ID12- BIG PLASTIC MASSES DETECTION USING SATELLITE IMAGES & MACHINE LEARNING

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Abstract
This communication describes a preliminary research on detection of big masses of plastic (marine litter) on the oceans and seas using EO (Earth Observation) satellite systems. Free images from the Sentinel 2 (Copernicus Project) platform are used. To develop a plastic recognizer, we start with an image where we can find a big accumulation of "non-floating" plastic: Almería. We made a test using remote sensing differential indexes, but we got much better results using all available wavelengths (thirteen bands) and applying Machine Learning (Neural Networks). Keywords – satellite, Earth Observation, Neural Networks.

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INTRODUCTION
Marine litter has become a major environmental problem. Consequently, there are many initiatives about it. Part of them are "proximity projects", focusing efforts on beaches and/or water near coastline [1].

Other initiatives aim to attack the problem of large masses of floating garbage that accumulate in the sea. Currents and tides tend to accumulate waste in large masses (litter islands). Within the categories of marine litter [2], in this case (floating debris), we must focus on plastic.

For large floating accumulations, the use of satellite imaging (EO: Earth Observation) is interesting [3,4]. The Sentinel 2 satellite produces multi-spectral images with thirteen wavelengths [5] that can be useful. Public images have a precision of 10m/px (on visible bands), which is low but enough for large masses. Automated vision applications can help fighting marine litter by detecting, quantifying, and monitoring large accumulations.

Sentinel 2 is limited to near-shore waters (although it includes the entire Mediterranean). In the ocean, we could extend development to the most recent Sentinel 3 (21 bands, 300m/px).

For this development, it is necessary to have images with significant amounts of plastic material. Although it is not floating plastic, an area known for huge plastic covers is Almería, Spain (where there exists an enormous extension of plastic greenhouses, figure 1).

USE OF DIFFERENTIAL INDEXES
In remote sensing, the so-called standard indexes are often used. These indexes are computed from pairs of chromatic components [6,7]. Another index-based methodology is presented in [8], where authors recommend a combination of two indexes. Testing this method on the former image, we get this result (figure 2).

Fig1. RGB composition from Sentinel 2, Almería, 100 Mpx,
10 m/px (100x100 Km2).

Studying plastic behavior at different wavelengths, we thought about an alternative index using bands 9 and 8. Id EST: computing (B8-B9)/(B8+B9).

Fig2. Indexes from [8].

Fig 3. Bands 8 & 9.

Combining these methods with a cloud detection method [9] and discarding the land areas with the help of maps, we could meet the purpose. However, in next section we will see more powerful tools that getting better results more directly.

NEURAL NETWORKS
With thirteen numerical values per pixel, we can think of this as a pattern recognition problem. For each point, we naturally obtain a feature vector.

The idea is using artificial neural networks [10] to learn the implicit relationships between different bands that may characterize plastic.

Network structure.
We use a single output network training it to obtain values of 1.0 for plastic and 0.0 otherwise. Under these conditions, a multilayer perceptron structure (MLP [10]) may work well. With three layers (one hidden level). Testing with ten hidden neurons (slightly less than number of inputs), we obtain good results and so we do not try more complex structures.

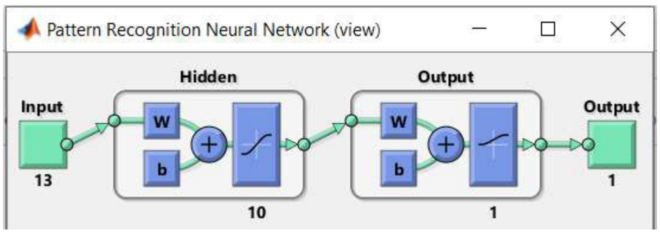

Fig 4. Network structure.

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Training and Test

We have started by labeling the original image manually (drawing a detailed mask on top of plastic areas, figure 5). Number of samples is more than enough. Even at smallest resolution, we have 3,348,900 samples for: 14 * 10 + 11 = 151 weights (number of samples should be over fifteen times the number of weights). We also balance the training samples (dropping randomly some samples of the majority class to avoid training problems).

We use MATLAB [11] training with Back-propagation algorithm [12]. 70% samples are dedicated to training, 15% to validation (verification for algorithm stop) and 15% to final testing.

Training has been successful, obtaining an error rate of 2%, see figure 6 (confusion matrixes) and figure 7: recognition result on a different image of the same place (to demonstrate generality of method).

Fig 5. Truth table.

Fig 6. Confusion matrixes.

Fig 7. Neural network result.

CONCLUSIONS

We have studied methods for the automatic detection and quantification of plastic waste floating in the sea. Although the use of differential indexes (very typical in remote sensing) may have some utility, the use of neural networks is the solution that provides the best result. In the future, it is planned to develop an application that automatically downloads and analyzes images to detect, quantify, and track large accumulations on sea. To study the great oceans, the work would have to be extended to the OLCI sensor of Sentinel 3 (21 bands).

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