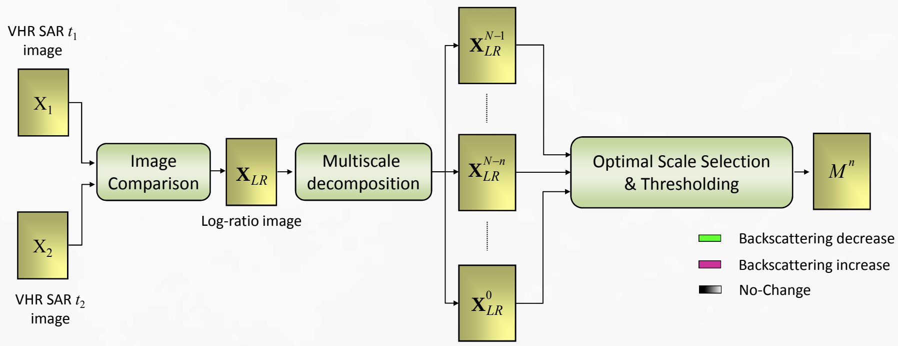
Architecture for Building Change Detection



F. Bovolo, C. Marin, L. Bruzzone, "A Novel Approach to Building Change Detection in VHR SAR Images," Proceedings of the SPIE Conference on Image and Signal Processing for Remote Sensing, Edinburg, UK, September 2012.

Architecture for Building Change Detection

Goal: detect changes associated with increase and decrease in backscattering.



F. Bovolo, L. Bruzzone, "*A Detail-Preserving Scale-Driven Approach to Unsupervised Change Detection in Multitemporal SAR Images*", *IEEE Transactions on Geoscience and Remote Sensing*, 2005, Vol.43, No. 12, pp. 2963-2972, December 2005.

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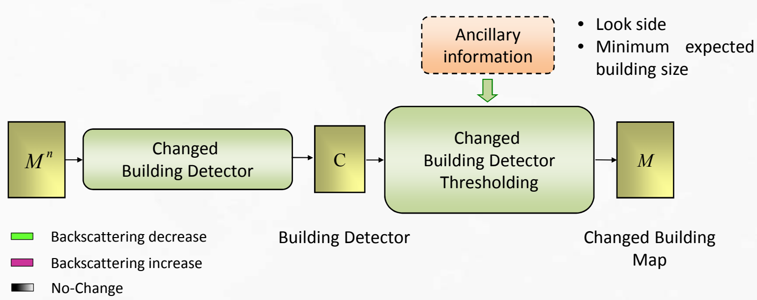
Architecture for Building Change Detection

Goal: detect new/destroyed buildings.



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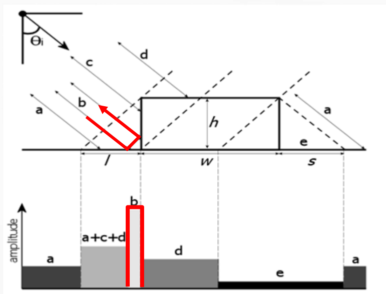
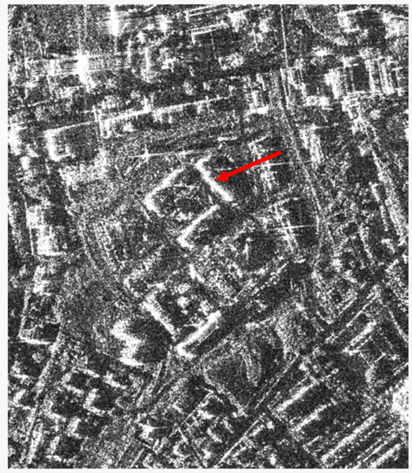
Architecture for Building Change Detection



Building EM model



VHR satellite SAR image

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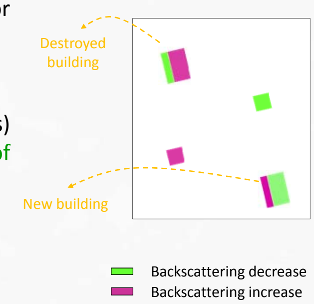
Architecture for Building Change Detection

- ✓ Changes in VHR SAR images implies increase or decrease of backscattering values.
- ✓ Changes in buildings (i.e., new/destroyed buildings) implies simultaneous increase and decrease of backscattering.

⇩

Search for pairs of increase/decrease backscattering pattern.



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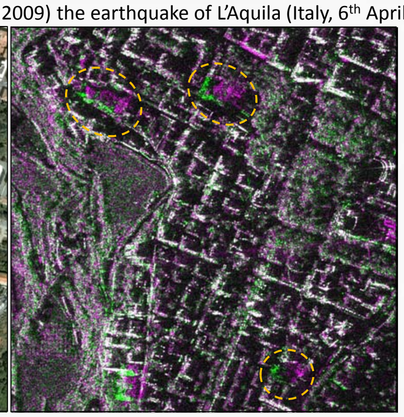
Example: L'Aquila Earthquake

Multitemporal data set: section (1024×1024 pixels) of two spotlight (CSK®) images acquired before (5th April 2009) and after (12th September 2009) the earthquake of L'Aquila (Italy, 6th April 2009).



- 1m×1m resolution
- X-band
- 1-look
- Amplitude
- HH-polarization
- 57-58 degree incidence angle
- Ascending orbit
- Right look
- CSKS1
- Calibrated
- Co-registered
- Geo-referred

5th April 2009 — Optical image GeoEye, Tele Atlas 2011 Google ©

12th September 2009 — RGB multitemporal composition (R:09/12/2009, G:04/05/2009, B:09/12/2009)

Backscattering decrease   Backscattering increase   Unchanged areas

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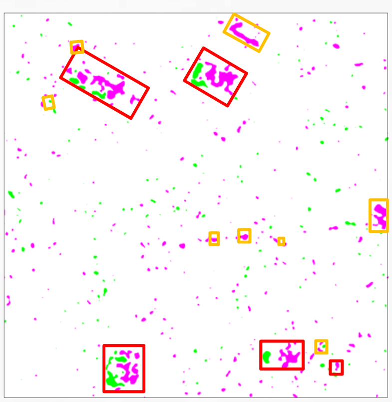
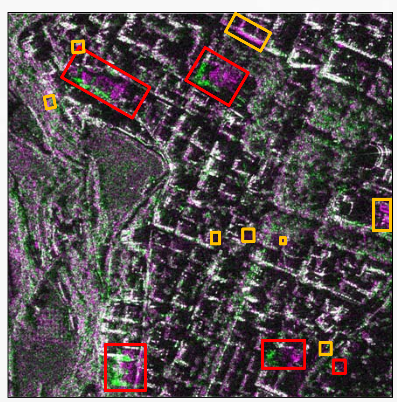
Example: L'Aquila Earthquake

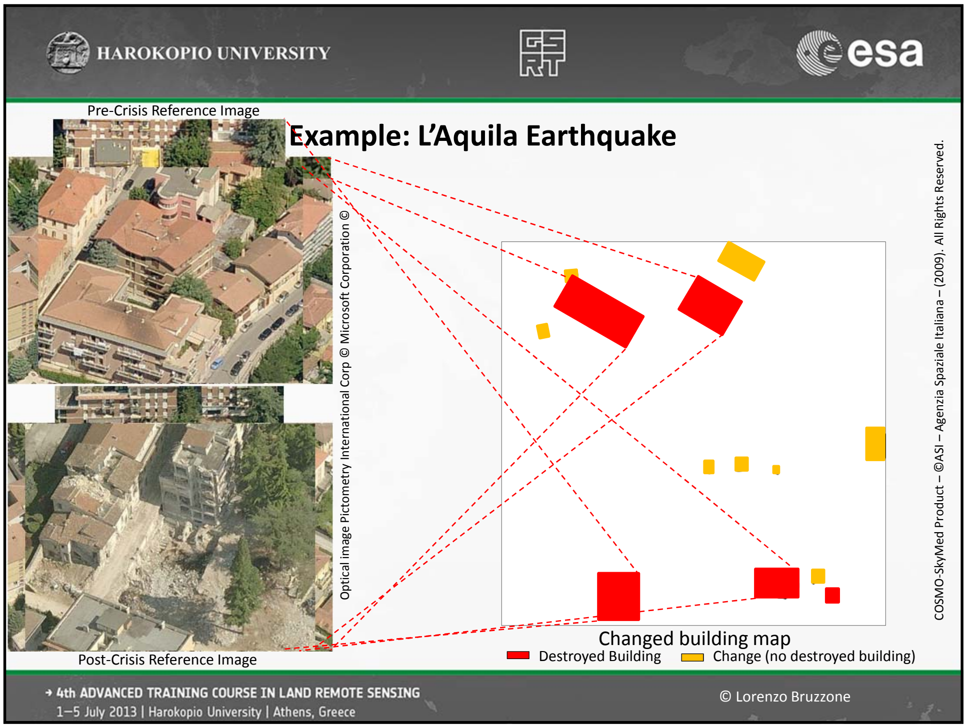


Changes in backscattering



Candidate building map

Backscattering decrease   Backscattering increase   Destroyed Building   Change (no destroyed building)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Example: L'Aquila Earthquake
Pre-Crisis Reference Image
Post-Crisis Reference Image
Optical image Pictometry International Corp © Microsoft Corporation ©
Changed building map
Destroyed Building
Change (no destroyed building)
COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana – (2009). All Rights Reserved.
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