Towards Geospatial Intelligence with AI

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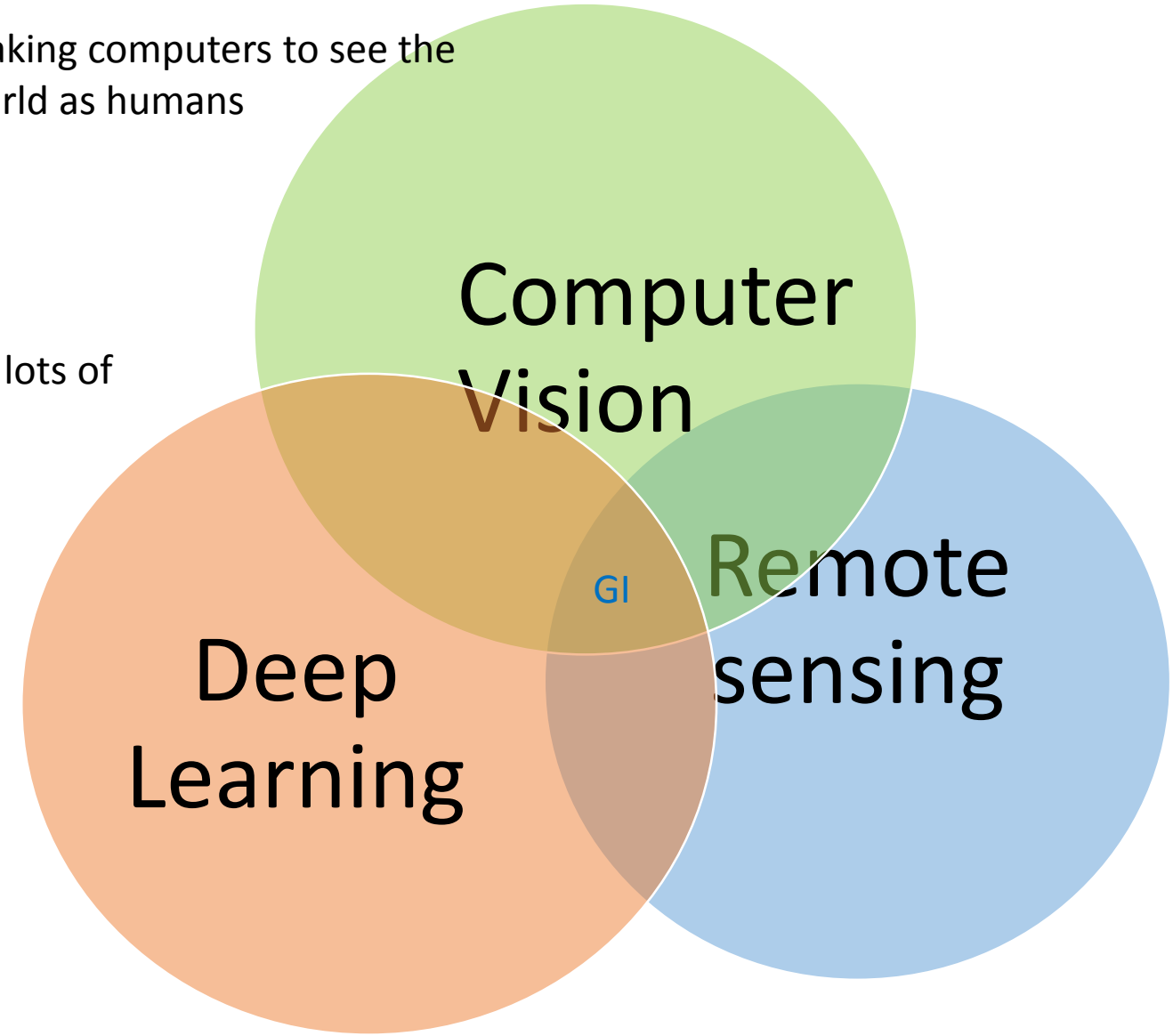
What is Geospatial Intelligence?

Making computers to see the world as humans

Learn patterns through lots of examples



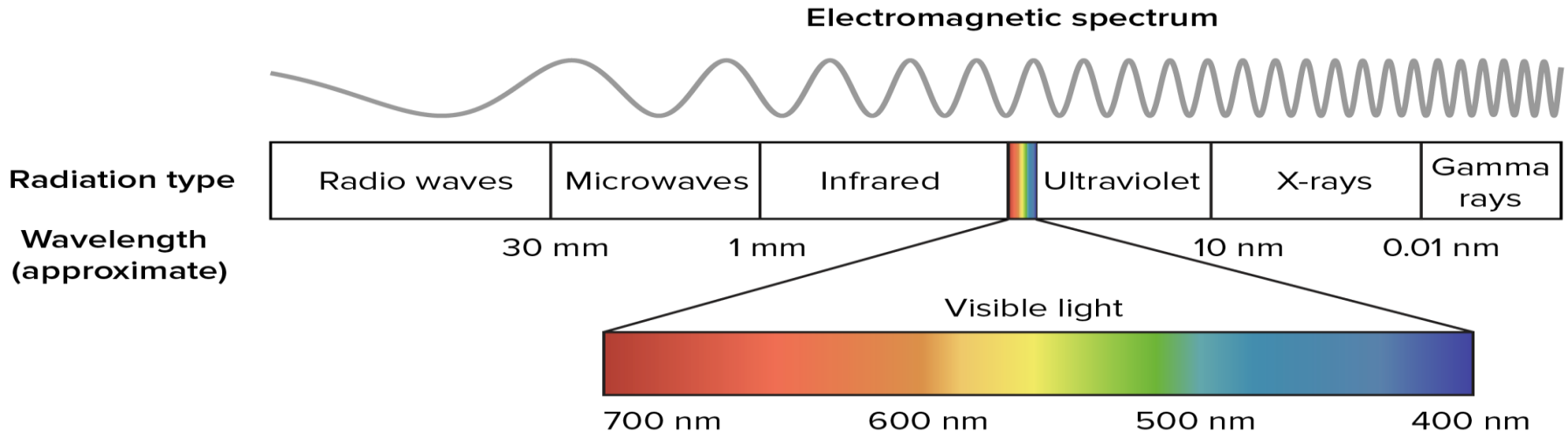
Taking measurements of the Ea
from a distance
tool to provide Earth observatio
images (just like you take from
camera in an airplane!) add you
Russia picture

Why do we care?

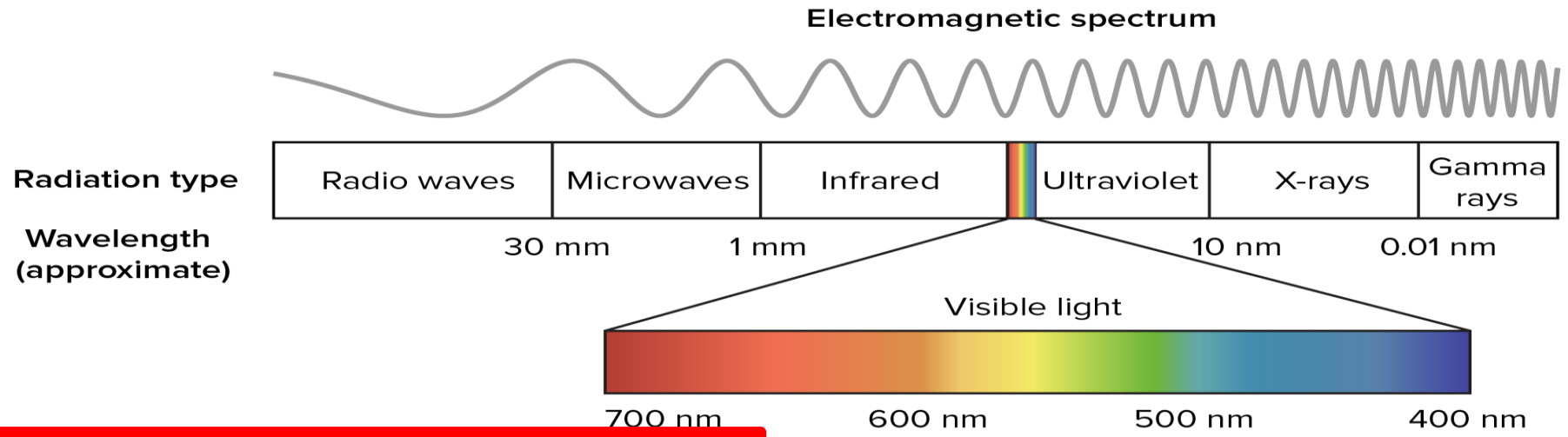
- Currently only 25% of the Earth's surface is seen by ground sensors

- Remote sensing (Satellite Earth Observation) is 'Eye from the Sky'

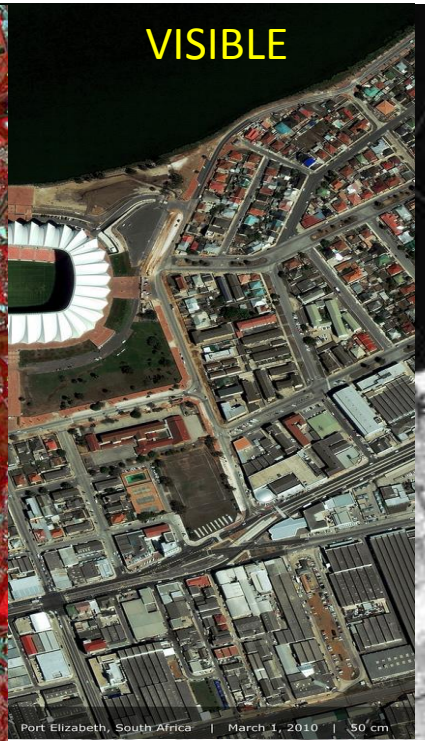
How we see earth?



How EO sees earth?

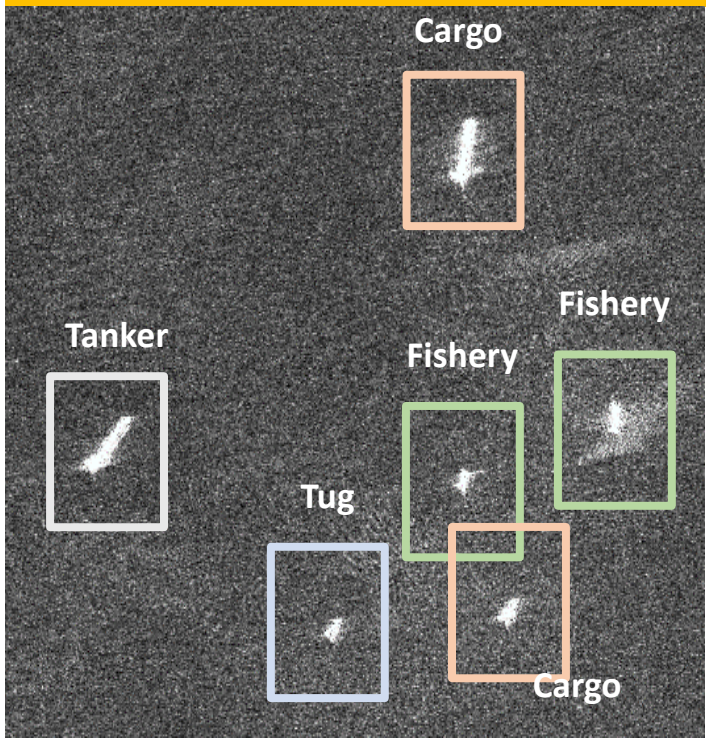


- Gray-scale
- RGB
- RGB + IR
- Microwave



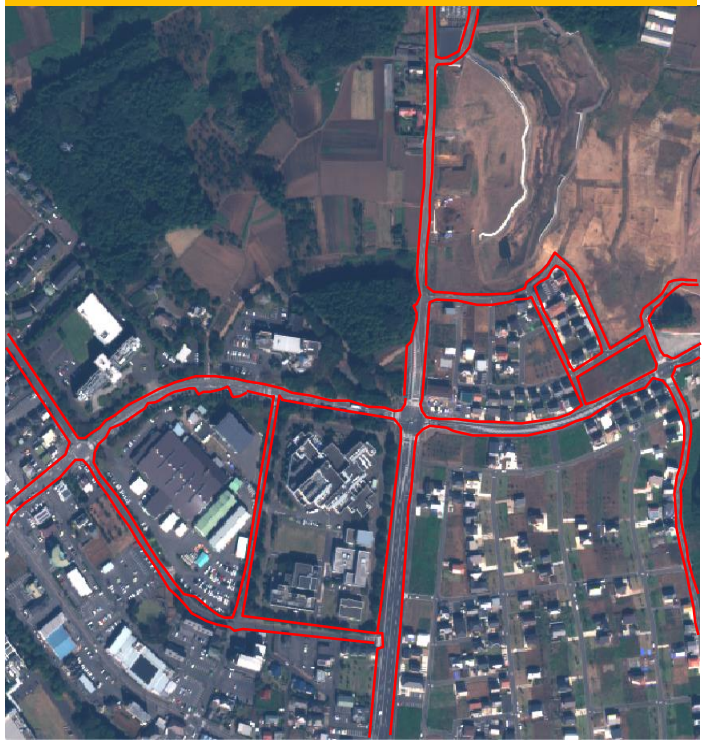
Applications

Surveillance



Disaster Mgmt.

Infrastructure



So many datasets…

My Research Work

I. Ship Classification

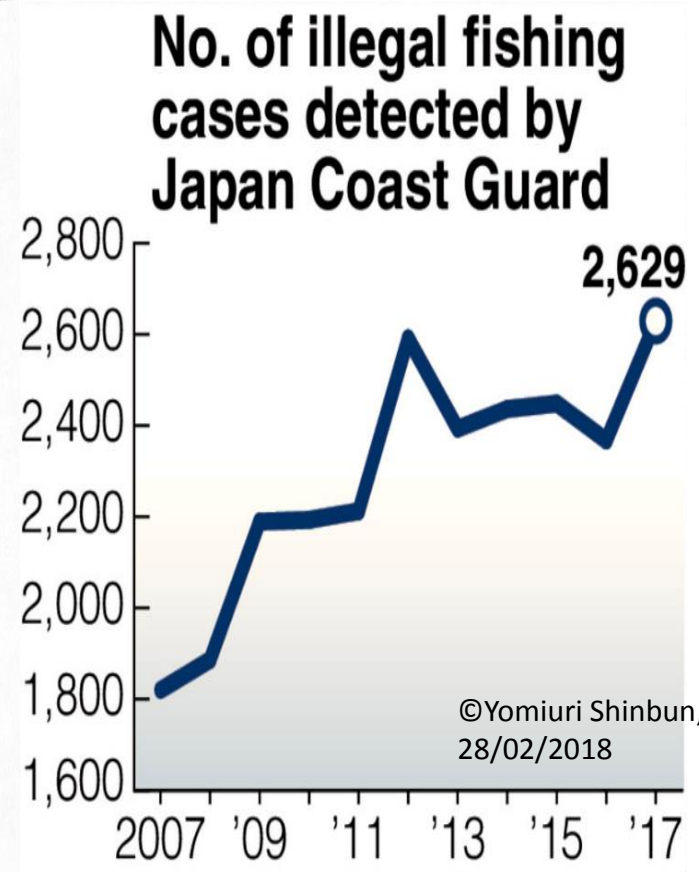
II. Change Detection (brief)

Microwave Image =>

Motivation

Ship classification is a key application in of maritime surveillance

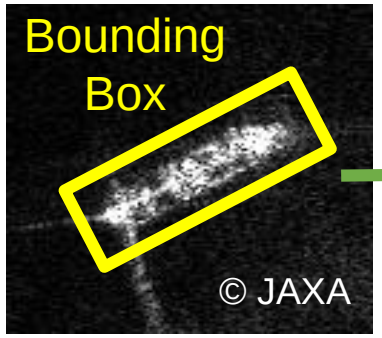
Helps in quick identification of ships involved in illegal activities



Microwave image is very useful as it is ‘cloud-free’ and image even in night

Existing SAR Ship Classification Methods

1. Hand-crafted Features (HCF)-based



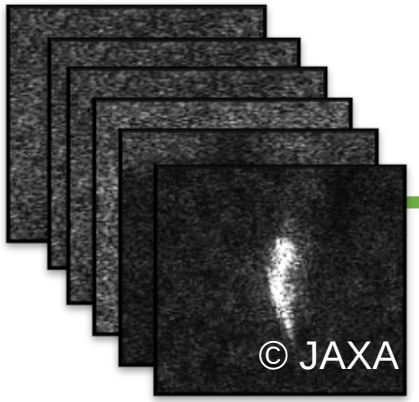
Feature* extractor → Classifier (SVM) → Class

*Length, Area, Intensity, … etc.

Pros
- Intuitive features

Cons
- Requires expert knowledge of ships

2. Convolutional Neural Network (CNN)-based



CNN → Class

Pros
- Does not require expert knowledge

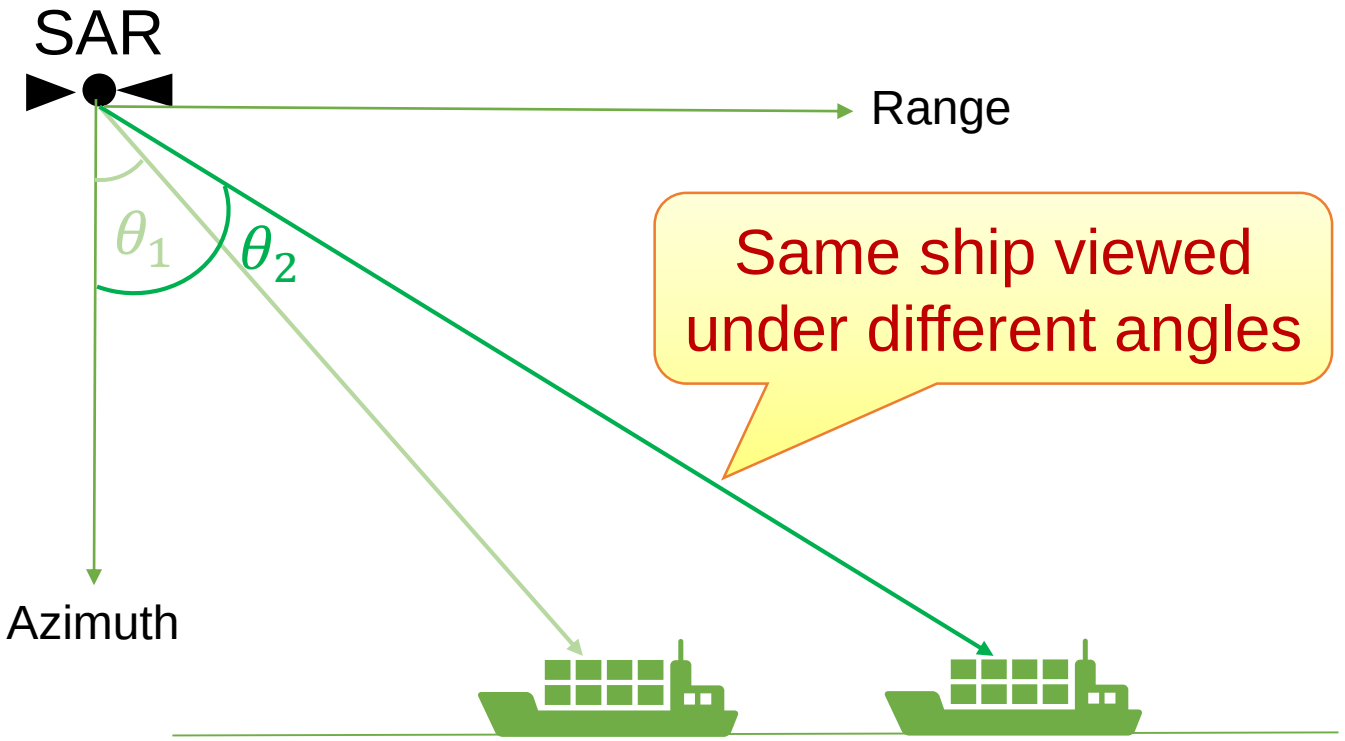
Cons
- Requires huge training data

These methods classify a ship based on its appearance

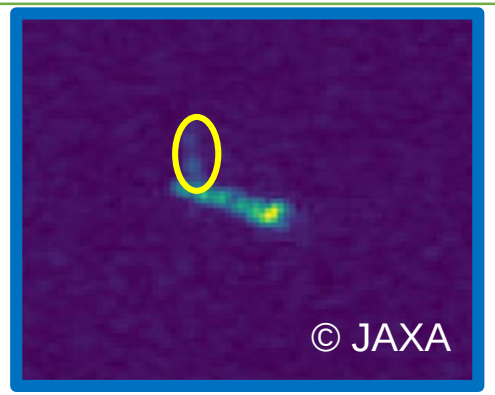
Problem

Appearance of a ship varies with satellite viewing angle

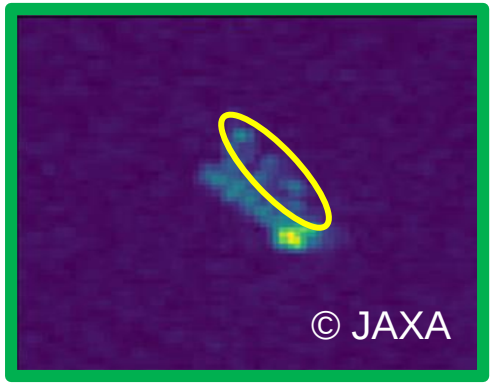
Labelled images are very few to learn all possible variations



Same ship viewed under different angles



$\theta_2 = 40^\circ$



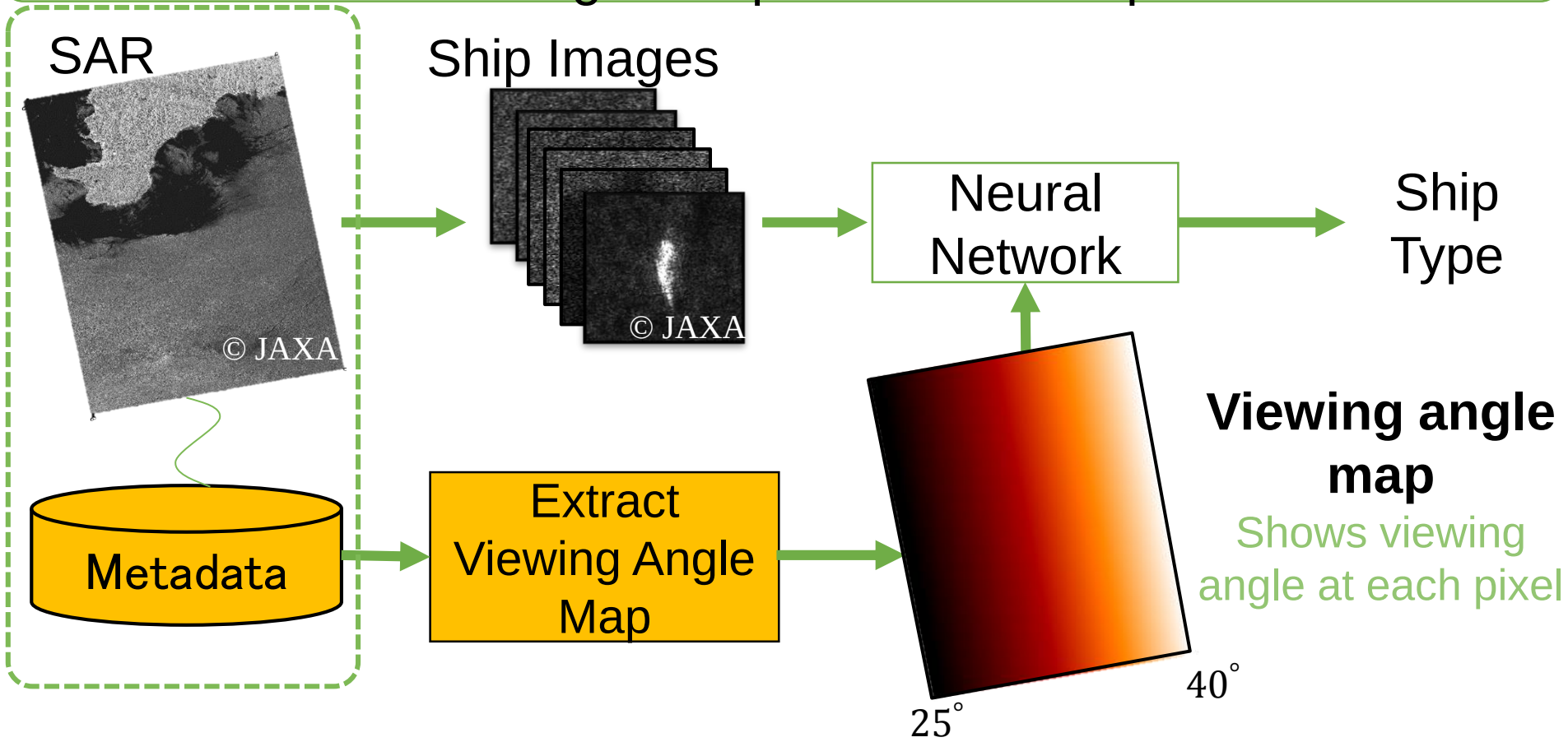
Only image information is insufficient for robust recognition

Appearance information is not sufficient to achieve robust classification

Proposed Method

Use viewing angle as an additional information in a NN

Helps the neural network follow the appearance changes by learning an implicit relationship

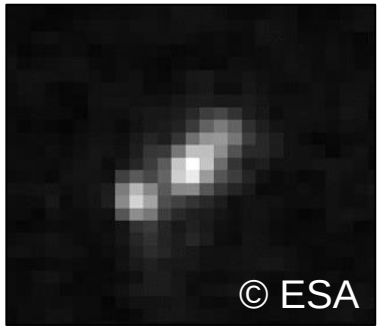


Sharma et al., CNN-based ship classification method incorporating SAR geometry information, SPIE RS 2018.

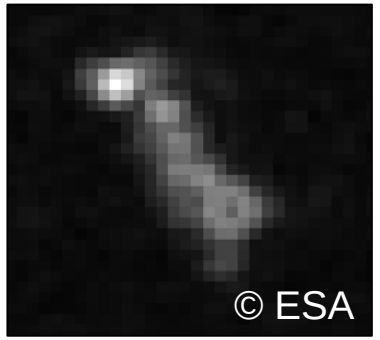
Experimental Set-up

Dataset: OpenSARShip*

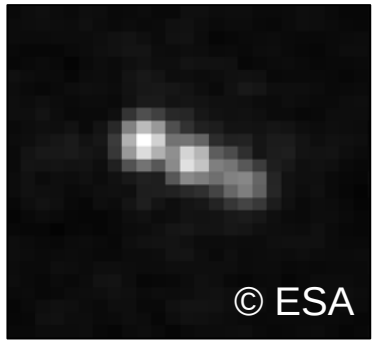
Container



Bulk-carrier



Tanker



Specifications

Satellite	Sentinel-1
Resolution	20m
Polarization	HH
Image size	128x128
No. images	200/class
Ground truth	AIS + Marine Traffic

Conventional Methods

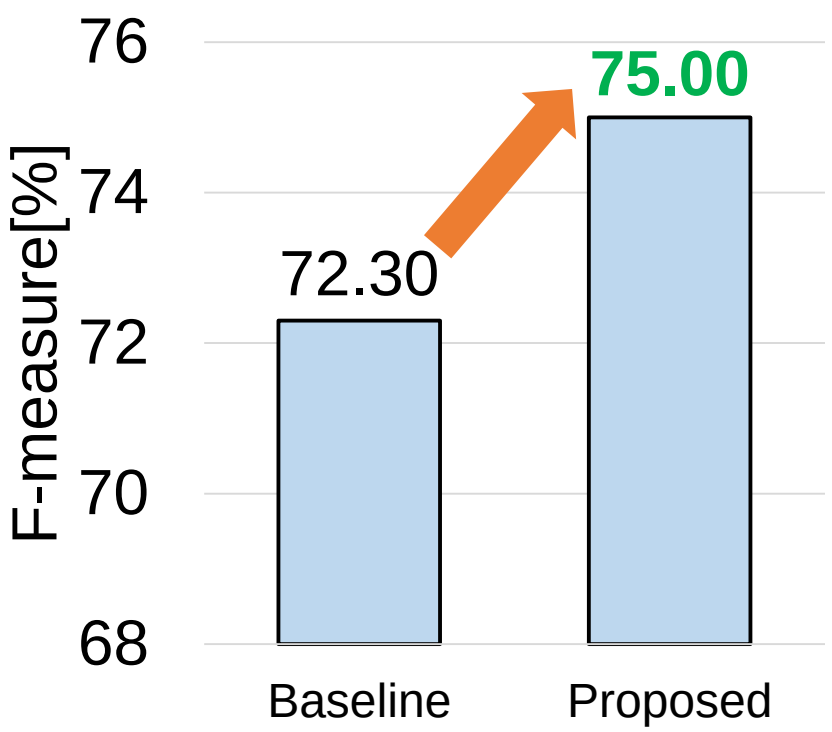
HCF	10 Features + SVM
CNN	w/o incident angle

*Huang, L et al., "OpenSARShip: A dataset dedicated to Sentinel-1 ship interpretation," IEEE Journal of Sel. Top. in App. Earth Obs. and Rem. Sen. 11(1), 195-208 (2018).

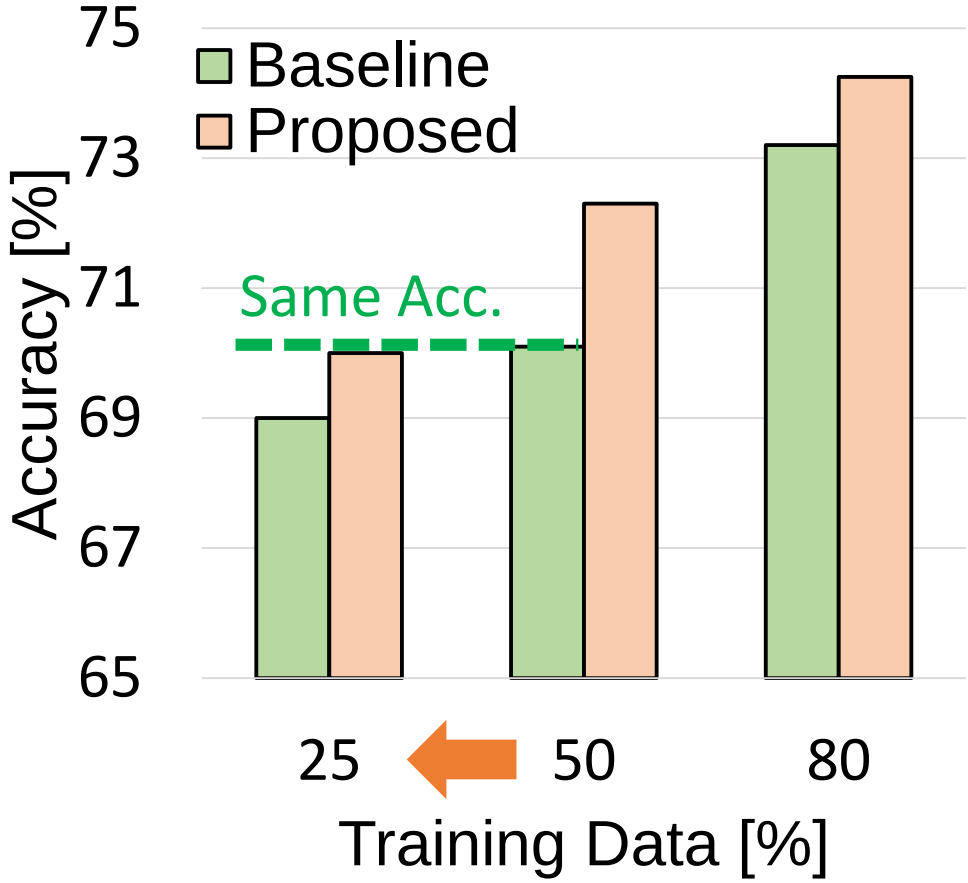
Experimental Result

Proposed method outperforms the conventional method

4.2% improved f-measure



25% reduced training data requirement



Demo

Change Detection - Motivation

Change detection enables us to understand dynamics of our planet

SAR images provide reliable visual evidence to detect changes

Image 1

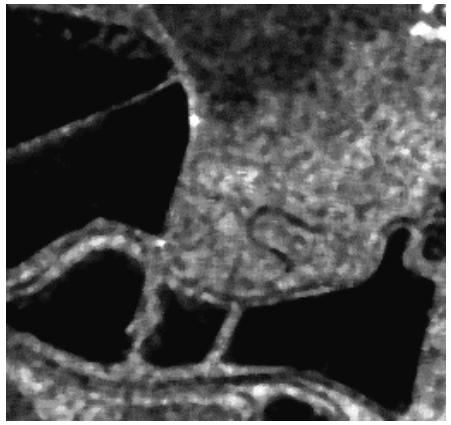
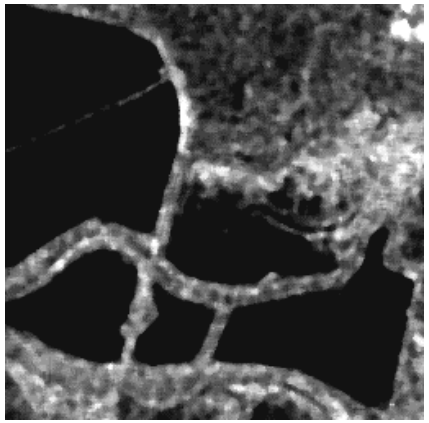
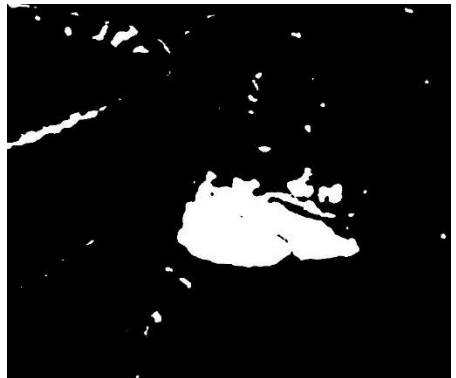


Image 2

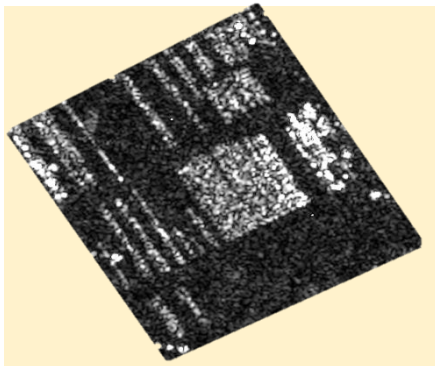


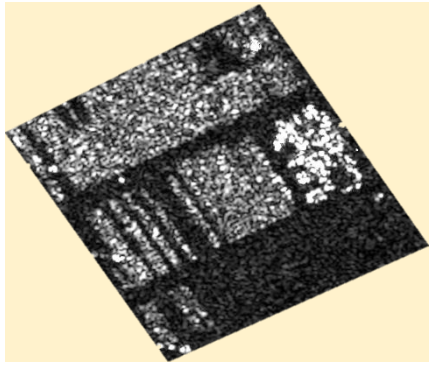
Change Map



Conventional Method

Based on pixel-to-pixel difference followed by classification

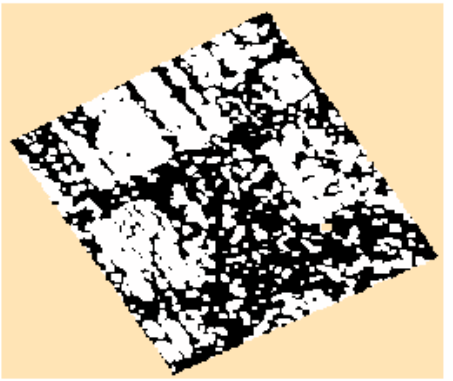




Pixel-to-pixel difference

Classification

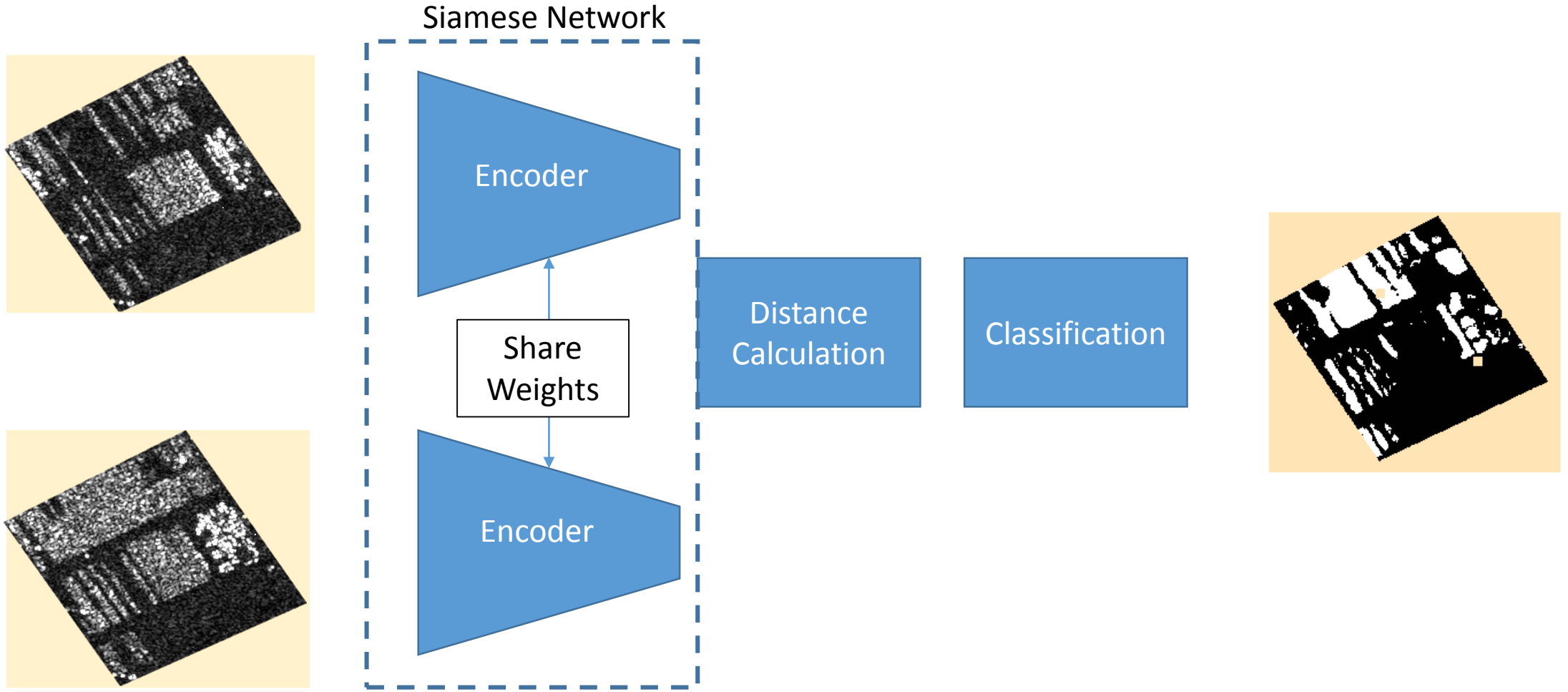
Change Map



Problem: Many False Changes in high resolution images!

Proposed Method

Transform the images into features and compute distance between features



Sharma et al., Very high resolution SAR change detection with Siamese Networks, The 66th Academic Conference of the Remote Sensing Society of Japan, 2019.

Experimental Evaluation

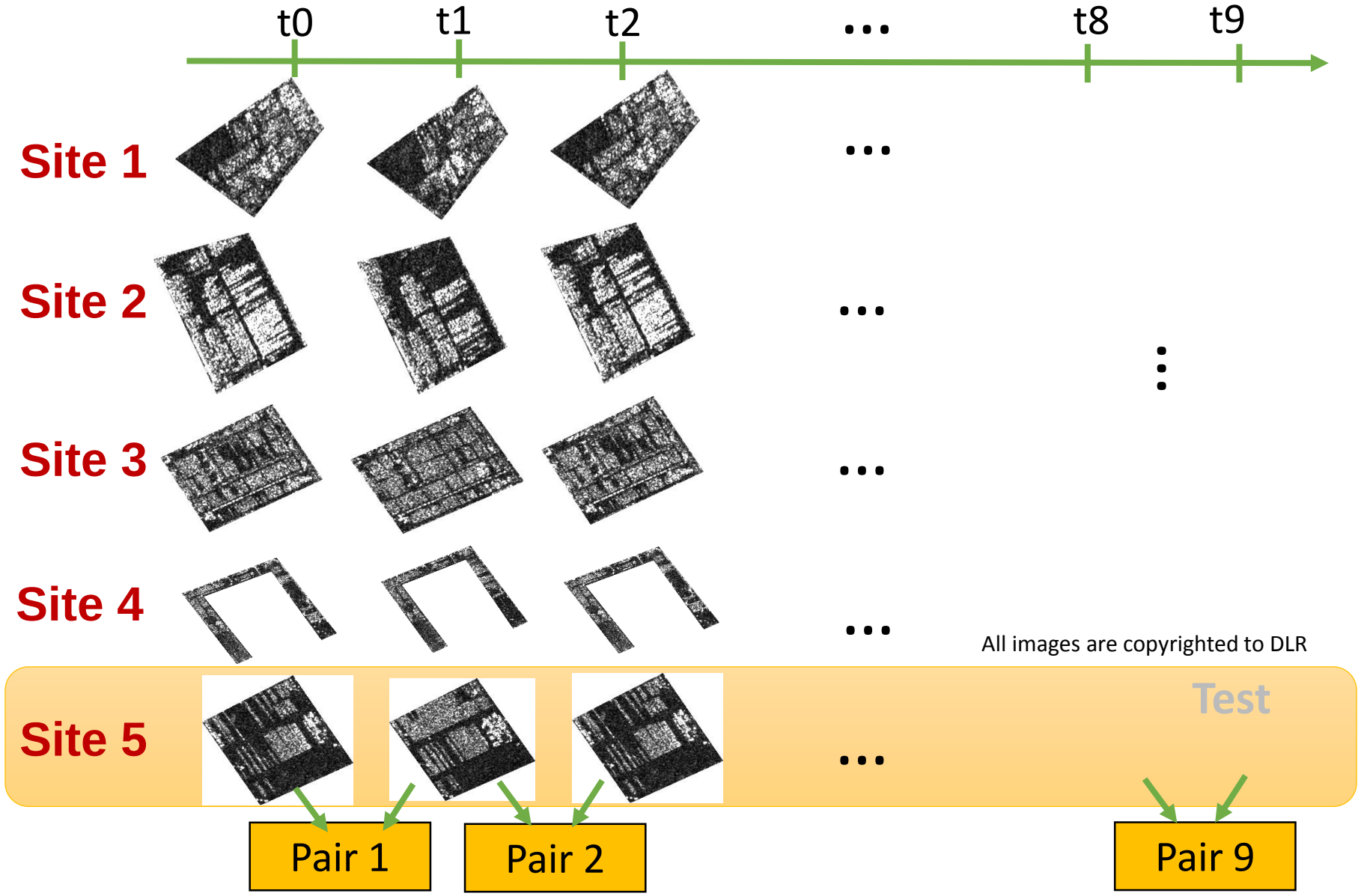
- **Application**
  - Parking Lot Monitoring
- **Baselines:**
  - PCA + Kmeans [1]
  - Sparse AE + Kmeans [2]
- **Evaluation Metrics**
  - f-measure
  - ROC-AUC

Specifications	
Satellite	TerraSAR-X
Resolution	1m
Polarization	HH
No. of parking sites	5
No. of images/site	10
No. of pairs/site	9
Patch sizes	10x10, 16x16
Ground Truth (GT)	Manual interpretation

[1] T. Celik: Unsupervised change detection in satellite images using principal component analysis and k-means clustering, IEEE Geoscience and Remote Sensing Letters, vol. 6, no. 4, pp. 772-776, 2009.

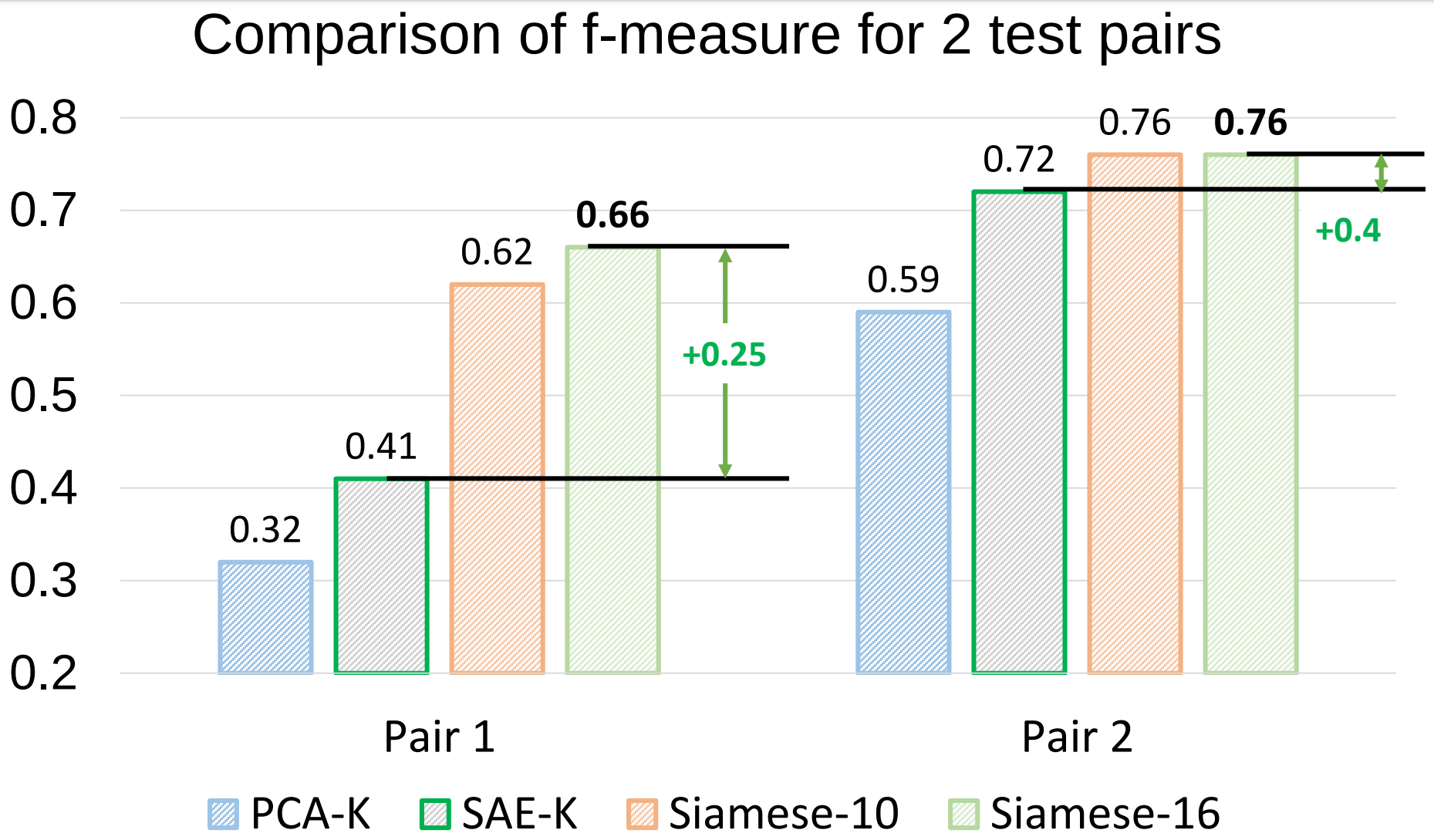
[2] M. Gong., H. Yang, and P. Zhang: Feature learning and change feature classification based on deep learning for ternary change detection in SAR images, ISPRS Journal of Photogr. and Remote Sensing, no.129, pp.212-225, 2017.

Dataset



Result [1/2] : f-measure

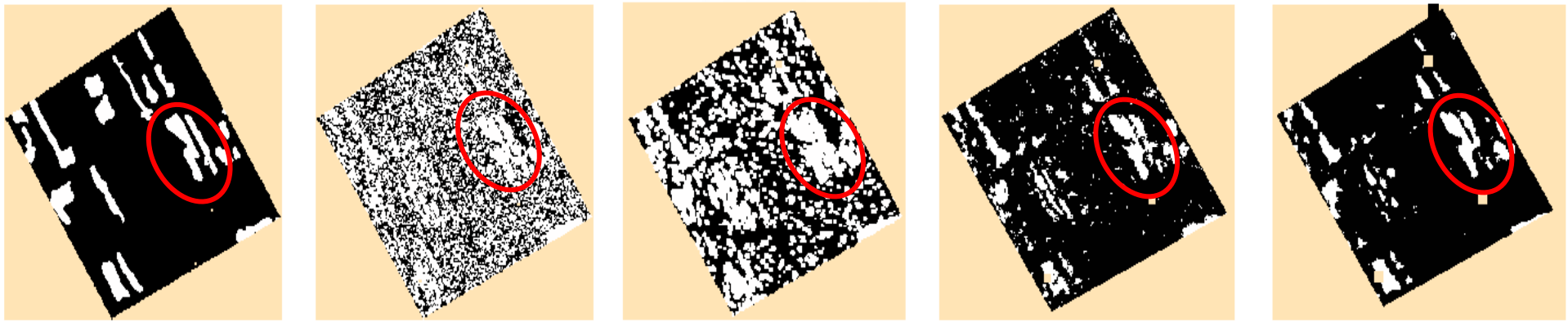
Siamese networks outperforms the conventional methods



Result [2/2] : Change Maps

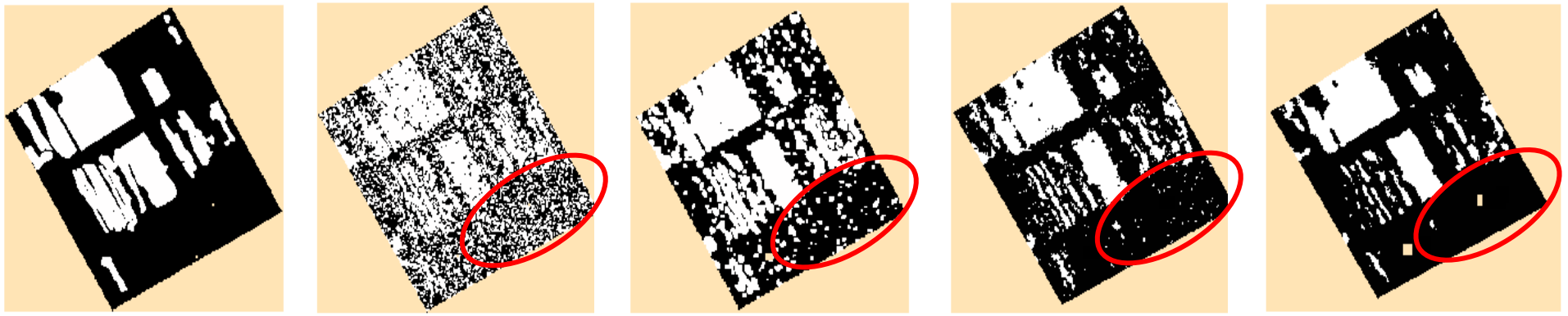
Siamese networks produce visually better change maps

Test Pair 1



GT | PCA-K | SAE-K | Siamese-10 | Proposed

Test Pair 2



GT | PCA-K | SAE-K | Siamese-10 | Siamese-16

Conclusion

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