



PROMPT

UCPM-2022-PP/G.A-101101263

Work package 3 Del. Number D3.2

Deliverable Name: Report on the development of detection and tracking algorithms from satellite images

WP No	Del Rel. No	Del . No	Title	Description	Lead Beneficiary	Nature	Dissemination level	Est.Del. Date
WP 3	D.3.2	D.7	Report on the development of detection and tracking algorithms from satellite images	Literature investigation, Experiment planning, Containers detection approaches	ERI	visibility materials	Public	07 May 2024





Table of content

1 DETECTION OF FLOATING CONTAINERS: STATE OF THE ART	3
1.1 RELATED WORK	3
1.1.1 MAPPING FLOATING DEBRIS	4
1.1.2 SMALL SHIPS	4
1.1.3 CONTAINERS IN PORTS	4
1.1.4 SIMULATIONS	5
1.1.5 SENSING FLOATING CONTAINERS FROM OTHER VESSELS	5
2 EUROPEAN MARITIME SAFETY AGENCY (EMSA)	5
3 HISTORICAL ACCIDENTS	6
4 SKYWATCH	6
5 EXPERIMENT SETUP	6
6 APPROACHES FOR DETECTING CONTAINERS.....	7



1 DETECTION OF FLOATING CONTAINERS: STATE OF THE ART

We continued our investigation of the literature, and while the topic of finding and identifying vessels with EO data is a very well-established task, and a highly active field of research, no scientific articles that addressed specifically the topic of automatically detecting or segmenting floating shipping containers using satellite-borne Earth Observation methods could be found. This is rather unexpected, and we can only guess why. Probably, one of the reasons is that the resolution of public imagery is not high enough to image floating shipping containers. Commercial VHR is required, but there are two obstacles to sharing it:

1. That type of data is expensive
2. The licences for the usage of this type of data, generally, do not allow sharing

The first issue means that VHR images are an asset that might provide a competitive advantage, and in fact companies have no incentive in sharing the images they may have, since these could be adopted by their competitors. We have no information about the impact on universities and research centres. Possible explanations include the fact that the problem is not perceived as relevant by academics, or that the funds do not allow the acquisition of commercial data.

The second issue is relevant too and deserves an in-depth analysis. Usually, providers distinguish between:

1. *Value-Added Products (VAP)*, which are products that still contain the original pixels, or that allow the reconstruction of the values of the original pixels. Typical examples include format conversion and metadata supplementation.
2. *Derivative Work*, which does not allow the reconstruction of the original image. Typical examples include extraction of a down sampled RGB image (typically for the press) or the creation of maps which do not include the original image.

While Derivative Work can be shared with most licences, VAP cannot. This means that it will be legally challenging to distribute the images acquired by WASDI in the project.

1.1 RELATED WORK

Returning to literature, excluding the body of work on the use of IoT devices and other dedicated hardware, and that on vessel/ship detection, related research include:

1. Mapping floating debris with satellite imagery
2. Mapping small ships with satellite imagery
3. Mapping ports congestion
4. Sensing floating containers from other vessels
5. Simulations

1.1.1 MAPPING FLOATING DEBRIS

Most applications are about the use of remote sensing, especially Sentinel-2, to detect floating debris, especially plastic. However, floating containers are different, since they are few objects, and so leave a less evident spectral signature.

1. Lavender, S., 2022. Detection of waste plastics in the environment: application of Copernicus earth observation data. *Remote Sensing*, 14(19), p.4772. <https://www.mdpi.com/2072-4292/14/19/4772>
2. Sannigrahi, S., Basu, B., Basu, A.S. and Pilla, F., 2021. Detection of marine floating plastic using Sentinel-2 imagery and machine learning models. *arXiv preprint arXiv:2106.03694*. <https://arxiv.org/ftp/arxiv/papers/2106/2106.03694.pdf>
3. Mifdal, J., Longépé, N. and Rußwurm, M., 2021. Towards detecting floating objects on a global scale with learned spatial features using sentinel 2. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, pp.285-293. <https://isprs-annals.copernicus.org/articles/V-3-2021/285/2021/isprs-annals-V-3-2021-285-2021.pdf>
4. De Vries, R., Egger, M., Mani, T. and Lebreton, L., 2021. Quantifying floating plastic debris at sea using vessel-based optical data and artificial intelligence. *Remote Sensing*, 13(17), p.3401. <https://www.mdpi.com/2072-4292/13/17/3401>
5. Carmo, R., Mifdal, J. and Rußwurm, M., 2021, September. Detecting macro floating objects on coastal water bodies using Sentinel-2 data. In *OCEANS 2021: San Diego-Porto* (pp. 1-7). IEEE. <https://ieeexplore.ieee.org/abstract/document/9705668>

1.1.2 SMALL SHIPS

Techniques for detecting small ships, might possibly be tried for detecting containers:

6. Wu, T., Li, B., Luo, Y., Wang, Y., Xiao, C., Liu, T., Yang, J., An, W. and Guo, Y., 2023. MTU-Net: Multilevel TransUNet for space-based infrared tiny ship detection. *IEEE Transactions on Geoscience and Remote Sensing*, 61, pp.1-15. <https://ieeexplore.ieee.org/abstract/document/10011449>

1.1.3 CONTAINERS IN PORTS

7. Yasuda, K., Shibasaki, R., Yasuda, R. and Murata, H., 2024. Terminal Congestion Analysis of Container Ports Using Satellite Images and AIS. *Remote Sensing*, 16(6), p.1082. <https://www.mdpi.com/2072-4292/16/6/1082>
8. Murata, H., Shibasaki, R., Imura, N. and Nishinari, K., 2023. Identifying the operational status of container terminals from high-resolution nighttime-light satellite image for global supply chain network optimization. *Frontiers in Remote Sensing*, 4, p.1229745. <https://www.frontiersin.org/articles/10.3389/frsen.2023.1229745/full>
9. Bovolo, F., Marin, C. and Bruzzone, L., 2012. A hierarchical approach to change detection in very high-resolution SAR images for surveillance applications. *IEEE*



Transactions on Geoscience and Remote Sensing, 51(4), pp.2042-2054.
<https://ieeexplore.ieee.org/abstract/document/6392252/>

1.1.4 SIMULATIONS

10. Stolle, J., Nistor, I. and Goseberg, N., 2016. Optical tracking of floating shipping containers in a high-velocity flow. *Coastal Engineering Journal*, 58(02), p.1650005.
<https://www.worldscientific.com/doi/abs/10.1142/S0578563416500054>

1.1.5 SENSING FLOATING CONTAINERS FROM OTHER VESSELS

Surveillance system proposal based on sensing from other vessels

11. Molina-Padrón, N., Cabrera-Almeida, F., Araña-Pulido, V. and Tovar, B., 2024. Towards a Global Surveillance System for Lost Containers at Sea. *Journal of Marine Science and Engineering*, 12(2), p.299. <https://www.mdpi.com/2077-1312/12/2/299>

2 EUROPEAN MARITIME SAFETY AGENCY (EMSA)

Given the lack of precedents in the literature, we have been invited to contact EMSA to understand the state of the art. In the call, the officers from EMSA explained that they do use EO data to map maritime incidents and their consequences, including oil spills and floating containers.

In general, they ask their providers to produce timely evidence of the incidents, with very high Service Level Agreements (SLA), which usually include strict time windows on the delivery of the services, in the range of 20 - 40 minutes from the acquisition of the images. To this purpose, EMSA rents dedicated bandwidth from ground segment providers, and the satellite providers themselves offer not just the images but also the intelligence, maps in particular. To respond to the requests with such high service levels of timeliness, the providers need to have powerful and effective processing chains in place. In any case, the officers mentioned that they prefer to obtain the images too, not just the maps, and to inspect them in a post processing phase.

About floating containers, they confirmed that it is a relevant issue under any point of view:

1. economic, for the cost of the lost goods, but also for the safety and possibly environmental operations that must be ensued
2. environmental, due to the leakage of several types of pollutants
3. safety: floating containers pose a threat to navigation

While the officers did not describe the methods for mapping containers in EO data, possibly because the methods used by the operators are kept proprietary, they pointed out that the frequency of acquisition of satellite images is very low, and therefore the incidents cannot be





monitored very precisely. For this reason, EMSA relies heavily on modelling too, to predict the possible evolution of the dispersed items and pollutants.

In the following days, the officers from EMSA provided us with the references to a couple of naval incidents involving shipping containers, and one involving cars.

3 HISTORICAL ACCIDENTS

We later integrated the list of incidents provided by EMSA, with other known ones, summing up to 13. The reason behind this research, is that, if after the real scale experiment in Tripoli we still had some credit from our provider, we could search for the presence of historical images of the incidents in their archives. If images were available, we might be able to get a larger dataset. Note that the licence restrictions described above apply here too.

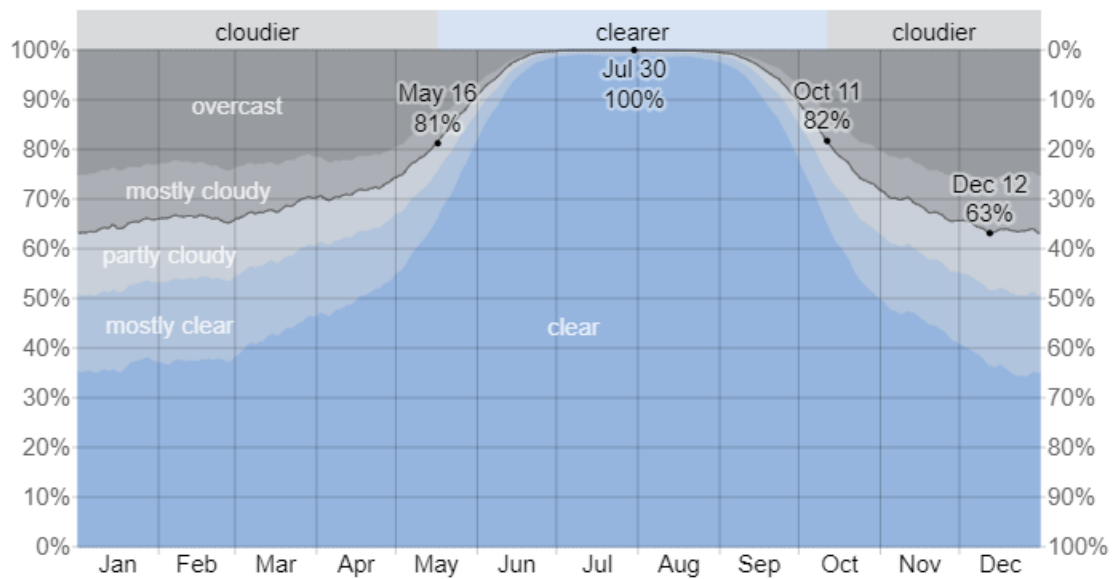
4 SKYWATCH

Our provider, SkyWatch is a reseller of satellite images produced by companies that own the satellites. They sell both archived images, and acquisitions on demand. We had several discussions with them, and we identified some constraints on the setup and duration of the real scale experiment. In particular, the credits we have allow us to acquire images daily from two missions for up to two weeks. We will for sure buy 50 cm 4 bands optical images (from Planet Skysat), and possibly another type of data. We are still refining the choice with the support of SkyWatch, but we are inclined to test Umbra VHR SAR data. That would leave us with some residual credit, and we plan to acquire mid-resolution 3 m Planet PlanetScope/Dove/SuperDove archive images, which are acquired on a daily or higher basis. Other available data from the archives will be considered if the remaining budget allows. Should it be still rather high, we may be able to also purchase images from the historical incidents we identified.

5 EXPERIMENT SETUP

We agreed with OEPT to conduct the experiment in the first half of July, and this is because the weather is expected to be clear, with close to no clouds, at least according to the [MERRA-2 Modern-Era Retrospective Analysis](#) data conducted by NASA (retrieved from the [weatherspark website](#), consulted last on the 24th of April 2024)





The clearest window would be from late June to early September. However, our credit is expiring by the end of August, and the first two weeks seemed the safest option, with some slack in case of problems.

We agreed on floating both the containers in the area to the North-East of the port breakwater, at about 50-100 metres from the breakwater. This is the configuration that would allow us to optimise the acquisition campaign: small area, two-weeks duration, clear sky.

OEPT is conducting some preliminary experiments, and will communicate timely about them, so that we can search for public and low-cost archive images of the area and start collecting data.

6 APPROACHES FOR DETECTING CONTAINERS

The dataset we expect to collect will be rather small, therefore we will initially consider classical statistical methods, based on colour difference. Classical machine learning algorithms may also work, such as unsupervised clustering approaches.

We do not expect to be able to use deep learning models such as the ones that in recent years have proved their effectiveness, including EfficientNet, YOLO (You Only Look Once, currently at version v9), U-Net, ResNet (Residual Net), Mask R-CCN:

12. Tan, M. and Le, Q., 2019, May. **Efficientnet**: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning* (pp. 6105-6114). PMLR. <http://proceedings.mlr.press/v97/tan19a.html?ref=jina-ai-gmbh.ghost.io>

13. Redmon, J., Divvala, S., Girshick, R. and Farhadi, A., 2016. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 779-788). <https://arxiv.org/abs/1506.02640>
14. Jiang, P., Ergu, D., Liu, F., Cai, Y. and Ma, B., 2022. A Review of Yolo algorithm developments. *Procedia computer science*, 199, pp.1066-1073. <https://www.sciencedirect.com/science/article/pii/S1877050922001363>
15. Ronneberger, O., Fischer, P. and Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. In *Medical image computing and computer-assisted intervention—MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18* (pp. 234-241). Springer International Publishing. <https://arxiv.org/abs/1505.04597>
16. He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778). <https://arxiv.org/abs/1512.03385>
17. He, K., Gkioxari, G., Dollár, P. and Girshick, R., 2017. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision* (pp. 2961-2969). <https://arxiv.org/abs/1703.06870>

More recent models, such as [OpenAI's CLIP](#), are more flexible but still require fine tuning to perform optimally:

18. Radford, A., Kim, J.W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J. and Krueger, G., 2021, July. Learning transferable visual models from natural language supervision. In *International conference on machine learning* (pp. 8748-8763). PMLR. <https://arxiv.org/abs/2103.00020>

A more promising alternative seems to be the use of Foundation Models, which can of course be fine-tuned, but that are more capable of working out-of-the-box, DINOv2, by Meta, and Segment Anything, by Meta (SAM), that have recently been used successfully in a fast-growing number of EO-based tasks:

19. Oquab, M., Darcet, T., Moutakanni, T., Vo, H., Szafraniec, M., Khalidov, V., Fernandez, P., Haziza, D., Massa, F., El-Nouby, A. and Assran, M., 2023. Dinov2: Learning robust visual features without supervision. *arXiv preprint arXiv:2304.07193*. <https://arxiv.org/abs/2304.07193>
20. Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A.C., Lo, W.Y. and Dollár, P., 2023. Segment anything. In *Proceedings of the IEEE/CVF International Conference on Computer Vision* (pp. 4015-4026). <https://arxiv.org/abs/2304.02643>