

## Vessel detection from spaceborn optical and SAR images

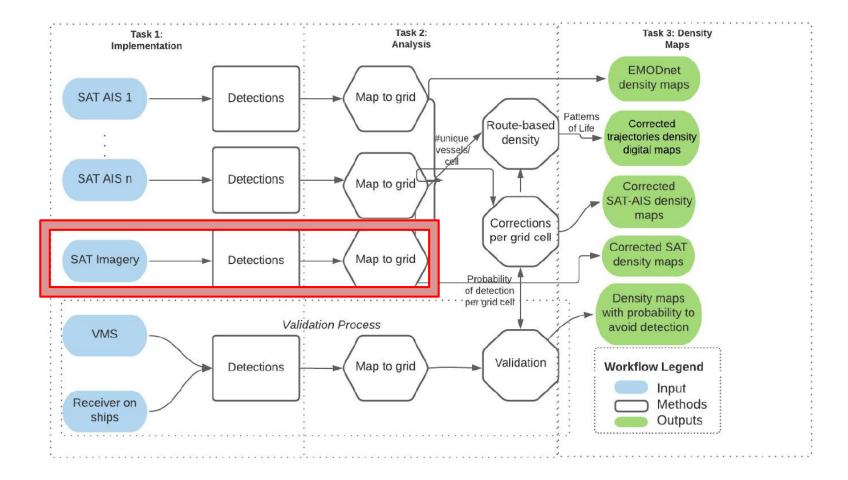


UBITECH ubiquitous solutions

Interim review presentation

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#### **Overall workflow**



#### Satellite image detection architecture

Satellite image p	processing s	tack			Al stack	
Data acquisition	Sentinel-1 Copernicus Sentinel-hub	Sentinel-2 http:// asf.alaska.edu/			Training	90%
Pre-processing	Format conversion	Pan-sharpening	Tiling		Detection	90%
Filtering	Sea-masking	cloud-masking				
Fusion	AIS Interpolation	Data fusion	Æ	<b></b>	GRID Analytic	
					Analysis	Statist

Al sta	ack		
Training	90% accuracy		
Detectio	90% accuracy		
GRID	Analytics		
Analysis	Statistics	Comparisons	
Density	Maps SAT-based density	Dark vessel mapping	W

#### Data acquisition

- Sentinel-1 SAR data
  - 5000 images in OCT 2021 (1000 for MED)
  - GRD IW products
- Sentinel-2 Optical data, (cloud coverage up to 10%)
  - 10m TCI images (bit), IR, RGB bands (16-bit)
  - Volume:
  - OCT21: 5.25 TB, 5895 images
  - NOV21: 2.08 TB, 3501 images
  - DEC21: 2.20, 3616 images
- Repositories:
  - <u>https://scihub.copernicus.eu/</u>
  - <u>https://asf.alaska.edu/</u> (for archived S1 images)

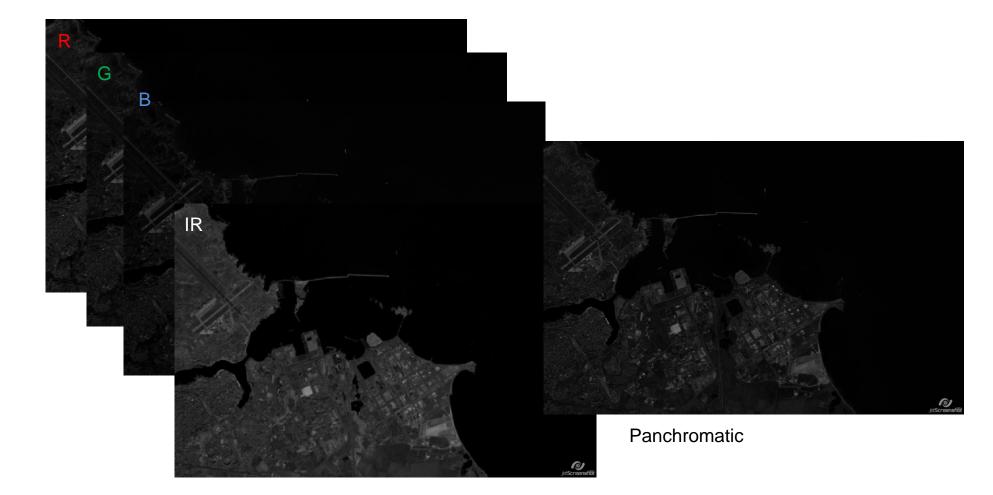
#### **Pre-processing**

#### • Pre-processing operations

- Geocoding
- Transformation to another CRS
- Transformation to another format (e.g., JP2 to GeoTIFF)
- Panchromatic image composition (S2)
- Pan-sharpening

#### Constructing a pan-chromatic image

• Computing the average of RGB + NIR 10m



#### Pan-sharpening

 Fuse the higher spatial information from the panchromatic image and the spectral information from a lower spatial information multispectral image. (20 MS (RGB, SWIR) + Panchromatic = 10m RGB + SWIR)



10m & SWIR

Problem: Deep Learning can be a bottleneck for large data volumes

Solution: Use image processing before NN detection to reduce the number of image tiles

#### Filtering: From TBs to GBs

- Most tiles do not contain vessels
- We use image processing to prune tiles that do not contain vessel
- Sentinel 1: we maintain statistics per tile (e.g., white/black pixels), thresholding
- Sentinel 2:
  - SCL band (clouds, sea, land)
  - Cloud masking, land masking
  - **R,SWIR** for filtering (thresholding)

#### AI tasks: Training and Detection

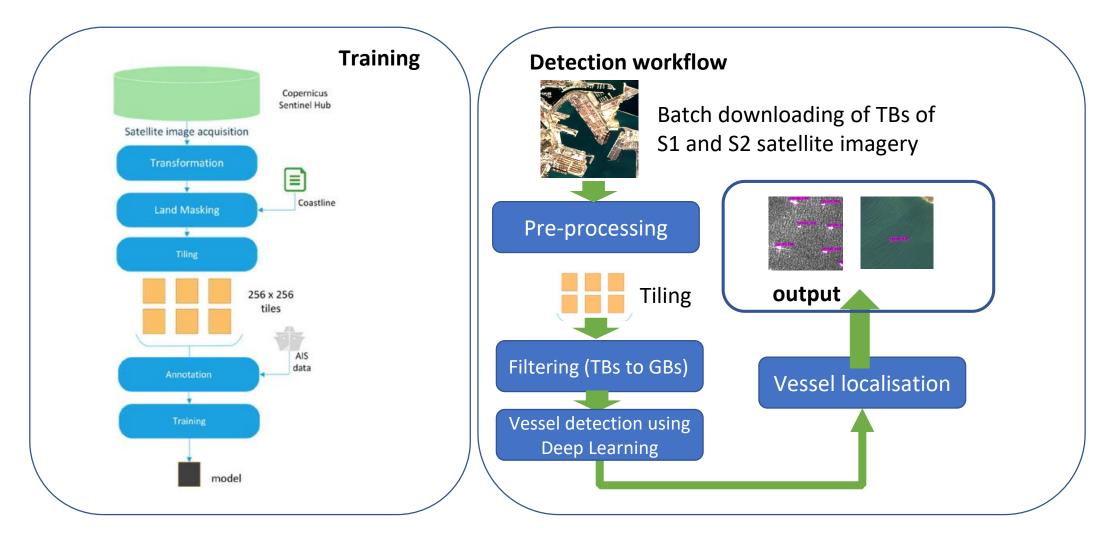
- We have trained a CNN-based object detection framework for vessel detection and localisation
- We use 2 models for vessel detection, one for S1 and another for S2 imagery (using the same network)
- We are training 2 respective models for vessel type classification
- Experiments

```
Sentinel-1: precision = 0.92, recall = 0.93, F1-
score = 0.92 (TP = 80, FP = 7, FN = 6)
```

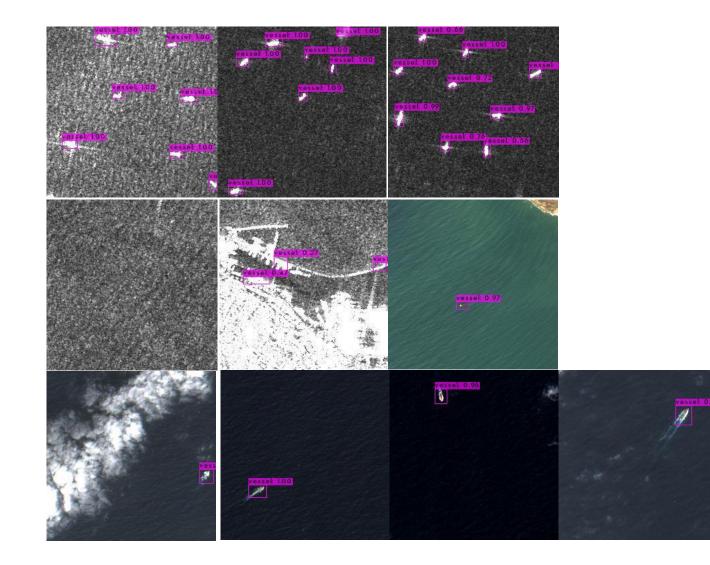
```
Sentinel-2: precision = 0.90, recall = 0.88, F1-
```

```
score = 0.89 (TP = 60, FP = 7, FN = 8)
```

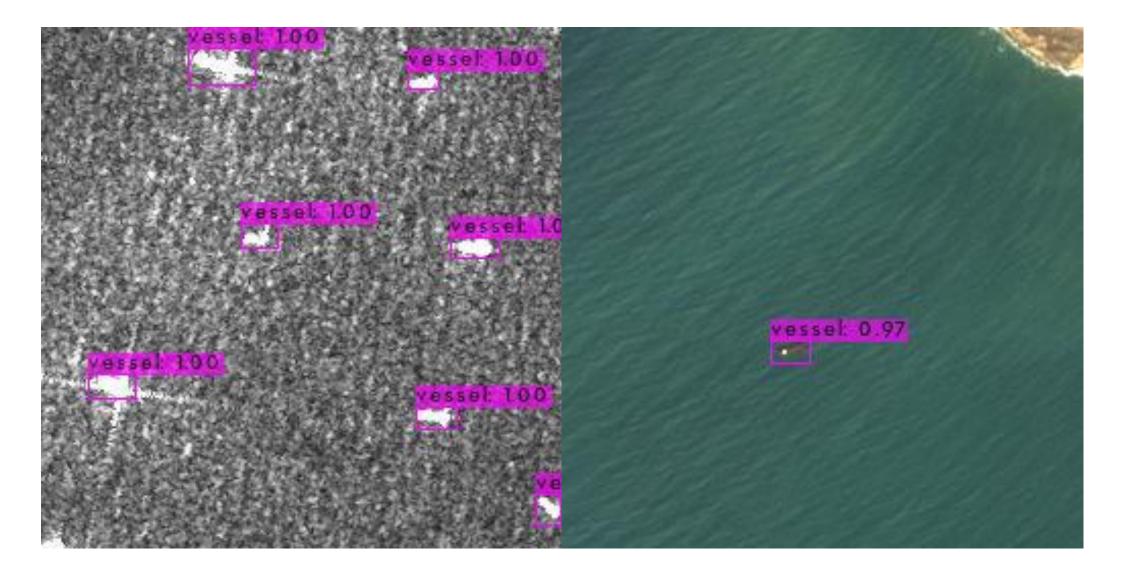
# Al vessel detection tasks: training and detection



#### Examples of vessel detection



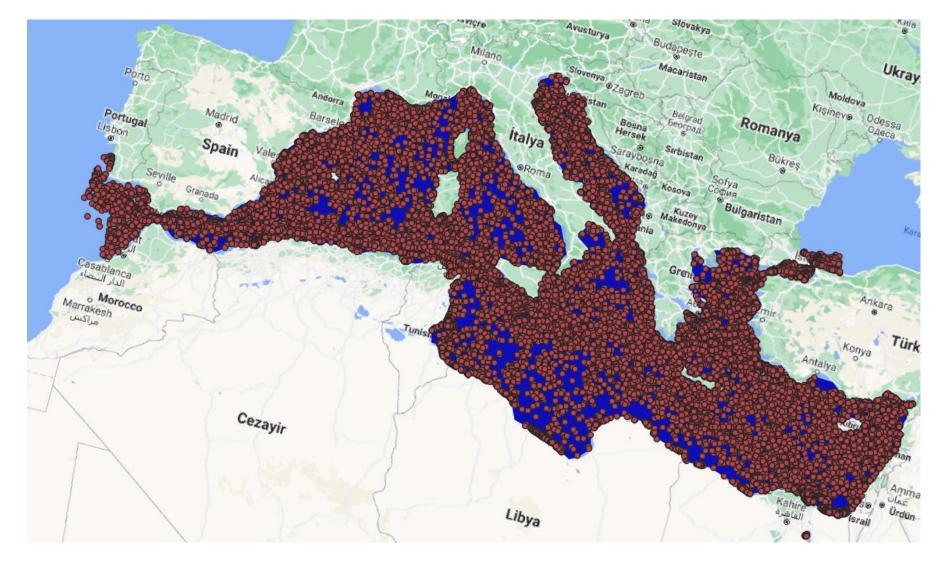
#### Examples



#### Post-processing

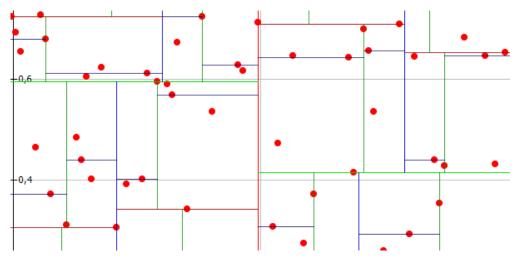
- Vessel detections with>0.5 confidence level are discarded.
- Image coordinates are translated into geographic coordinates
- Final output: CSV containing the location of vessels detected in a satellite image

#### Vessels detected in S1 images in MED (OCT21)



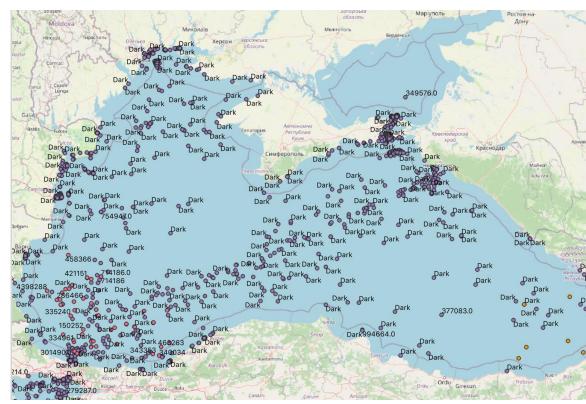
#### Fusion

- Correlation of AIS data with sat-imagery detections
- Data partitioned per image footprint
- Time window (30 mins +- acquisition time
- KNN-join using KD-index



#### Fusion

- Correlation of AIS data with sat-imagery detections
- Un-correlated vessels: Dark



### Future work

- Sentinel-2 workflow execution in progress
- Sentinel-1 execution for the other seas and the rest of the time period
- Classification by vessel type
- Konstantina Bereta, Ioannis Karantaidis, Dimitris Zissis. Vessel Traffic Density Maps based on Vessel Detection in Satellite Imagery. Submitted to IGARSS 2022.