Remote Sensing Laboratory
Dept. of Information Engineering and Computer Science
University of Trento
Via Sommarive, 9, I-38123 Povo, Trento, Italy

Deep learning methods for Change detection in SAR images

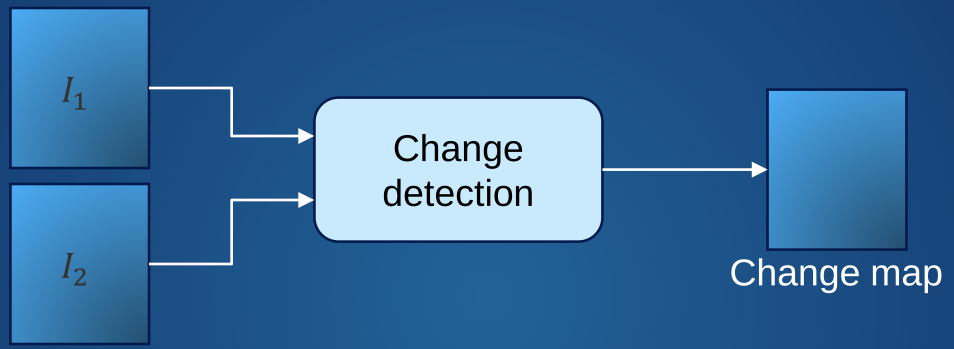
Luca Bergamasco

E-mail: lbergamasco@fbk.eu
Web page: rslab.disi.unitn.it

Outline

Introduction

- ✓ Change detection (CD) is a process that identifies changes occurred on the ground by means of multi-temporal data.



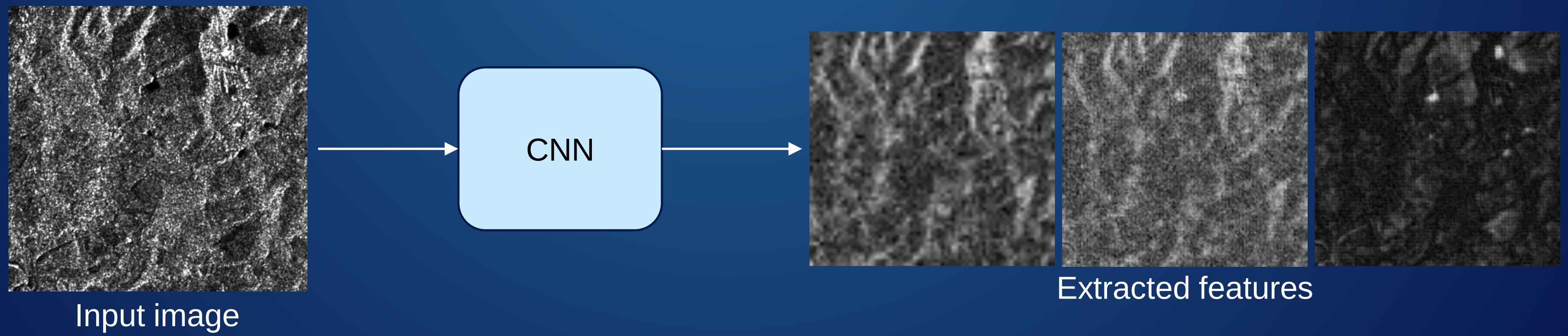
- ✓ Synthetic Aperture Radar (SAR) images are often preferred for CD in those applications that require a quick response (i.e., detection of damaged areas after a natural disaster like floods).

- ✓ SAR images exists with various geometrical resolutions. As we move toward the Very high resolution (VHR) one amount of geometrical details increases but we observe:
  - Heterogeneous backscattering for semantically homogeneous objects;
  - Stronger impacts of the lateral visions of SAR images;

  that call for advanced processing methods.

Introduction

- ✓ Deep learning (DL) methods are widely used for their capability to automatically learn complex features from input data during the training phase, for example some fully connected models are autoencoder and multi layer perceptron.
- ✓ However, the DL models that exploit fully connected are inefficient for the analysis of HR/VHR SAR images since they do not analyze the spatial context information.
- ✓ Convolutional Neural Networks (CNNs) are DL models that can analyze the spatial context information of images.
- ✓ CNNs automatically learn semantic features from input during the training. These features are captured and extracted by the convolutional layers of CNNs, and they model the information in input images.



Introduction

- ✓ Most of DL models are trained in supervised way and need many labeled training data. The gathering of the labeled data is almost impossible in multi-temporal case.

- ✓ Some supervised DL CD methods try to overcome the problem by using:

  - pre-classified data as reference for the training [1,2].
  - a pre-trained model [3].

- ✓ The use of pre-classified data introduces errors in the training.

- ✓ Pre-trained models do not consider correlation between multi-temporal images, and there are few of them pre-trained with SAR data.

[1] F. Gao, J. Dong, B. Li, and Q. Xu, “Automatic change detection in synthetic aperture radar images based on PCANet,” IEEE Geosci. Remote Sens. Lett., vol. 13, no. 12, pp. 1792–1796, Dec. 2016.
[2] F. Gao, X. Wang, Y. Gao, J. Dong, and S. Wang, “Sea ice change detection in SAR images based on convolutional-wavelet neural networks,” IEEE Geosci. Remote Sens. Lett., vol. 16, no. 8, pp. 1240–1244, Aug. 2019.
[3] S. Saha, F. Bovolo, and L. Bruzzone, “Unsupervised deep change vector analysis for multiple change detection in VHR images,” IEEE Trans. Geosci. Remote Sens., vol. 57, no. 6, pp. 3677–3693, Jun. 2019.

Introduction

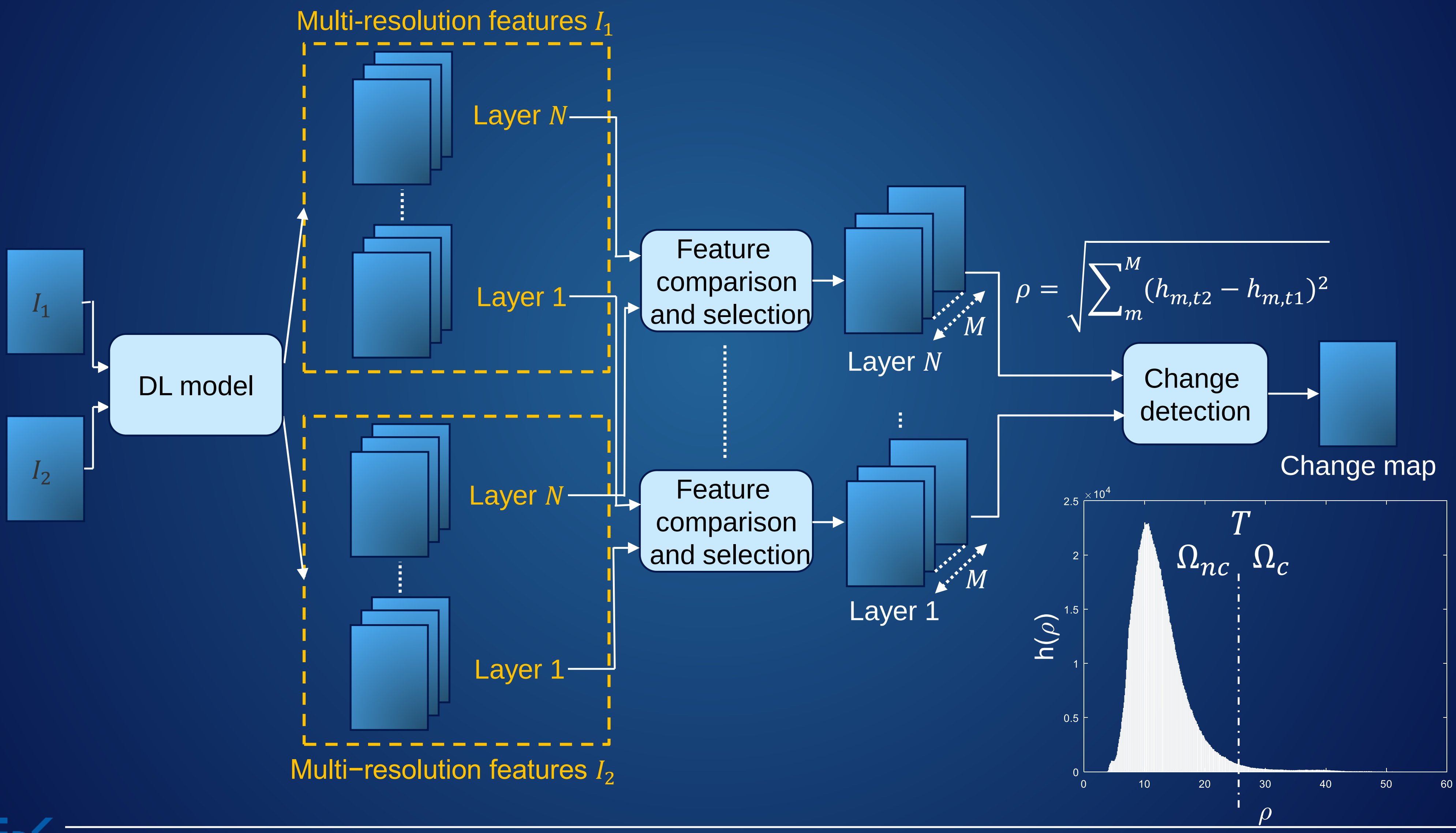
✓ To deal with the problems of supervised Deep Learning Change Detection in SAR images, three approaches have been presented in the literature:

- a transfer learning method that adapts a model pre-trained with optical images to process SAR images, but with similar characteristics.

- a DL model trained in an unsupervised way by using unlabeled training data sampled from SAR images to extract SAR-optimized features. These features have to be filtered.

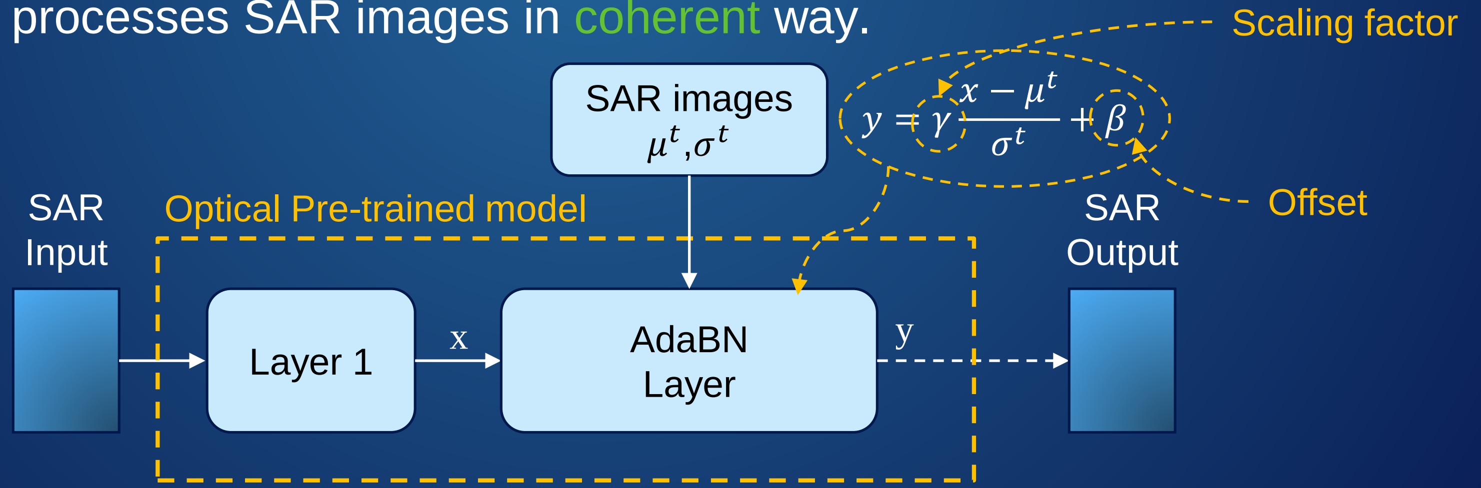
- a DL model trained in unsupervised way to transcode SAR images into optical images and find informative features for the CD. The method is accurate and can process heterogeneous images with different spatial resolution, but it is computationally complex.

Block scheme of DL CD method



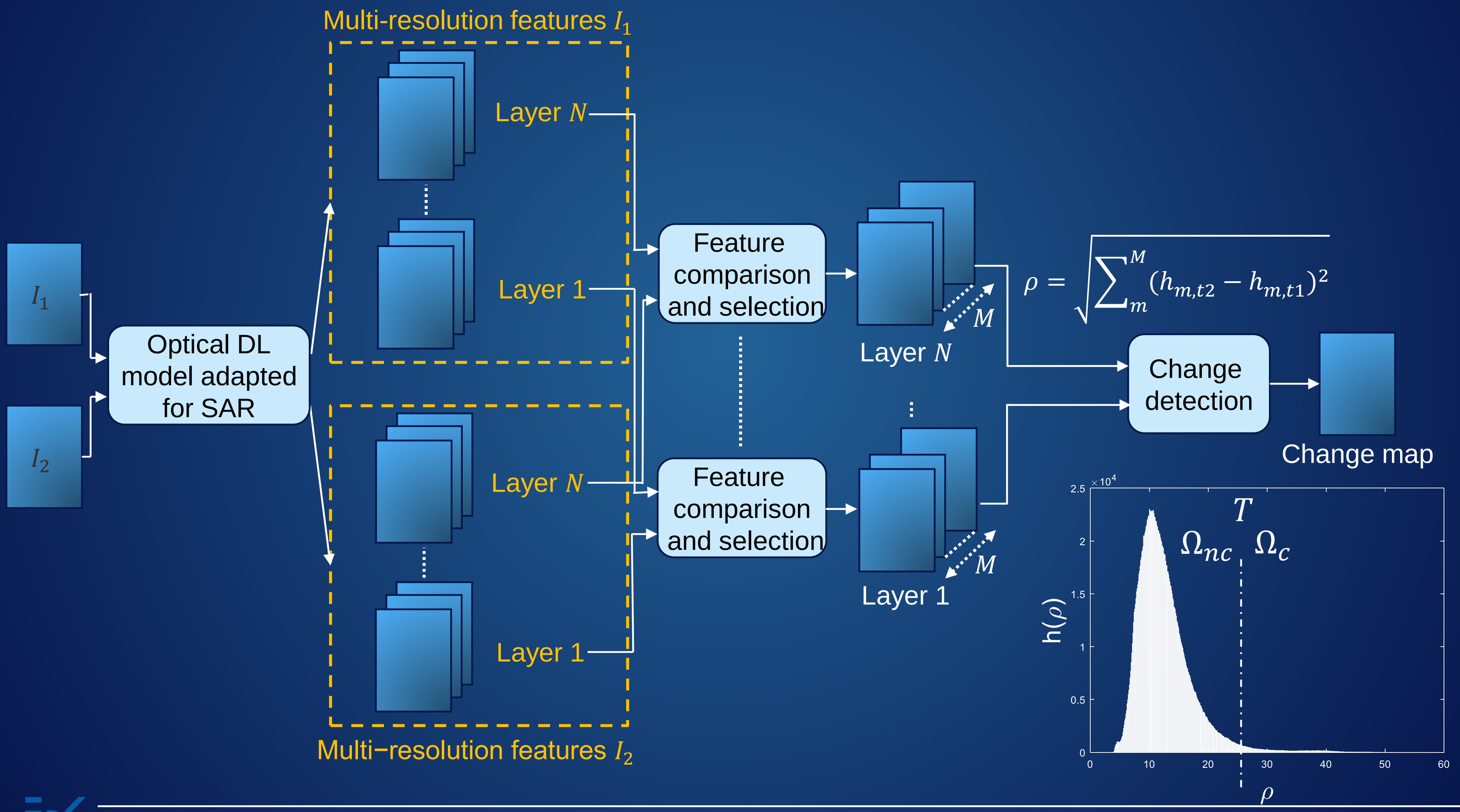
Transfer learning for Change detection using AdaBN

- ✓ A DL model pre-trained for a specific data/task can be adapted to other applications/data by transfer learning, such as Adaptive Batch Normalization (AdaBN) [5]:
  - it allows to adapt the CNN domain without any additional re-training and optimization steps.
  - domain information is contained in statistical parameters of batch normalization layers.
- ✓ The pre-trained DL model can process SAR images by using AdaBN layers with statistical parameters of SAR images instead of standard Batch Normalization layers.
- ✓ The adapted DL model processes SAR images in coherent way.



[4] S. Saha, F. Bovolo, and L. Bruzzone, "Destroyed-buildings detection from VHR SAR images using deep features," Proc. SPIE, vol. 10789, Oct. 2018, Art. no. 107890Z.
[5] Li, Y., Wang, N., Shi, J., Liu, J. and Hou, X., 2016. Revisiting batch normalization for practical domain adaptation. arXiv preprint arXiv:1603.04779.

Block scheme of DL CD method

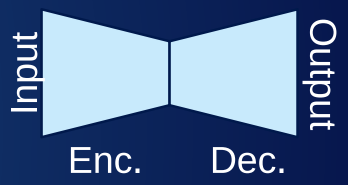


Convolutional Autoencoders

- Convolutional-autoencoders (CAEs) merge the concept of autoencoders (AEs) with the capability of Convolutional-Neural-Networks (CNNs) to exploit spatial context information.

- CAEs learn complex spatial features from the input during the training process in an unsupervised way.

- CAE can be divided in two blocks:
  - Encoder: reduces the spatial resolution of the input image and increases the number of features.
  - Decoder: increases the spatial resolution and reduces the features by aggregating them.



- The output of each layer $h_l, (l = 1, \dots, L)$ is computed as

$$h_l = f(W_l * h_{l-1} + b_l)$$

activation function

bias

weights

- The training aims to achieve an output as similar as possible to the input.

- The standard CAE training loss function (e.g., MSE) achieves a high-quality reconstructed image, but it applies to the input and output only and does not account for the hidden layer features.

$$MSE = \frac{1}{I}\sum_{i=1}^{I}(x_i - x_i')^2$$

total number of samples

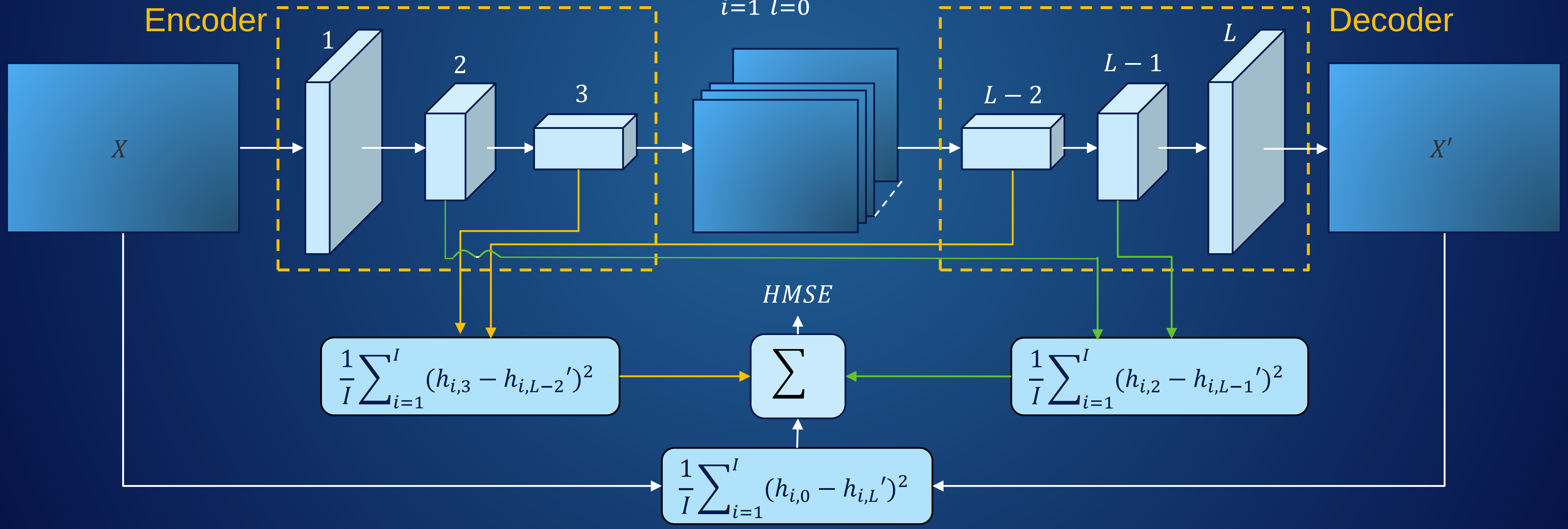
reconstructed version of x_i

$x_i \in X$

CD in SAR using CAE trained with hierarchical loss function

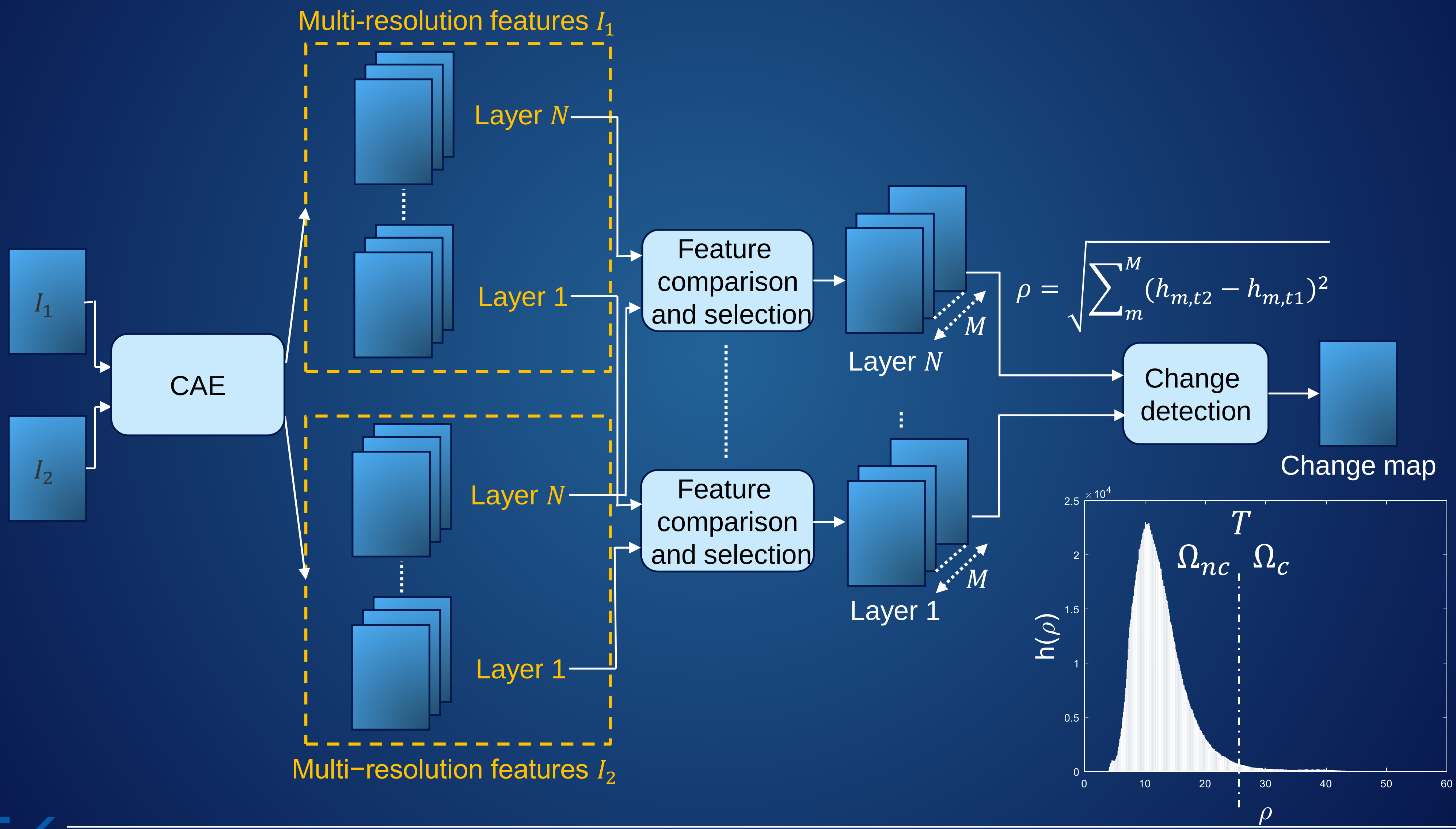
✓ To improve the hidden layer feature quality in terms of geometrical details preservation and objects homogeneity a hierarchical loss function can be defined.

$$HMSE = \frac{1}{I}\sum_{i=1}^{I}\sum_{l=0}^{L/2}(h_{i,L-l} - h_{i,l})^2$$



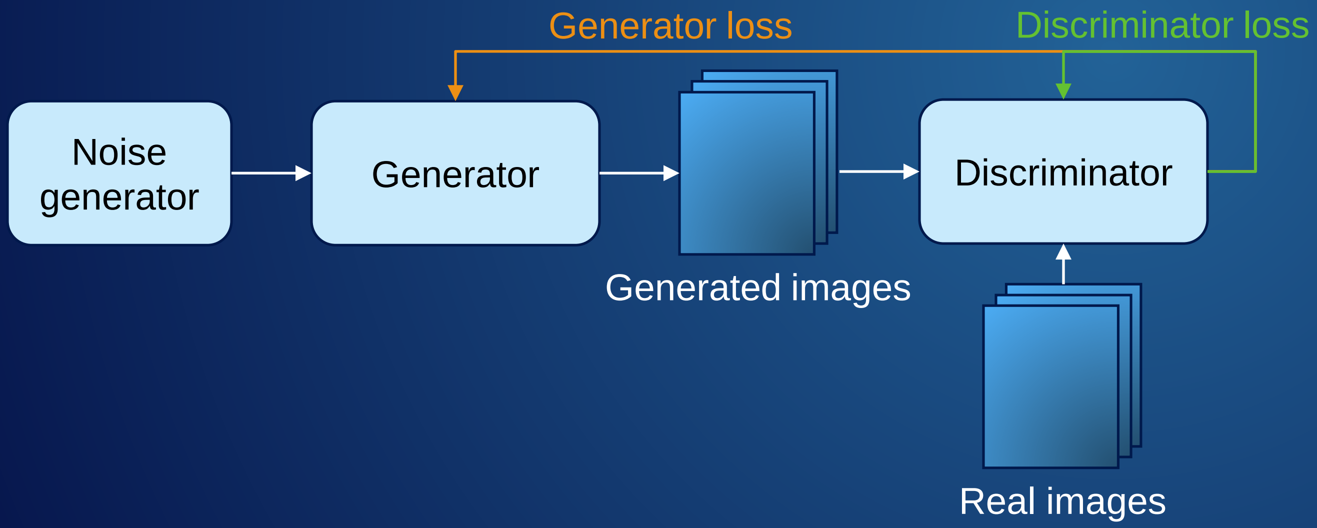
[6] L. Bergamasco, F. Bovolo, and L. Bruzzone, "Unsupervised change detection using hierarchical convolutional autoencoder," Proc. SPIE, vol. 11533, Sept. 2020, Art. no. 11533D.

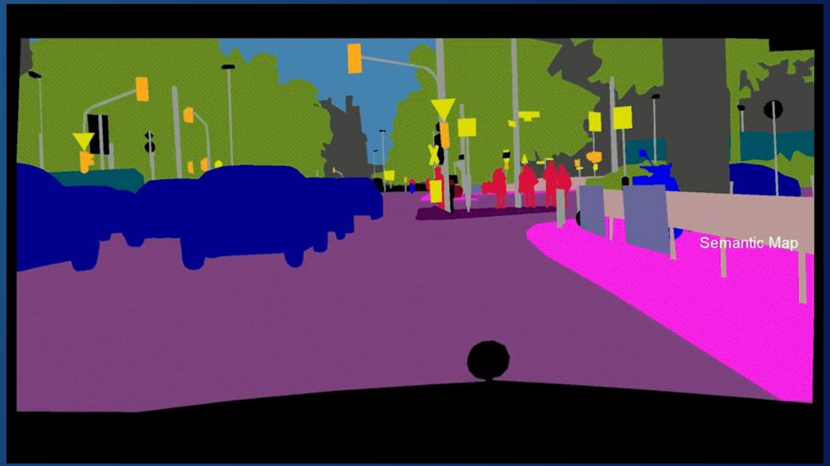
Block scheme of DL CD method



Generative Adversarial Networks

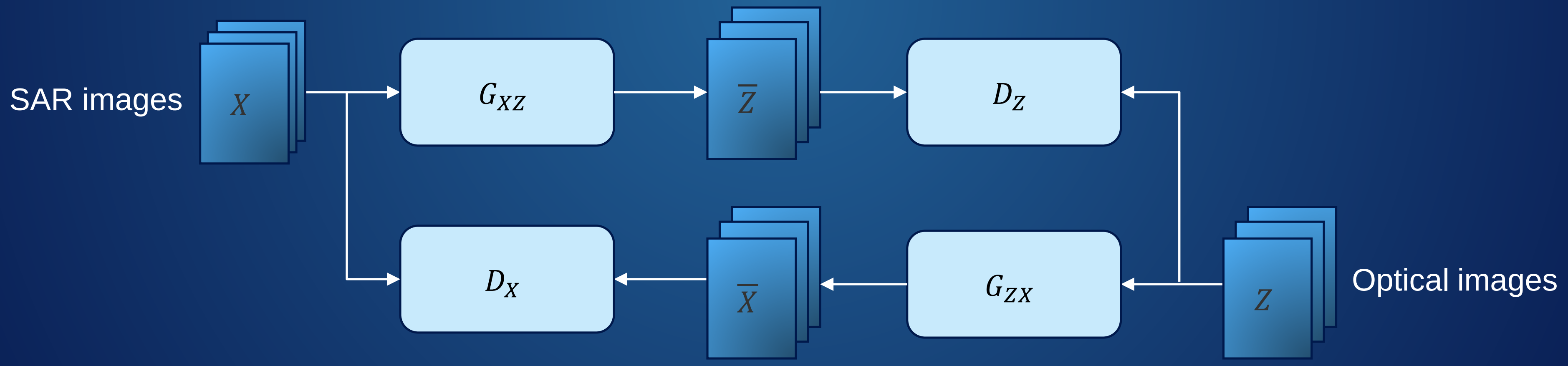
- ✓ Generative Adversarial Networks (GANs) are unsupervised DL models widely used in data generation tasks.
- ✓ GANs are composed by a generator and a discriminator, and they are trained with min-max strategy.





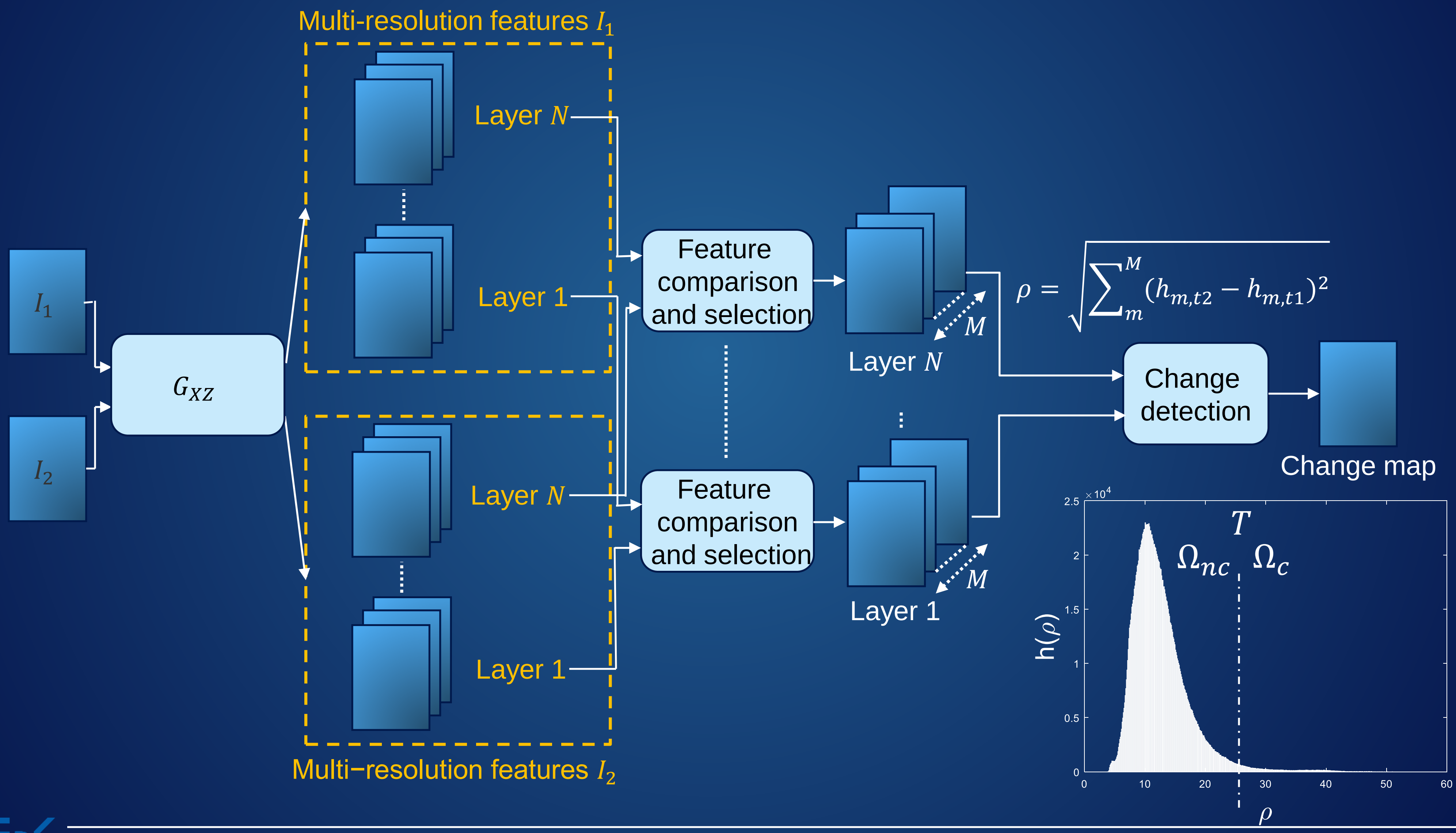
CD in SAR using deep unsupervised transcoding

- ✓ CycleGAN models are widely used in State-of-the-Art transfer learning since their capability to train in unsupervised way DL models that transcode an input image from a domain to another one.
- ✓ CycleGANs can be used to transcode SAR images into optical images and extract informative features for CD.



[7] S. Saha, F. Bovolo, and L. Bruzzone, “Building Change Detection in VHR SAR Images via Unsupervised Deep Transcoding,” IEEE Trans. Geosci. Remote Sens., Jun. 2020.

Block scheme of DL CD method



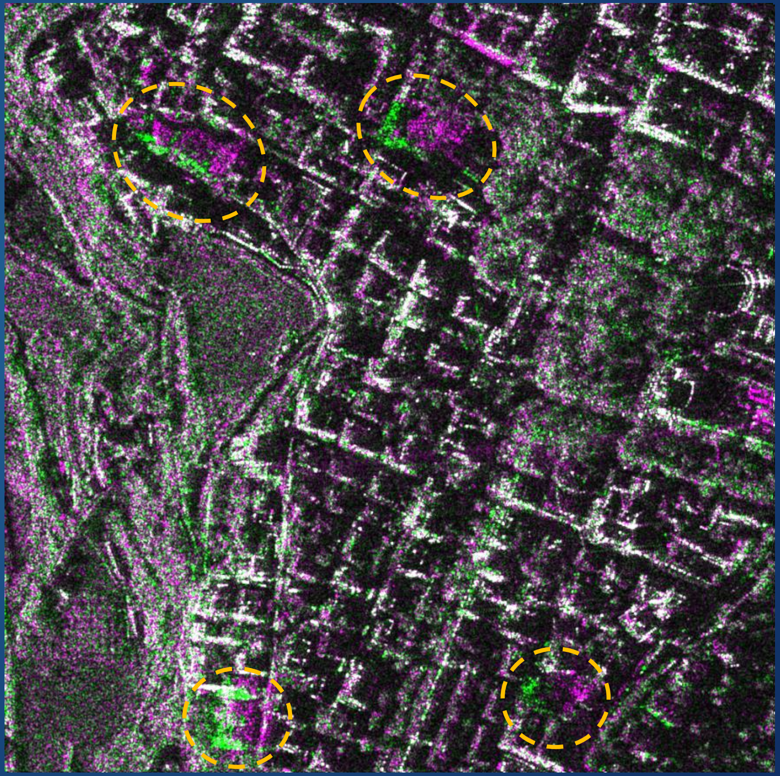
Dataset

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).

COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana – (2009). All Rights Reserved.

Optical image GeoEye, Tele Atlas 2011 Google ©

5th April 2009



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

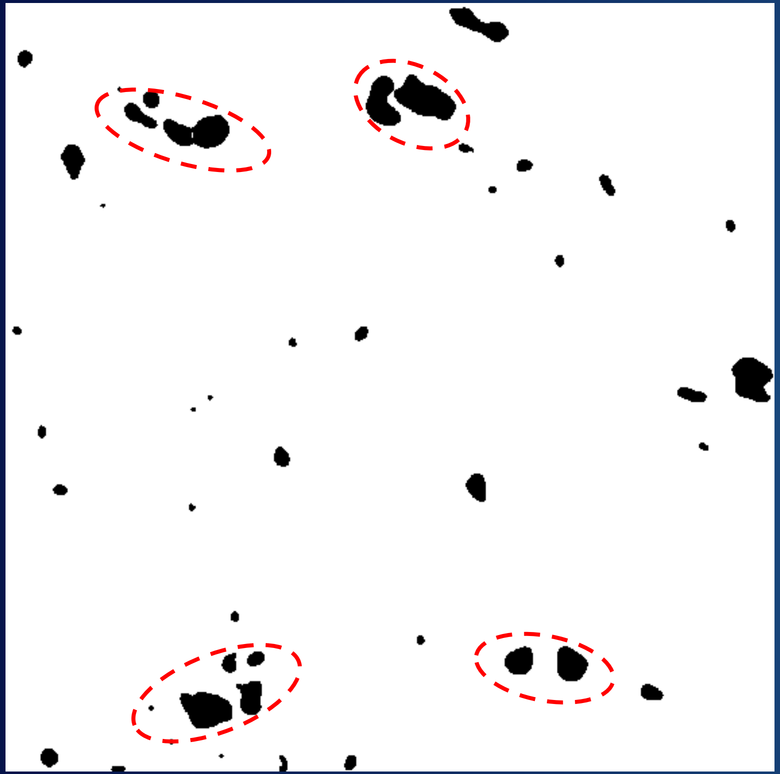
12th September 2009

Backscattering decrease Backscattering increase Unchanged areas

- 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

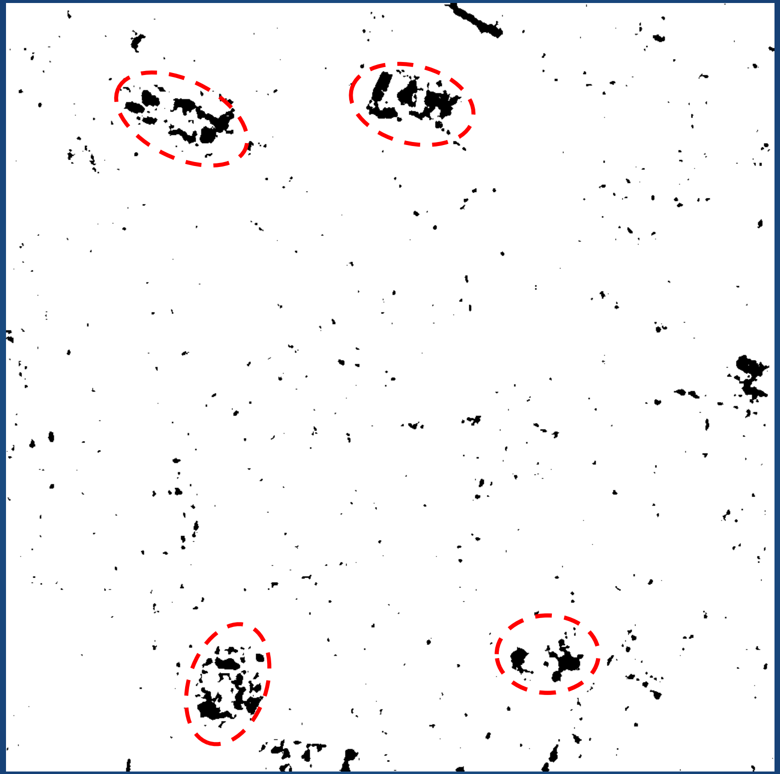
Results

CD using AdaBN



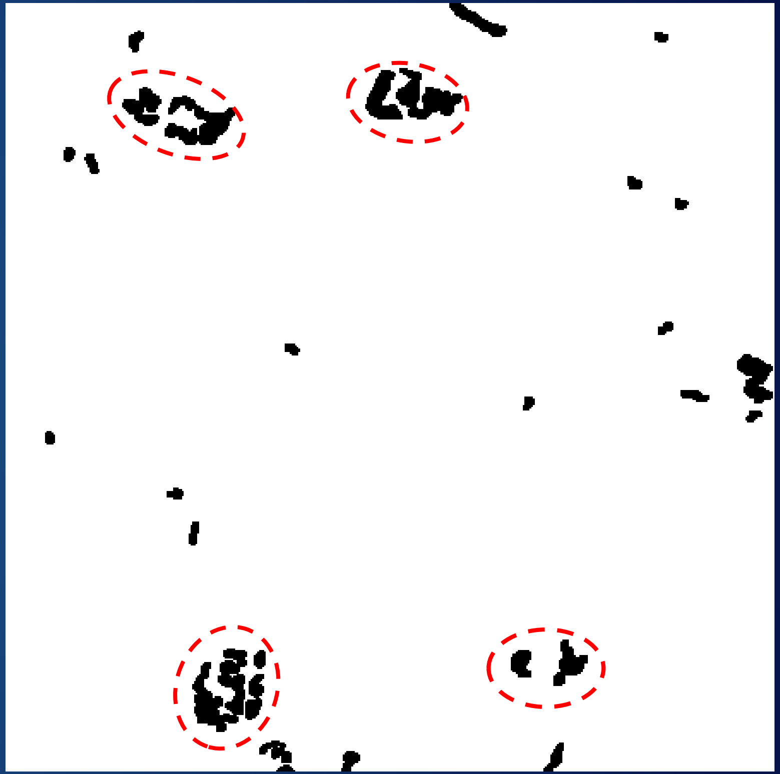
Pre-trained with postdam dataset [8] with a spatial resolution of 1m that is compatible With Cosmo-SkyMed

CD using CAE



Trained with Cosmo-SkyMed images with a Spatial resolution of 1m

CD using CycleGAN



Trained with SARptical dataset [9] composed of TerraSar-X and UltraCam optical images

[8] F. Rottensteiner, G. Sohn, M. Gerke, and J. D. Wegner, "ISPRS Test Project on Urban Classification and 3D Building Reconstruction," ISPRS Working Group III / 4 - 3D Scene Analysis, Tech. Rep., 12 2013.
[9] Y. Wang and X. X. Zhu, "The SARptical dataset for joint analysis of SAR and optical image in dense urban area," in Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS), Jul. 2018, pp. 6840–6843.

Conclusions

- ✓ DL models can be exploited to automatically learn, and extract features providing spatial context and semantic information from bi-temporal SAR images and used for unsupervised CD.

- ✓ Transfer learning methods, such as AdaBN, can be used to adapt a DL model pre-trained with optical images to process SAR images. AdaBN does not perform a complete domain adaptation, and the adapted DL model efficiently works only with images with similar spatial resolution.

- ✓ CAE learns ad-hoc features for SAR images during a training performed with unlabeled data. The learned features well handle the noise of SAR images, CAE needs a feature selection but overcomes limitations of AdaBN.

- ✓ CycleGAN learns a trascoding function from SAR images to optical ones. The retrieved features belong to a common domain and they provide relevant information that can be used in CD. The changes are detected in very accurate way, and it can process heterogeneous images. The training is computationally heavy and unstable.