

MICROPLASTIC DISCRIMINATION WITH HYPERSPECTRAL MICROSCOPY

Carolina Blanch-Perez-del-Notario^a, Aala Azari^b, Murali Jayapala^a and Andy Lambrechts^a

^aImec, Kapeldreef 75, 3001, Leuven, Belgium; ^bEnvironment and Health, Department of Public Health and Primary Care, KU Leuven, Herestraat 49, 3000 Leuven, Belgium.

ABSTRACT

Hyperspectral imaging combines the characteristics of computer vision and point spectroscopy by obtaining an image with both spatial and spectral information. Therefore, in combination with microscopy, it can increase material discrimination possibilities with respect to regular microscopy imaging. We explore the potential to assess microplastic contamination and discriminate the plastic material. For this purpose, a hyperspectral short wavelength-infrared (SWIR) camera is used in combination with reflection microscopy for pellet material identification. This camera provides high spectral and spatial resolution in the 1100-1650 nm range, 100 spectral bands and up to 640x512 spatial resolution and high acquisition speed. The analysis performed shows potential to accurately discriminate 22 tested plastic pellets. In addition, the band relevance analysis performed shows that only a few specific bands are needed to provide accurate discrimination of the tested materials. The hyperspectral method presented could lead to a faster contamination assessment than traditional techniques used for microplastic discrimination.

Index Terms— Hyperspectral, microscopy, microplastic, pellet.

1. INTRODUCTION

The growing world population is increasing its demands for consumer products such as textiles or plastic consumer goods like food packaging. In this respect, industrial production processes account for a considerable share of the overall pollution and are accountable for many environmental problems [1]. This way, the increasing production of plastic products within the last decades together with the throw-away culture has led to millions of tons of plastics being disposed yearly in our oceans and lands, which often take hundreds of years to break down [2]. To solve this major environmental issue, reduction of unnecessary single-use plastics and improving waste management systems and recycling is required. In this respect, both computer vision and hyperspectral imaging play an important role in the recycling industry [3], [4] but also as inspection systems for pollution monitoring and

microplastic discrimination. Microplastics are defined as solid, polymeric particles with at least three dimensions greater than 1nm and smaller than 5 mm in size. They contaminate marine, freshwater, and terrestrial habitats, and have been recently detected in drinking water and food. For this reason, humans are frequently exposed to them, and it is believed their impact on health goes from inflammation and tissue damage to impaired reproduction capacity [5]. In this context, the Eximious European H2020 project [6] is studying the link of exposure to contaminants like silica particles or microplastics with the development of diseases such as immune-related ones.

In [7] several methods are presented for microplastic identification, namely Scanning electron microscopy [8] with Energy-dispersive X-ray Spectroscopy (SEM-EDS), Fourier Transform InfraRed Spectroscopy (FTIR), Raman, Near Infrared Spectroscopy (NIR) and Nuclear Magnetic Resonance (NMR) spectroscopy. The authors conclude that there is a need for more economical and portable techniques for microplastic discrimination. As discussed also in our previous work for particle identification [9], all these methods require complex and costly instrumentation and are time-consuming. In [10] the authors present a macroscale Raman imaging method that can image a 12x12mm sample area with microplastics in about 10 minutes. Five types of plastic materials (PP, PVC, PS, PE and PMMA) are discriminated against sea sand and dust particles with close to 100% accuracy on validation. The microplastics are of size 100-500 μm beads while the sea sand and dust particles ranged 100-300 μm . The method proposed is much faster than traditional Raman point-based imaging and in addition it shows suitability for imaging of microplastic samples suspended in water or bound to a metallic mesh.

This paper presents the use of Hyperspectral Imaging Systems (HSI) in combination with microscopy for the identification of microplastic samples. Hyperspectral imaging combines the characteristics of computer vision and point spectroscopy by obtaining an image with both spatial and spectral information. This technique enables therefore to analyze the chemical composition of materials while visualizing their spatial distribution [11], with its key advantages being that it is a non-invasive, non-contact and non-destructive technology. Both HSI and FT-IR methods

can obtain reflectance or transmittance spectra in IR of the dust deposits. The key differences are in their limitations with respect to time, area coverage, and spectral range. In FT-IR each measurement is a single point spectrum, so inspecting a wider area is more time consuming. Hyperspectral imaging, instead, produces spectra of a full image and it can therefore cover larger areas in less time (few minutes for linescan systems [12], below a second for snapshot camera systems [13]). In addition, FT-IR imaging systems are highly complex and expensive (~200 k€) [14]. FT-IR spectra often cover the 2500-25000 nm range while HSI focuses on a smaller range, typically visible (400–700 nm) and the near infrared (from 700 nm up to 2500 nm). HSI spectra have a narrower spectral range, but imaging large areas can be done in a much faster way than for FT-IR. There are many applications where hyperspectral imaging has gained high interest in recent years [15].

In [16] the authors propose a discrimination method based on RGB images where microplastics are stained with Nile-red fluorescence dye. Particles sized between 50 and 1200 μm are considered and high classification accuracy of 88% is achieved on 7 types of microplastics and 10 types of non-plastic nature-based source materials. A time-consuming sample preparation is required in this approach with respect to methods that may not require staining. There is a considerable amount of research dedicated to microplastic particle detection with hyperspectral imaging, mostly focusing on particle sizes over 500 μm . This way, four types of microplastics (PP, PE, PS and EPS pellets) have been imaged in the SWIR range (1000-2500 nm) and discriminated from organic material [17]. Similarly, pellets over 1mm of similar materials (PP, PE, PET, and PS) and other debris have been imaged in the SWIR range (1000-2500 nm) achieving accurate discrimination [18]. The same authors [19] have showcased hyperspectral imaging in the SWIR range as a high potential technology to analyze microplastics (< 5 mm), especially when compared to more expensive and time-consuming techniques such as Raman and FT-IR. The authors indicate however that insufficient spatial resolution is a current limitation in hyperspectral imaging to address smaller microplastics. Our work also focuses on microplastics discrimination in combination with reflection microscopy. In our case we address discrimination of up to 22 different microplastic types. Moreover, a band relevance analysis is performed to identify the subset of a few required spectral bands from the original set of 100 bands in the 1100-1650 nm range. This technology allows faster microplastic inspection than traditional methods without the need of specific sample preparation. In this respect, the already available compact hyperspectral cameras [12],[13] can pave the way for a faster and more cost-effective on-site microplastic inspection system.

2. MATERIALS AND METHODS

The 22 types of material pellets used in this study are summarized in Table 1. All materials in Table 1 are presented in pellet form and have a dimension below 5mm, except for Cellulose Acetate (CA), which is in powder form.

Table 1: Pellet material description

Abbrev	Material description	Form
ULDPE	Ultra low-density polyethylene	Pellet
LDPE.1	Low-density polyethylene	Pellet
LDPE.2	Low-density polyethylene	Pellet
LLDPE.13	Linear low-density polyethylene	Pellet
LLDPE.2	Linear low-density polyethylene made with metallocene catalyst	Pellet
MDPE	Medium-density polyethylene	Pellet
HDPE.1	High-density polyethylene	Pellet
HDPE.2	High-density polyethylene	Pellet
PP	Polypropylene	Pellet
PEST	Polyester	Fabric
PET.1	Polyethylene terephthalate	Pellet
PET.2	Recycled polyethylene terephthalate	Pellet
EVA	20% Ethylene-vinyl acetate	Pellet
ABS	Acrylonitrile-Butadiene-Styrene	Pellet
EPS	Expanded polystyrene foam	Beads
PS	Polystyrene	Pellet
PA6	Nylon 6	Pellet
PA66b	Nylon 6.6	Pellet
PVC.1	Polyvinyl chloride	Pellet
PVC.2	Polyvinyl chloride with phthalates	Pellet (flex)
CR	Crumb rubber from used tires	Particles
CA	Cellulose acetate	Powder

The imaging system used is composed of a Snapscan camera [12], which offers both high spatial resolution (up to 640x512px) and high spectral resolution (100 bands) over the wavelength range of 1100 to 1650 nm. This camera is coupled to a Seiwa transmission microscope [20] and performs the scanning internally. Thanks to its internal translation stage, there is no need for an external scanning movement. Moreover, performing data-set acquisition is as easy as with a snapshot camera and full hyperspectral images can be acquired in less than 1 minute. A 2.5x magnification objective is used in combination with bright field imaging. The microscope has a broadband tungsten-halogen light source, covering the 1100-1650 nm range of our hyperspectral camera. The set of 22 microplastic pellets are placed under the 2.5x objective lens and imaged with the Snapscan SWIR on the reflection microscope.

The classifiers are implemented with PerClass software [21] in combination with Matlab processing software [22]. We use pixel-based classifiers; therefore, no spatial information is used to support classification. We use the Quadratic Discriminant Classifier (QDC) [23] with, as preprocessing steps, either none, Linear Discriminant Analysis (LDA) [24] and Median Filtering (MF) [24] over a 5x5 block of surrounding pixels.

To find the most discriminative bands in our wavelength range, an in-house developed Genetic Algorithm (GA) [25],[26] in combination with the pixel classifier is used. The algorithm aim is to find a near-optimal subset of bands providing the highest mean classification accuracy in the test set. The behavior of the Genetic Algorithm is summarized here:

1. For any desired number of subset wavelengths an initial ‘population’ of individuals is created. Every ‘individual’ consists of a specific set of random band selections (e.g. [1100nm, 1250nm, 1460nm]).
2. For each solution (band selection), the fitness function of the GA is computed as the mean classification accuracy obtained for that band subset on the training/testing set.
3. The GA iterates for a given number of iterations and the best “individual” (band selection) is kept.

3. RESULTS AND DISCUSSION

Figure 1 shows the mean reflectance spectra obtained with the Snapscan SWIR and the reflection microscope for the plastic material samples described in Table 1. We can see the characteristic absorbance peaks of plastic around 1200 and 1400 nm. The best results are obtained with the pixel-based quadratic classifier (QDC) with LDA and median filtering (MF) 5x5 as preprocessing steps, as shown in Table 2. A small ROI is selected covering around 30% of the microplastic bead, with 20% of the ROI pixels used for training and the remaining 80% for testing. Discrimination based on the spectral characteristics of all 23 tested materials is possible, achieving a mean pixel classification accuracy per material of 92%, with a minimum classification accuracy of 61% for LLDPE 1. This is the only material where lower classification accuracy is obtained. However, even in that case, correct material recovery is feasible since a bigger percentage of pixels would still be assigned to the right category and majority vote can be applied. Figure 2 shows classified images for all 23 microplastic pellets. We can see how the pixel classification accuracy is good, despite few pixel misclassifications at bead borders, where the spectra may deviate due to object curvature or specular effects. Note that at object level (microplastic particle) a pixel majority vote can be used to determine the resulting material label of a full

particle. Therefore, for instance a 70% accurate pixel classification would translate into noticeably higher classification accuracy at particle level.

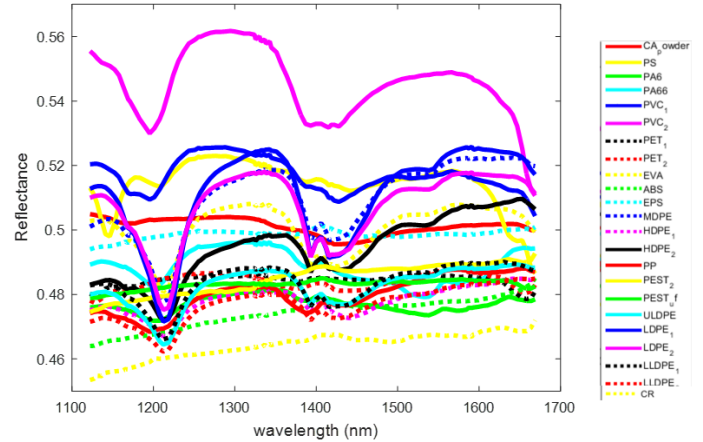


Figure 1: Mean reflectance spectra of plastic pellets.

Table 2: Accuracy for different preprocessing steps

Prep	No	LDA	MF3x3	MF5x5	MF5x5 +LDA
Mean (%)	66.3	68.1	84.4%	90.3%	92.1%
Min (%)	32.3	28.1	54.1%	61.1%	60.7%

Figure 3 shows the classified images for ABS and LDPE2 materials, where classification accuracy is increase from 45-47% respectively for no preprocessing applied to 76-73% when MF5x5 and LDA are used as preprocessing steps. The band relevance analysis presented previously is applied here by means of the genetic algorithm. This helps identify a subset of fewer wavelengths with still high levels of discrimination.

Table 3: Band relevance analysis

#Bands	Bands (nm)	Mean/Min	<50%
All 101	1100...1650 nm	92.1%/61%	-
Best 9	1131-1171-1212 1237-1294-1363 1399-1474-1668	82.4%/44%	Abs, uldpe
Snapshot bands	1122-1131-1152 1183-1201-1288 1374-1452-1641	78.3%/31%	Lldpe1, uldpe ldpe 2, abs
Best 6	1127-1212-1263 1381-1572-1658	78.3%/37%	abs,uldpe, lldpe1
Best 5	1224-1294-1411 1538-1658	73.4%/31%	hdpe1, uldpe, abs ldpe2, lldpe1
Best 3	1218-1255-1427	60.3%/13%	mdpe, hdpe1, Uldpe, ldpe2, Lldpe1, ps,abs

We also mimic the impact of using only the bands available in a lower resolution Snapshot SWIR camera [27], which would allow much faster acquisition than the high-resolution system of 101 bands. As we can see in Table 3, a smaller set of bands than the original 100 available in the Snapscan SWIR camera is sufficient to achieve high pixel discrimination accuracy. This way, the best 9 bands found by the algorithm only degrade performance from 92.1% to 82.4%, with two materials, abs and uldpe, having the lowest performance slightly below 50% accuracy. When compared to the 9 bands available in the snapshot SWIR camera, we see that the performance is slightly better in the found set of either best 6 or best 9 bands. However, the accuracy is still estimated to be good with the use of the snapshot SWIR camera, which allows in turn a very fast acquisition. Only when reducing the number of spectral bands to 5 or below, we start to see a more noticeable performance degradation, with more materials starting to reach pixel classification accuracies below 50%.

of microplastic material discrimination. The goal is to develop a method for fast assessment of the pellet materials by means of a cost-effective hyperspectral system. Twenty-three different pellet materials have been tested with reflection microscopy in combination with a hyperspectral camera (100 bands) and a multispectral camera of 9 bands in the same range. The results show that by high classification accuracy (over 90% at pixel level) of 23 types of microplastic particles can be obtained with a simple pixel-based classifier. A band relevance analysis of the high-resolution hyperspectral camera with 100 bands has shown that a few bands (<10) in the short wavelength-infrared range are sufficient to still achieve high classification accuracy.

ACKNOWLEDGEMENTS

We want to acknowledge the Eximious project, European Union's Horizon 2020 research and innovation programme under grant agreement No 874707, for which this research has been done.

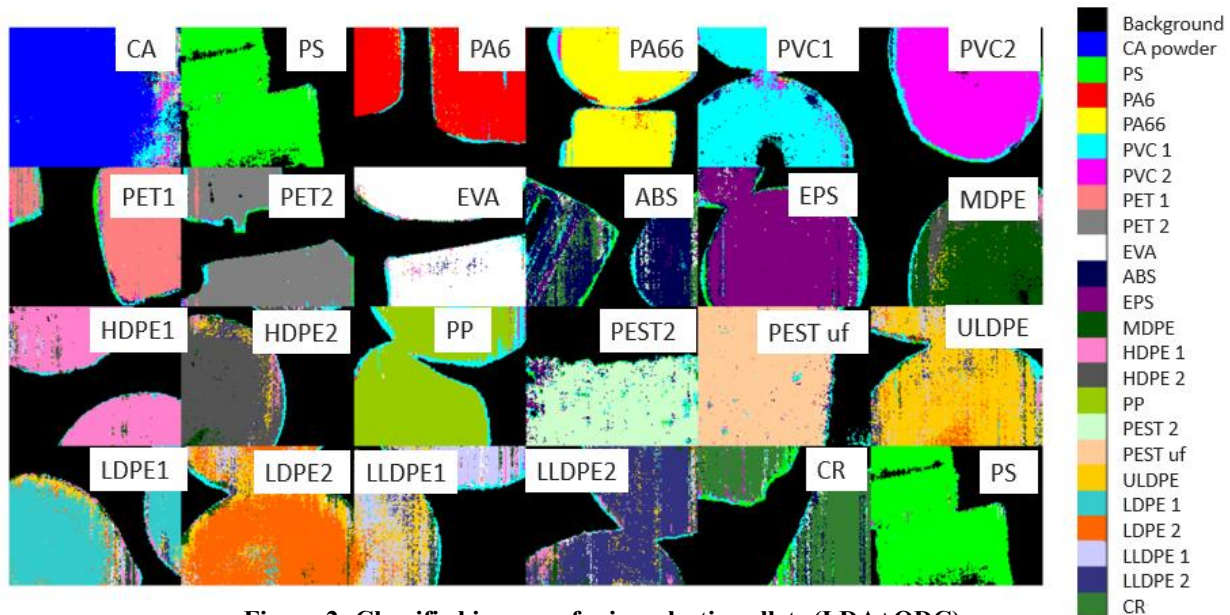


Figure 2: Classified images of microplastic pellets (LDA+QDC).

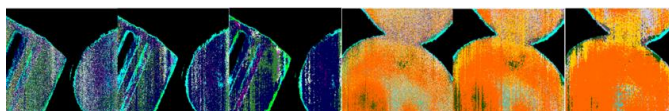


Figure 3: Classified images of ABS (left, purple) and LDPE2 samples (right, orange) for no preprocessing, MF3x3 and MF5x5+LDA respectively.

4. CONCLUSIONS

This paper has explored the potential of hyperspectral imaging in combination with microscopy with the purpose

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