

Real-time plastic litter detection using hyperspectral sensing on drone

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Abstract— A hyperspectral sensing system operating in the SWIR band (900-1700nm) was previously developed for drone-based detection of plastic litter in the environment. The detection software is based on a linear classifier trained on examples, that detects plastics and transmits information to a ground station that visualizes on a map the location of points surveyed, labeled as plastics where applicable. In this paper, we report on implementation of plastics litter detection in real time, while the drone is flying.

Index Terms— drones, environmental monitoring, hyperspectral sensors, plastics waste.

I. INTRODUCTION

PLASTIC litter causes damage to the environment and is difficult and expensive to remove. Environmental programs are active internationally to enhance prevention of plastic waste dispersion and collection of litter in the environment (e.g. public initiatives of the European Union [1], USA [2], United Nations [2][3], as well as private organizations [4]).

Dealing with plastic litter in waters involves considering the whole system of sea, rivers, basins, and coastal areas in an integrated view, because floating litter is transported by the rivers to the sea, and can be temporarily held on the coast and along rivers [5]. This means that monitoring of litter in different water and ground environments is necessary for preventing such materials to reach the sea and for collection in all areas where they are dispersed [6][7].

The authors developed a custom sensor system [8] based on a push-broom hyperspectral sensor for the lower SWIR band (1000-1700nm) to detect plastic objects by aerial survey from drone, also appropriate for deploying on other types of platforms (e.g. on boats) or from fixed supports (e.g. for floating debris in rivers). Such system was employed in experimental missions intended to validate the hardware setup and to test the algorithms that were originally developed in Matlab for offline processing of recorded data.

The system was later upgraded to add a second hyperspectral sensor operating in the visible and near infrared (VIS/NIR)

band (400-1000 nm), and to add an inertial navigation system (INS) to obtain synchronized geo-localization of the acquired data. The latter sensor was also instrumental in the development of the operational concept of the system, intended for real-time detection of plastic litter in support of waste collection systems.

In this paper, we describe the upgraded hardware system, discuss the algorithmic strategies used to obtain real-time operation, and the software implementation. While the detection methodology and algorithms were validated by qualitative and quantitative tests as reported in our previous publications [8][9], in this work we report an experiment that validates proper operation of the system in real time, and the concept of operational application of the future fully-engineered system is discussed.

II. MATERIALS AND METHODS

A. Real-time plastic litter detection concept

Plastic litter collection is a time-consuming and expensive task [10], and its cost is only marginally balanced by the value of recyclable materials, especially in open sea, while it may be more manageable in relatively confined environments [11]. In any case, orienting the cleanup effort to areas where a significant amount of litter is located can significantly enhance the efficiency of such activity. For this reason, we developed the sensor system described in this paper, in particular for its application to plastic waste detection.

When we tackle floating debris detection and collection, of course we must take into account that the material is continuously moving under the action of currents and wind, therefore aerial detection should not be aimed at static mapping, but rather used in direct synergy with collection systems to orient them, possibly in a fully automatic fashion, to the areas where a larger amount of waste is present. For this reason, the detection system must operate in real-time, and provide a flow of information continuously to monitoring stations and waste collection vessels.

B. Sensor system hardware architecture

We assembled a stand-alone push-broom hyperspectral sensor system (fig. 1) based on two camera-spectrometer

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M. Balsi and M. Moroni developed the hardware and algorithmic architecture of the detection system, L. Conti and R. Scalia contributed to the development of the real-time software, written by the latter; S. Bouchelaghem participated to the experimental validation.

A video documenting the experiment of section III is available at <https://youtu.be/nxFZu-k07VU>

devices operating in the bands 400-1000 nm (VIS/NIR) and 900-1700 nm (SWIR – short-wave infrared), with the purpose of realizing a stand-alone payload for a relatively small drone covering a large wavelengths range for high versatility. It is worth recalling that, through a slit, the spectrometer captures a narrow line image of the target and disperses the light from each line pixel into a spectrum, orthogonally with respect to the line. An Intel-based board PC performs data acquisition and storage, and data processing for detection and communication with a ground station. A compact INS provides Global Navigation Satellite System (GNSS)-based geolocation and attitude sensing, for hyperspectral cube generation and georeferentiation. An additional RGB camera equipped with a standard lens provides images with strong superposition, adding the option of mosaicking and of real-time transmission to ground of relevant scenes corresponding to alerts.

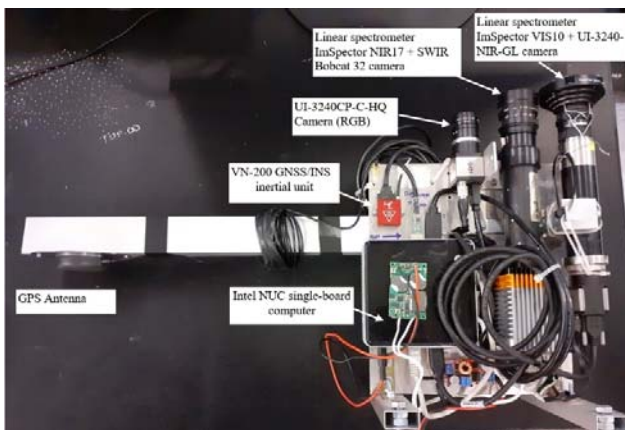


Fig. 1. Hyperspectral sensor system

The sensors chosen for this project are

- a Xenics Bobcat 320 featuring sensitivity between 900 and 1700nm (SWIR) and 320×256 pixels (easily replaceable by a camera of the same family with 640×512 pixels), assembled with a linear spectrometer ImSpector NIR17 OEM by Specim capturing light through a narrow slit aligned in the direction of the smaller side of the sensor, so that a spectral image of 256 spatial positions × 320 wavelengths (individual bands about 3nm wide) is obtained.
- an IDS UI-3240CP-NIR-GL camera, sensitive in the visible and NIR bands (400 to 1000nm), assembled with a Specim ImSpector V10 spectrometer. The combination of reflected power spectrum and camera spectral sensitivity made it necessary to roughly equalize the radiation by applying an optical filter Schott BG64.

The payload was mounted on a DJI Matrice 600 drone (fig. 2), operated by Oben srl [12], that was normally flown at 5-15m height and 2m/s speed, obtaining pixel size of roughly 2-4cm.

In a first prototype of the system [8], to build the hyperspectral cube we employed images obtained by a visible camera IDS UI-3240-CP-C-HQ synchronized with the other cameras by hardware trigger. A mosaicking algorithm was used to stitch

such images together, and the same roto-translation parameters obtained were applied to the spectral images. Such method proved quite effective and avoided further complication (and cost) of the system, but it occasionally failed on poorly structured surfaces (in particular over water), and did not allow for georeferentiation of the data. Therefore, in a recent upgrade of the system, we integrated a Vectornav VN-200 GNSS-aided Inertial Navigation System to provide synchronized position and attitude data for easy and accurate hyperspectral cube reconstruction.



Fig. 2. Drone and sensor

C. Plastics detection algorithms and software implementation

Our detection methodology [8] is based on linear classifiers, obtained by Linear Discriminant Analysis applied on a subset of spectral bands selected by the minimum-redundancy-maximum-relevance. The 10 nm bands automatically chosen by this algorithm are mostly located between 1180 and 1270 nm and between 1510 and 1620 nm. It is known, that additional absorption bands of plastic polymers appear at wavelengths beyond 1700nm [13], but in this project we chose a compact and lightweight non-cooled sensor that is not sensitive to them. Nevertheless, consistently with findings of other authors [14], we already proved [15] that the band 1000-1700 nm contains enough information to properly detect even individual polymers one from the others. The classifier is obtained by optimization on a wide set of manually labeled examples taken from data gathered in various sites and environmental conditions. A mosaicking algorithm, applied to the recorded set of hyperspectral images, allows to reconstruct a hyperspectral cube, that can be processed offline to obtain a map of plastic objects at few centimeters resolution. However, for waste collection assistance purposes, we need to process the data in real-time on-board the drone, and send detection results to a ground station by radio-link. In this case, we do not need high spatial resolution, and even the localization accuracy is not so strict, so that we may process each hyperspectral image (that has a footprint on the surface of several meters across the flight trajectory) at once, giving a single detection response, and associate a relatively rough geo-localization by reading the

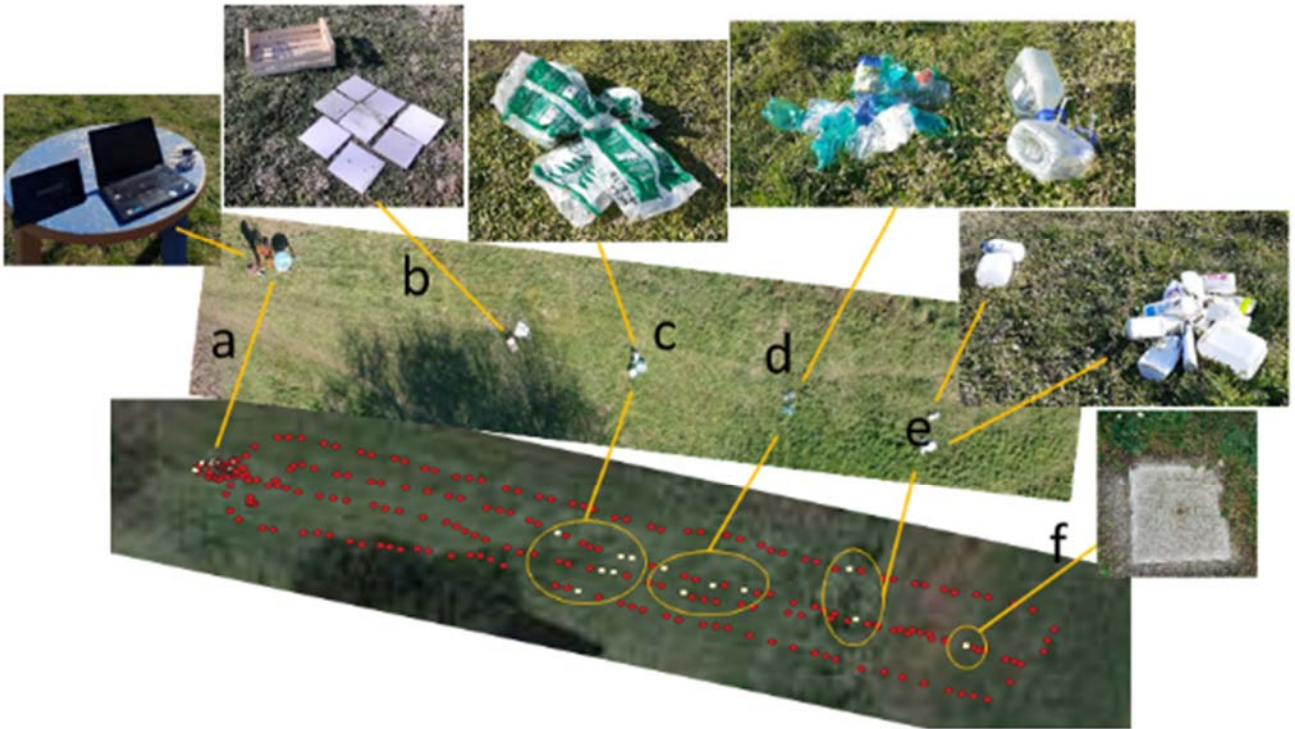


Fig. 3. Experimental setup and results. (a) Table; (b) floor tiles and crate; (c) LDPE bags; (d) PET bottles; (e) HDPE containers; (f) manhole cover. The bottom part of the figure shows the results re-mapped offline over Google Earth imaging; The aerial image in the center was taken from the drone and manually approximately oriented and sized to match the bottom image.

GNNs position of the drone simultaneously with each image acquisition.

The data acquisition and processing software for the on-board computer was written in C++ and structured as follows:

- The data acquisition thread polls the three cameras and the INS continuously, and acquires images and position data from them at a pre-defined HW trigger frequency, currently 12.5 Hz. Such data are stored in separate folders in the SSD memory of the computer.
- The detection thread monitors the SWIR images folder and every time it finds a new image it applies the linear classifier to determine if at least one of the pixels in the line scanned contains plastics. Then, it reads the position from the INS and sends a short message to a serial port containing latitude, longitude, and a flag indicating presence or absence of plastics.
- The message is received by radio link at the ground station, a computer running a real-time mapping thread that frequently refreshes a map where green or red dots are plotted according to the plastics indicator.

III. VALIDATION

After debugging and testing on several sets of recorded data, a validation experiment was performed on a grassy field where several small heaps of household plastic waste objects (sorted between PE and PET materials) were placed on the ground, together with other relatively bright objects (white floor tiles

and a wooden crate) used for control (fig. 3). As we already proved, recognition of plastics floating in water (that absorbs SWIR radiation almost entirely) is easier than on vegetation, ground, or other materials in background, so that this experiment is quite representative of wide range of practical cases.

A notebook PC was used as ground station, and an Android tablet used as interface for the on-board computer, just for setup and activation of the software. The flight was pre-programmed to be executed automatically following four parallel lines along the line where the plastic samples were placed. The flight height was 6m, so that the swath of the hyperspectral sensor at ground level is also about 6m and the pixel size about 2.5cm. The system generates a detection signal when the classifier detects plastics in at least 3 pixels of the line scanned across the flight path. The map was generated in the ground station during the flight, and correctly corresponds to the situation on ground (fig. 4). In fact, all plastics objects present in the scene surveyed were correctly detected and approximately geo-located, including two plastic objects that were not put on purpose, namely the plastic table used to hold the computer and the tablet on one side, and the plastic cover of a small manhole of the irrigation system of the adjacent orchard on the other side. On the other hand, the non-plastics objects were correctly not detected. A video of the experiment is provided as additional material.



Fig. 4. Map produced in the ground station during flight. Background: Open Street Map.

It is apparent from comparison of the maps obtained and the aerial photograph (fig. 3), as well as by superposition of the accurate flight logs obtained from the drone (not shown here to avoid overloading the figures), that the plastics heaps are correctly detected and geolocated, even if the points do not appear perfectly located on the map. In fact, it is to be noted, that the georeferencing accuracy is affected by several sources of error. Part of the error is caused by GNSS receiver (our INS uses the GPS and Galileo constellations). Moreover, the detection signal is associated to the longitude/latitude location of the drone at the time of detection and is related on ground to a line of points that was in this experiment about 6 m wide across the flight path. Any pixel along this width may contribute to a detection that is mapped in the current position of the drone. An additional source of error is due to the fact that the drone does not fly in an exactly flat orientation with respect to ground, so that the coordinates of the drone position may project slightly displaced on ground. Nevertheless, considering the scenario described in sec. II, where we expect the drone to be exploring an area of operation on water, where the floating litter is continuously moving, the few meters of error introduced by the system are to be considered negligible. It is reasonable to expect, that in a real scenario the scale of the plastic masses to be detected is larger, so that wider areas will be surveyed from greater altitude, and positioning accuracy will be even less relevant.

IV. CONCLUSION

A custom hyperspectral sensing system was developed, that allows real-time detection of plastics litter from an aerial platform, and simultaneous mapping of results in a ground station. The system, previously validated by off-line processing, was in this work validated experimentally in real-time, proving that it accurately detects the objects, mapping the results in the remote ground station.

Our hyperspectral system requires manual setting of focus and exposure. When operating in diverse environments it requires careful settings prior to flight, because the data acquired may easily saturate or be overall very dark, thus losing the relevant information conveyed by relatively small variation of perceived reflectance.

In perspective, the data received in this way, may be used to automatically guide a waste collection vessel to the area where most litter is present.

REFERENCES

- [1] European Commission. https://ec.europa.eu/environment/marine/good-environmental-status/descriptor-10/index_en.htm
- [2] US Department of Commerce, National Oceanic and Atmospheric Administration. <https://marinedebris.noaa.gov/info/patch.html>
- [3] United Nations Environmental Program. <https://www.unep.org/cobsea/what-we-do/marine-litter-and-plastic-pollution>
- [4] The Ocean Cleanup, The Netherlands. <https://theoceancleanup.com/about/>
- [5] G. Cesarini, M. Scalici, "Riparian vegetation as a trap for plastic litter", *Env. Poll.*, vol. 292, part B, 118410, 2022. doi: 10.1016/j.envpol.2021.118410.
- [6] K. Topouzelis, D. Papageorgiou, G. Suaria, S. Aliani, "Floating marine litter detection algorithms and techniques using optical remote sensing data: A review", *Marine Poll. Bull.*, 112675, 2021. doi:10.1016/j.marpolbul.2021.112675.
- [7] S.P. Garaba, J. Aitken, B. Slat, H.M. Dierssen, L. Lebreton, O. Zielinski, J. Reisser, "Sensing ocean plastics with an airborne hyperspectral shortwave infrared imager", *Environ. Sci. Technol.* 52, 11699–11707, 2018
- [8] M. Balsi, M. Moroni, V. Chiarabini, G. Tanda, "High-Resolution Aerial Detection of Marine Plastic Litter by Hyperspectral Sensing", *Remote Sens.*, vol. 13, no. 8, 1557, 2022. doi: 10.3390/rs13081557J.
- [9] M. Balsi, S. Esposito, M. Moroni, "Hyperspectral characterization of marine plastic litters". *2018 IEEE International Workshop on Metrology for the Sea; Learning to Measure Sea Health Parameters, MetroSea 2018*, pp. 28–32
- [10] NOAA. <https://response.restoration.noaa.gov/about/media/how-much-would-it-cost-clean-pacific-garbage-patches.html>
- [11] Ranmarine, The Netherlands. <https://www.ranmarine.io/>
- [12] Oben srl, Italy. <https://www.oben.it/>
- [13] S.P. Garaba, H.M. Dierssen, "Hyperspectral ultraviolet to shortwave infrared characteristics of marine-harvested, washed-ashore and virgin plastics". *Earth Syst. Sci. Data*, 12, 77–86, 2020. doi:10.5194/essd-12-77-2020
- [14] M. Moshtaghi, E. Knaeps, S. Sterckx, S.P. Garaba, D. Meire, "Spectral reflectance of marine macroplastics in the VNIR and SWIR measured in a controlled environment", *Sci Rep* 11, 5436 (2021). doi:10.1038/s41598-021-84867-6
- [15] M. Moroni, A. Mei, A. Leonardi, E. Lupo, F. La Marca, "PET and PVC separation with hyperspectral imagery". *Sensors* 2015, 15, 2205–2227