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Exploiting the Deep Learning Potential for Sea Plastic Detection

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***Abstract* – Plastic debris are one of the most harmful product for the health of the marine ecosystem. Usually, they enter the oceans as macroplastics through river deltas and tend to aggregate with other materials, floating on the sea surface. With the time passing, the macroplastics tend to degrade in microplastic and enter in the marine life because of ingestion. A fast and precise detection of floating plastics is necessary for monitoring and saving the sea ecosystem. Recent studies have demonstrated how remote sensing (and in particular satellites) can be helpful in such detection. Moreover, in the recent years, deep learning (DL) methods have shown great performance particularly in classification and detection. DL methods can help to overcome some pre-processing step that are time consuming and speed-up the detection. The aim of this paper is to exploit the possibility of constructing a large database of satellite images and correspondent mask of detected plastic. Such database will be freely available in order to promote the research on this topic and on the use of DL.**

I. INTRODUCTION

The marine pollution by plastic debris is one of the most critical and emerging global issues that represents a considerable threat to the ecosystems of oceans environments. The plastic pollution is the chemical debris that requires the deeper insight from the scientific community in order to manage and mitigate the consequent threats of their related issues. Plastics are low cost and ease the manufacture of synthetic materials that more than any other material has interred to marine and freshwater ecosystems all around the globe.

Thanks to the great attention moved to the global ecosystem, in the recent years plastic passed from being one of the cheapest and most useful material in the world to the most harmful product for the environment health. Most of the plastics enters the oceans through rivers outlet and starts to float in the coastal waters. The fate of these plastics is either floating in the marine environment moving to open sea or sinking. In both cases, macroplastics tend to fragment and degrade into microplastics and to enter in the marine life through ingestion. For the health of sea ecosystem, it is fundamental to adopt a quick strategy for detecting plastic litters in order to remove them as soon as possible.

The issue of marine plastic pollution has been revealed in the 1990s and is currently secured by some universal guidelines [1]. At present, shoreline surveys designed to identify the distributions of plastic litter in oceans and lakes are time-consuming, costly and provide limited areal coverage. Remote sensing technology has the potential to overcome the limitations of open-water and shoreline surveys. Remote sensing has the ability to monitor coastal and open-sea and to detect areas where plastic debris tend to aggregate. Remote sensing sensors mounted on drone, aircrafts and satellites give the possibility to easily and rapidly investigate a large area reducing the human intervention.

Recent studies have demonstrated the ability of optical satellites (like Sentinel-2) in detecting floating litters. The Marine Remote Sensing Group from the University of the Aegean within the Plastic Litter Projects of 2018 and 2019 [2]-[3], have placed standardised plastic objects in coastal waters and have shown the possibility to detect them from Sentinel-2 images. More recently, *Biermann et al.* have defined a new spectral index, the Floating Debris Index (FDI) that, combined with Normalised Difference Vegetation Index (NDVI), allows the detection of floating debris from Sentinel-2 images after atmospheric correction. In order to validate their method, *Biermann et al.* have acquired images based on information given by LITTERBASE portal [5] that collects the scientific researches on plastic detection and lists the correspondent study areas.

Anyway, a pre-processing step is necessary: a segmentation for identifying land and sea, and an atmospheric correction are needed.

As in many application, deep learning (DL) solutions have shown great performance in detection, classification and segmentation [6]. In order to speed up the plastic detection and make it faster, using DL technique combined with satellite data could be very useful. The drawback is the need of an huge dataset for the training phase. Indeed, most of DL method are base on the training of a convolutional neural network that needs as many examples as difficult is the problem. Obviously, the bigger is the the dataset, better are the performance. Thanks to the findings of *Biermann et al.* and the huge information provided by LITTERBASE, the aim of this paper is to exploit the possibility of a database construction suitable for DL based detection of floating litter debris.

II. DETECTION OF FLOATING DEBRIS

Among several methods, the most recent has been proposed in [4] where the authors propose the detection and classification of floating litters from optical data acquired by Sentinel-2. To this aim, first an atmospheric correction has been performed on the optical image using ACOLITE (Atmospheric Correction for OLI lite version 20181210.0). Cluster of floating materials (phising net, plastics, algae, etc...) have been detected by means of spectral indexes and a Naive-Baysian classificator is trained for the final recognition step. They define a new spectral index named FDI that combined with NDVI are used for the detection. Their definition related to the Sentinel-2 bands are described in Equations 1 - 3. The NDVI quantifies vegetation by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs). The FDI is the subtraction of the baseline reflectance of the NIR from the NIR band relying on the high reflectance of the plastic at 700 nm. In seawater different materials such as clear seawater, wood, spume and pumice have a different response to the FDI and NDVI indexes. In particular, their ranges overlap with grouped plastic in the FDI, while are almost separated in NDVI. In fact, NDVI allows to distinguish plastics from other materials at pixel scale, while the FDI allows their detection at subpixel scale. In fact, FDI shows high response in those pixel composed by different material whit at least a concentration of 30% of plastic.

At this point, *Biermann et al.* used a combination of FDI and NDVI for the detection of floating debris composed mostly of plastic. Each material has high reflectance in a certain range of FDI and NDVI, so variation of this range allows the detection of cluster of different floating materials. An example is shown in Fig.1 where floating debris were detected in the coastal waters of Accra (Ghana). For a deeper insight, the reader is invited to refer to [4].

III. PROPOSED METHOD

The aim of this paper is to exploit the findings of *Biermann et .al* in order to construct an accessible database for implementing DL solutions that can predict the presence of floating debris directly from the satellite image without any pre-processing. In fact, the method proposed by *Biermann et al.* is very useful for the detection of floating material but it is time consuming given the pre-processing steps: the atmospheric correction takes several minutes and later the images need to be processed with satellite software (like SNAP) in order to extract the image and information such as FDI and NDVI. A detection of floating debris based on DL could provide fast and accurate performance working directly on the original acquired image. It is well known that DL has reached state-of-art performance in topics such as detection, segmentation and classification of natural images. Recently, many DL algorithms have been proposed for several task such as classification, detection, denoising, super-resolution (and so on) of remote sensed images outperforming model based approaches [10], [8], [7], [9]. Naturally, the good performance of DL methods is based on the presence of a good and wide training dataset.

Fig. 1. Example of the detection of floating debris with FDI and NDVI: in the top optical image of Accra, Ghana; in the bottom red box zoom is highlighted: optical image on the left, resulting mask on the right.

Nowadays, a database for detection of floating plastics is not available and its construction could produce a huge investment of the research in this topic. According to the information provided by the LITTERBASE portal, areas characterized by floating materials have been selected and correspondent Sentinel-2 images are acquired where available. Following, the detection of plastic material is performed applying the method proposed in [4].

Sentinel-2 is an optical satellite that provides thirteen multispectral bands images with low spatial resolution (10 - 60 m), details for each band are listed in the Table 1 . Let be I the multispectral image acquired from the sensor, the FDI and NDVI indexes can be computed as in the following:

$$FDI = I_8 - I'_8 \tag{1}$$

$$I'_8 = I_6 + (I_{11} - I_6) \times \frac{\lambda_8 - \lambda_4}{\lambda_{11} + \lambda_4} \times 10 \tag{2}$$

$$NDVI = \frac{I_8 - I4}{I_8 + I_4} \tag{3}$$

Relying on the results shown in [4], different ranges of FDI and NDVI have been exploited and used for the detection of grouped plastics.

Table 1. Sentinel-2 bands specifications

Band	Descriptor	S2A Wavelength (nm)	S2B Wavelength (nm)	Resolution (m)
I_1	Coastal	442.7	442.3	60
I_2	Blue	492.4	492.1	10
I_3	Green	559.8	559.0	10
I_4	Red	664.6	665.0	10
I_5	Red Edge1	704.1	703.8	20
I_6	Red Edge2	740.5	739.1	20
I_7	Red Edge3	782.8	779.7	20
I_8	NIR	832.8	833.0	10
I_{8a}	Narrow NIR	864.7	864.0	20
I_9	Water Vapour	945.1	943.2	60
I_{10}	SWIR Cirrus	1373.5	1376.9	60
I_{11}	SWIR1	1613.7	1610.4	20
I_{12}	SWIR2	2202.4	2185.7	20

IV. RESULTS

In this section, some results on the test cases shown in Figure 2 have been presented. In particular, a realistic case in Mytilene (Greece) and two real cases, one in Accra (Ghana) and another in South Gabriola (British Columbia), have been considered. For the detection, an interval for each index has been set: $0.018 < FDI < 0.7$ and $0 < NDVI < 0.22$. The choice of such intervals has been done according to the response of different materials to the FDI and NDVI [4]: this setting has been selected in order to have a relaxed interval allowing an initial detection of different materials, while a finer recognition of the targets is required at the classification step. The classification step can be performed by different methods like correlation among spectral signatures, clustering, DL based method and others, but this goes beyond the scope of this work. The Greece area shows three boxes of dimension 10 m $\times$ 10 m containing plastic targets placed by Marine Remote Sensing Group inside the Plastic Litter Project 2018 [2]. The two real cases are indicated in the LITTERBASE dataset and in [4].

The realistic case has been used as validation of the method and for a more precise setting of the intervals of the indexes. Indeed, in Figure 3 three targets have been detected has expected. The two real cases show the ability of the method in detecting grouped plastics both in a simple case like Ghana in Figure 4, where some material are almost visible directly from the satellite image, and in a more challenging case such as South Gabriola in Figure 5. According to the LITTERBASE portal and to the results of *Biermann et al.* the obtained data are reliable.

These three results show the possibility of constructing a dataset relying on the FDI and NDVI. The database will be composed of the original Sentinel-2 image and correspondent mask of detected debris. Once a wide dataset is ready, a neural network can be trained for the detection of such materials working directly on the acquired image without any atmospheric correction and land/sea segmentation that are very time consuming for large image (typical of satellites images). The idea of using Sentinel-2 is related to two main reason: first, the image are free and so it is possible to access as many images as it is necessary; second, the great amount of data available allows to train a network and its results can be used for transfer learning to another sensor with higher resolution and/or more bands (e.g WorldView-3 or hyperspectral sensors) but with poorer availability of data.

V. CONCLUSION

In this paper a database construction for floating debris suitable for DL methods has been exploited. Starting from the results of method proposed by *Biermann et al*, some Sentinel-2 images have been acquired in the area indicated by the LITTERBASE portal and detection of plastic by means of the FDI and NDVI have been performed. The results can be used as ground truth for defining a dataset composed of a satellite images and a reference mask. In future an extensive research will be conducted in order to process more areas. Once the dataset will be enough consistent, it will be freely available.

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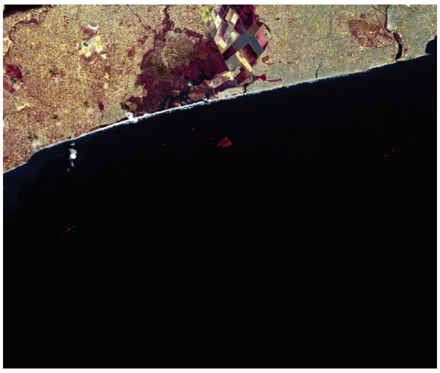
Greece



Ghana

South Gabriola

Fig. 2. Optical images acquired from Sentinel-2 of test cases, from the top to the bottom: realistic case in Mytilene (Greece), simple case in Accra (Ghana), challenging case in South Gabriola (British Columbia)

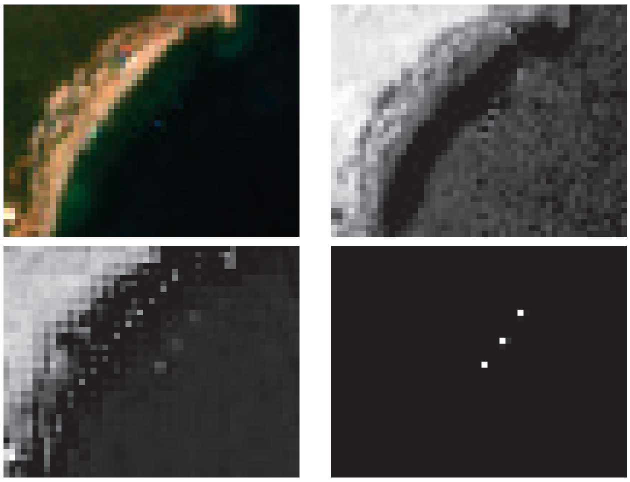


Fig. 3. Detection of floating debris with FDI and NDVI of Greece: a) Sentinel-2 image, b) NDVI, c) FDI, d) resultin mask

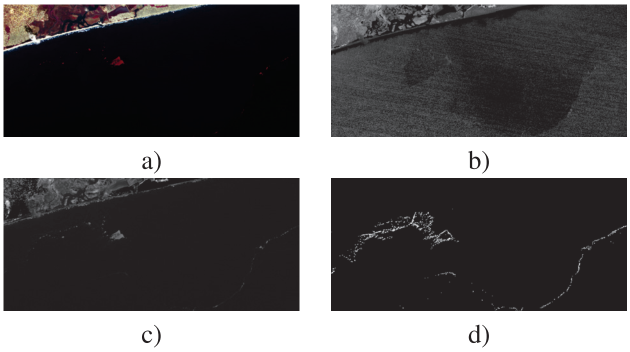


Fig. 4. Detection of floating debris with FDI and NDVI of Ghana: a) Sentinel-2 image, b) NDVI, c) FDI, d) resultin mask

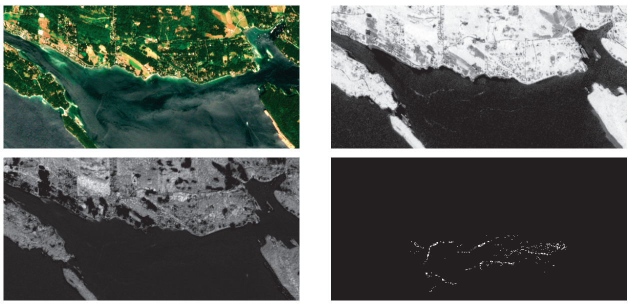


Fig. 5. Detection of floating debris with FDI and NDVI of South Gabriola: a) Sentinel-2 image, b) NDVI, c) FDI, d) resultin mask

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