Proceedings of the joint international event 9th ARQUEOLÓGICA 2.0 & 3rd GEORES, Valencia (Spain). 26–28 April 2021

Received: 12/11/2020
Accepted: 27/02/2021

ARTIFICIAL INTELLIGENCE APPLIED TO MULTISPECTRAL IMAGERY FOR FLUVIAL MACROPLASTICS DETECTION

Irene Cortesi

Department of Civil and Environmental Engineering, University of Florence, Via di S. Marta 3, 50121 Florence, Italy.
irene.cortesi@unifi.it

Abstract:

The research treats the detection of macroplastics in fluvial environments with multispectral images obtained by means of UAV proximity sensor. Further it will be developed an automatic classification methodology through Artificial Intelligence, machine learning and deep learning algorithms. The final goal of the project is to build a cheap methodology to be used for the periodic monitoring and create a digital georeferenced cartography to be updated and easily usable from local administrations and communities. Thanks to an efficient cleaning of riverfront, consequently it is possible to have an urban and social redevelopment of this fundamental area for the cities.

Keywords: plastic waste, river ecosystem, macroplastic, multispectral proximity sensor, artificial intelligence, machine learning

1. Introduction

Plastic is the third world's most produced material by industry, after concrete and steel (Lavers & Bond, 2017). In the last fifty years it has been recorded a significant growth of production thanks to its high resistance to deterioration and versatility in use. Today people recycle only 9% of plastic they have used. The other parts are burned and accumulated in landfills or in the environment (Geyer, Jambeck, & Law, 2017). Consequently, plastic pollution has become one of the major global environmental emergencies (United Nations Environment Programme, 2016), with a significant impact on many terrestrial and aquatic ecosystems.

Depending on size (linear dimensions), plastic litter are divided in three different categories: macroplastics (> 5 mm), microplastics (between 5 mm and 0.1 μm) and nanoplastics (0.1 – 0.001 μm) (Bråte et al., 2017). Macroplastics fragmentation produces microplastics. Macroplastics are present in greater quantities than microplastics in rivers and in other aquatic environments. The majority of plastic litter in seas and oceans comes from rivers (Lebreton et al., 2017). Consequently, the study of fluvial distribution and transportation mechanism is important because in these habitats macroplastics can be detected and recovered before they reach marine environments. However, only 20% of global studies about rivers concerns the problems related to macroplastics (Blettler & Wantzen, 2019).

Moreover, the mouth of the river and the riverfront will get more attention during this research because they are the most critical sections of the river where every waste flow into. In fact, the river basin is a closed system with a constant flow that runs from mountain to valley. In many cities the riverfront is an identity part of the place and often tells somethings of the past. In the last years, some big towns have started the regeneration process of the riverfront, for their cultural identity like Hamburg, London (Schubert, 2010) or Detroit (Detroit Riverfront Conservancy, 2021). For these reasons the detection of macroplastics in the river is not only an environmental topic but also urban.

2. State of art

The plastic pollution is a topic studied in many different disciplines, in particular remote sensing technologies have provided effective methods for the identification of plastic waste in aquatic environments. Most of the surveys for the detection of plastic waste use only Infrared bands (from 900 nm to 1700 nm of electromagnetic spectrum on), in particular NIR (Near InfraRed) and SWIR (Short-Wave InfraRed) because this part of electromagnetic spectrum is not influenced by the colour of objects (Salzer & Siesler, 2014), and satellite imagery for remote detection of large accumulations of floating plastics in natural seawater (Topouzelis, Papakonstantinou, & Garaba, 2019). It is important to consider that remote sensing from satellites returns multispectral images with a spatial resolution that varies from half a metre to some kilometres and high-resolution data are often not freely available. Other researchers have proposed an automated system for identification and separation of plastic resins based on NIR reflectance spectroscopy (Masoumi, Safavi, & Khani, 2012).

An alternative methodology has been developed by the author during the research work for her master's degree thesis based on the use of proximity sensors (i.e., MAIA-WV2 made by SAL Engineering and EOPTIS) (SAL Engineering and EOPTISSAL Engineering, 2018) combined with the Decision Tree algorithm (a multistage classifier based on binary decisions) for the detection and classification of macroplastics in fluvial ecosystems. An important step of this study was the analysis of the spectral signatures of plastic waste. In the NIR bands radiance values of plastic samples are higher than the other elements of environment but the VIS bands showed greater variations due to the different colour, as presented in Figure 1. Thanks to this knowledge it was possible to build the expressions and the rules to implement the decision tree algorithm (De Giglio et al., 2020). This method has some limits which will be probably overcome through Artificial Intelligence.

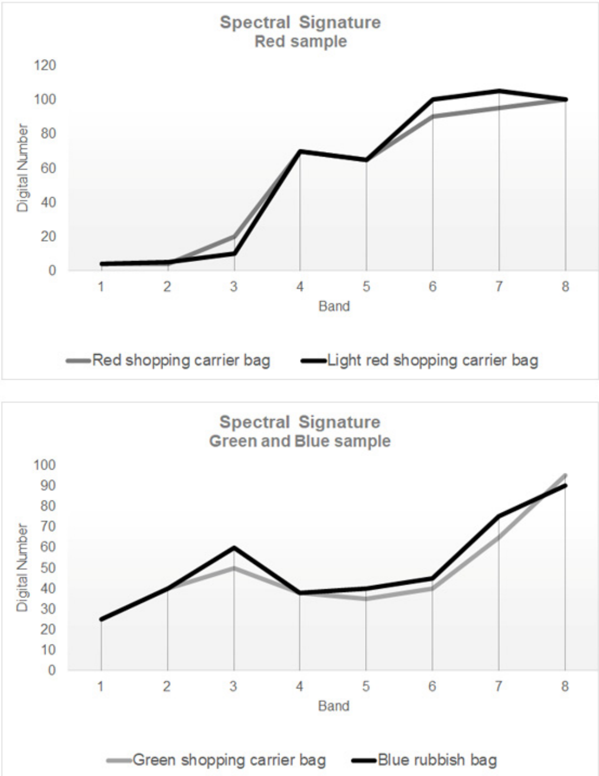

Figure 1: Spectral signature of plastic samples with a different colour.

3. Body section

This project aims to improve the previously developed procedure by using a machine learning approach. The use of Artificial Intelligence and Artificial Neural Networks (Anderson & McNeill, 1992) should provide effective tools to tackle the issues related to dealing with the large amount of information provided by multispectral sensors, and lead to an automatic and optimized plastic detection procedure.

Several machine learning based methods of classification will be investigated to determine the most suitable approach in the considered problem, ranging from the Random Forest algorithm, that creates sets of independent decision tree which share the same destination classes (Akar & Güngör, 2012), to advanced deep learning methodologies which implies a learning process through hierarchical multiple levels (Huang, Zhao, & Song, 2018). It considers worthwhile to apply a classification that combines multispectral image and spectral indices, in particular Plastic Index (PI) (Themistocleous, Papoutsa, Michaelides, & Hadjimitsis, 2020) and Normalised Difference Water Index 2 (NDWI) (Page et al., 2020). Machine learning methods should improve the accuracy of classification in respect to the previous result obtained by the Decision Tree method. In particular, the Random Forest method is known for its capabilities of reducing the overfitting issue (Segal, 2004) of the learning process of the Decision Tree.

One of the most distinctive characteristics of deep learning versus the machine learning technique, is the ability to automatically extract the best features from the input data to obtain the desired classification target (Aggarwal, 2018). Given the excellent results obtained by means of these tools in the classification field during the last decade (Belgiu & Drăguţ, 2016), their usage is expected to lead to noticeable improvement of findings in this project too.

The acquisition of various and numerous data sets is a sine qua non condition for the use of machine learning and deep learning technics (Kelleher, Mac Namee, & D'Arcy, 2015). Data collection campaigns will be carried out by using the multispectral sensor MAIA with the same spectral bands as the WorldView-2 satellite (from 395 nm to 950 nm of the electromagnetic spectrum). This sensor is characterized by reduced overall dimensions and weight (99x128x46 mm^3 and 400 g), being easily installed on UAV platforms (SAL Engineering and EOPTIS, 2018). It will be required to define a detailed flight plan through a dedicated software and to repeat the acquisitions periodically to have both a spatial and temporal data monitoring. A highly accurate georeferencing of the collected multispectral images will be performed through the measure of Ground Control Points (points of control distributed on the ground and measured by topography of GNSS methods) positioned before each UAV flight (Martin et al., 2018).

Finally, the obtained datasets will be shared online for free in order to promote the collaboration between different research teams, making future studies on these topics easier and providing shared data suitable to test different approaches.

4. Conclusions

The final goal of the whole project is to build a user-friendly and cheap methodology to be used for periodic monitoring of medium size areas.

Georeferenced images and classifications would allow setting up a digital cartography which can also be updated by crowdsourcing approaches, for example by using smartphones inputs of common citizens. This tool would provide live information on the position of plastic waste and on its transit sections for the development of related, efficient, systematic, and fast collection systems. Public administrations may take advantage of this tool both for developing prevention actions in the most impacted areas and for efficient and specific cleaning of fluvial areas.

The organisation of cleaning events of the Riverfront could be a way to requalify the area not just from environmental point of view but also urban and social purposes.

References

Aggarwal, C. C. (2018). *Neural Networks and Deep Learning*. Springer, 10, 978-3. https://doi.org/10.1007/978-3-319-94463-0

Anderson, D., & McNeill, G. (1992). Artificial neural networks technology. *Kaman Sciences Corporation, 258*(6), 1-83.

Akar, Ö., & Güngör, O. (2012). Classification of multispectral images using Random Forest algorithm. *Journal of Geodesy and Geoinformation, 1*(2), 105-112. https://doi.org/10.9733/jgg.241212.1

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing, 114*, 24-31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Blettler, M. C., & Wantzen, K. M. (2019). Threats underestimated in freshwater plastic pollution: mini-review. *Water, Air, & Soil Pollution, 230*(7), 1-11. https://doi.org/10.1007/s11270-019-4220-z

Bråte, I. L. N., Huwer, B., Thomas, K. V., Eidsvoll, D. P., Halsband, C., Almroth, B. C., & Lusher, A. (2017). *Micro-and macro-plastics in marine species from Nordic waters*. Nordic Council of Ministers. Copenhagen, Denmark.

De Giglio, M., Dubbini, M., Cortesi, I., Maraviglia, M., Parisi, E. I., & Tucci, G. (2020). Plastics waste identification in river ecosystems by multispectral proximal sensing: a preliminary methodology study. *Water and Environment Journal,* 1-11. https://doi.org/10.1111/wej.12652

Detroit Riverfront Conservancy (2021). Retrieved January 1, 2020, from https://detroitriverfront.org

Geyer, R., Jambeck, J. R., & Law, K. L. (2017). Production, use, and fate of all plastics ever made. *Science advances, 3*(7), e1700782. https://doi.org/10.1126/sciadv.1700782

Huang, B., Zhao, B., & Song, Y. (2018). Urban land-use mapping using a deep convolutional neural network with high spatial resolution multispectral remote sensing imagery. *Remote Sensing of Environment, 214*, 73-86. https://doi.org/10.1016/j.rse.2018.04.050

Kelleher, J. D., Mac Namee, B., & D'Arcy, A. (2015). Fundamentals of Machine Learning for Predictive Data Analytics: Algorithms. Worked Examples, and Case Studies. MIT press.

Lavers, J. L., & Bond, A. L. (2017). Exceptional and rapid accumulation of anthropogenic debris on one of the world's most remote and pristine islands. *Proceedings of the National Academy of Sciences, 114*(23), 6052-6055. https://doi.org/10.1073/pnas.1619818114

Lebreton, L. C., Van Der Zwet, J., Damsteeg, J. W., Slat, B., Andrady, A., & Reisser, J. (2017). River plastic emissions to the world's oceans. *Nature communications, 8*, 15611. https://doi.org/10.6084/m9.figshare.4725541

Martin, C., Parkes, S., Zhang, Q., Zhang, X., McCabe, M. F., & Duarte, C. M. (2018). Use of unmanned aerial vehicles for efficient beach litter monitoring. *Marine pollution bulletin, 131*, 662-673. https://doi.org/10.1016/j.marpolbul.2018.04.045

Masoumi, H., Safavi, S. M., & Khani, Z. (2012). Identification and classification of plastic resins using near infrared reflectance. *International Journal of Mechanical and Industrial Engineering, 6*, 213-20.

Page, R., Lavender, S., Thomas, D., Berry, K., Stevens, S., Haq, M., Udugbezi, E., Fowler, G., Best, J., & Brockie, I. (2020). Identification of Tyre and Plastic Waste from Combined Copernicus Sentinel-1 and-2 Data. *Remote Sensing, 12*(17), 2824. https://doi.org/10.3390/rs12172824

SAL Engineering and EOPTIS (2018). MAIA – the multispectral camera. Retrieved January 18, 2020, from https://www.spectralcam.com/maia-tech/

Salzer, R., & Siesler, H. W. (Eds.). (2014). *Infrared and Raman spectroscopic imaging*. John Wiley & Sons.

Segal, M. R. (2004). Machine learning benchmarks and random forest regression. UCSF: Center for Bioinformatics and Molecular Biostatistics.

Schubert, D. (2010). Waterfront revitalizations: from a local to a regional perspective in London, Barcelona, Rotterdam, and Hamburg. In *Transforming Urban Waterfronts* (pp. 90-114). Routledge.

Themistocleous, K., Papoutsa, C., Michaelides, S., & Hadjimitsis, D. (2020). Investigating Detection of Floating Plastic Litter from Space Using Sentinel-2 Imagery. *Remote Sensing, 12*(16), 2648. https://doi.org/10.3390/rs12162648

Topouzelis, K., Papakonstantinou, A., & Garaba, S. P. (2019). Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018). *International Journal of Applied Earth Observation and Geoinformation, 79*, 175-183. https://doi.org/10.1016/j.jag.2019.03.011

United Nations Environment Programme (UNEP) (2016). Inputs to the Secretary-General's Report on Marine Debris, Plastics and Microplastics. Retrieved Janury 18, 2020, from https://www.un.org/depts/los/general_assembly/contributions_2016/UNEP_Contribution_to_ICP_on_marine_debris.pdf