Optica Imaging Congress (3D, AO, COSI, IS, pcAOP) © Optica Publishing Group 2024

Wide-field microplastic identification based on spectrum and deep learning

Jingyan Chen,[1] Yuxing Li,[1] Jianqing Huang,[1,2] and Edmund Y. Lam[1,*]

[1] *Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam, Hong Kong SAR, China.*

[2] *Key Lab of Education Ministry for Power Machinery and Engineering, School of Mechanical Engineering, Shanghai Jiao Tong University, 800 Dongchuan Road, Shanghai, 200240, China.*

[*] *elam@eee.hku.hk*

Abstract: We present a wide-field dispersion system to capture spectral images with low cost and real-time imaging capability. The system demonstrates a high level of accuracy in identifying microplastic materials.

1. Introduction

In today's society, microplastic products are extensively used in various industries [1]. Plastic particles present in the environment are becoming increasingly smaller as they degrade, reaching the micrometer scale. Due to their potential ingestion through food and drinking water, the harmful effects of microplastics (MPs) on human health have significantly increased, making the detection and identification of MPs more crucial [2].

Spectral analysis, as a non-destructive and non-contact method of chemical analysis, is widely employed for material detection. Among them, Raman spectroscopy is more suitable for detecting MPs in drinking water and food because of its superior spatial resolution and lower water interference. Raman spectroscopy works based on the unique vibrational spectrum of molecules, acting like a fingerprint for each type of MP.. Spectral imaging, as a tool that combines spatial and spectral information, holds great potential for application [3]. However, traditional spectral imaging methods mostly rely on point-confocal scanning, which is time-consuming and involves larger system sizes [4, 5]. Apart from scanning approach, hyperspectral snapshot imaging enables real-time spectral imaging, but it is expensive and often sacrifices imaging resolution due to the use of filter arrays.

We propose an optical system that utilizes an inexpensive prism as a dispersive element to separate wide-field Raman signals in real-time, without sacrificing resolution and material preparation. Moreover, we apply ResNet to train raw images directly. This method facilitates cost-effective and highly accurate identification of MP materials and has the potential for 3D spectral image reconstruction as well.

2. Methods and experiments

Experiments were performed on well-labeled microplastic films, including polymethyl methacrylate (PMMA), polycarbonate (PC), polypropylene (PP), polyethylene terephthalate (PET), and polyvinyl chloride (PVC). In order to effectively assess the performance of our method, five samples were prepared for each type of MP, with all samples ranging in size from 1 to 5 mm. To facilitate subsequent deep learning analysis, twenty images were captured for each sample.

The setup of our system used in the experiment is shown in Fig. 1. A 532 nm single longitudinal mode continuous wave (CW) laser with a power of 500 mW is emitted and directed towards the sample placed in front of a mirror, after being reflected by a 532 nm dichroic beam splitter. The resulting light, containing Raman signals, undergoes reflection by the mirror, followed by splitting through the dichroic beam splitter. Light with a wavelength greater than 532 nm is transmitted through the beam splitter and then collimated. The collimated beam passes through a 532 nm longpass filter and is subsequently dispersed using a prism. Finally, the dispersed light is recorded using a CCD device. The wide-field dispersion images captured in this manner exhibit variations due to the distinct Raman signals emitted by different plastics under the same wavelength laser illumination. Notably, our approach does not require the use of precise spectrometers; instead, we directly train a ResNet model, which is a type of neural network architecture that incorporates residual connections, using the raw dispersion images for classification purposes.

3. Results and discussion

Figure 2 shows the Fig. 2(a) raw images of PVC and PET in along with Fig. 2(b) their corresponding amplitude graphs, as well as the Fig. 2(c) confusion matrix for the classification. As longpass filter cannot block all light of

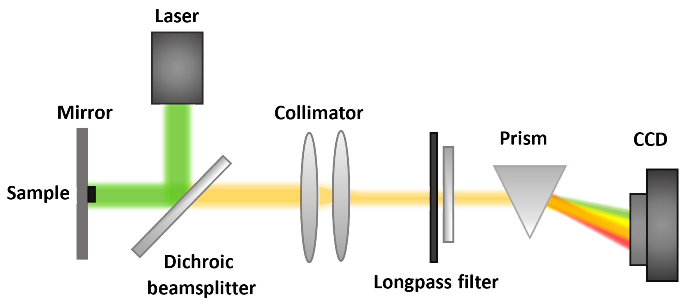

Fig. 1. Experimental setup.

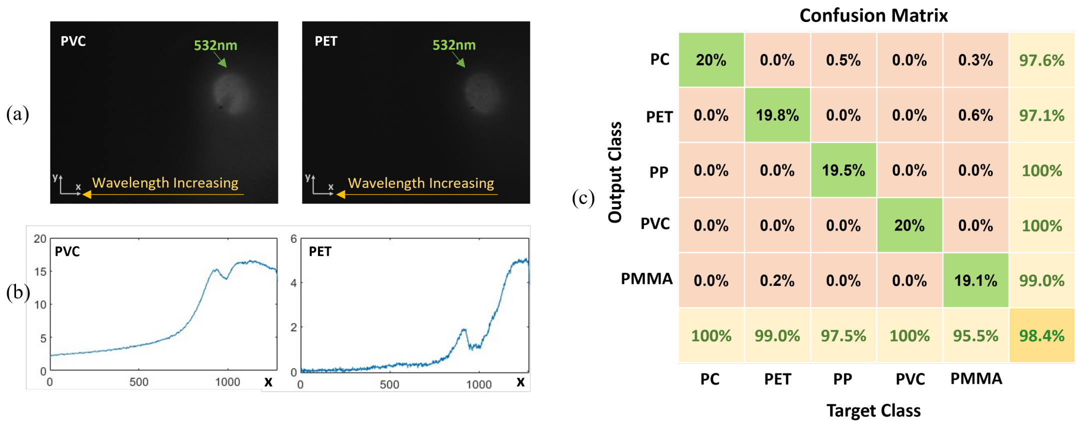

Fig. 2. (a) Raw images of PVC and PET ,(b) amplitude graphs and (c) confusion matrix.

532 nm beam, we can observe it in the raw images because the intensity of the transmitted 532 nm beam is still greater than the Raman signal. Due to the refractive properties of the prism, light of different wavelengths disperses in the direction indicated by the arrows in the diagram. The degree of dispersion increases proportionally with the longer wavelengths. The dispersion patterns can be visually discerned from Fig. 2(b), which is also a critical feature in deep learning analysis. Confusion matrix shows that our method can achieve 98.4% accuracy for MP materials classification using the ResNet model.

This system, characterized by its low cost, compact size, and real-time wide-field imaging capability, overcomes the limitations of point scanning and achieves high-accuracy classification of MP films through the integration of deep learning. While our experiments utilized Raman spectroscopy, this method can also be adapted for use with absorption spectroscopy and other spectroscopic techniques. The potential applications of this approach extend to portable devices and the reconstruction of three-dimensional spectral maps, enabling faster identification of detected samples with fewer samples needed.

This work is supported by Research Grants Council of Hong Kong (RIF7003-21).

References

1. K. Duis and A. Coors, “Microplastics in the aquatic and terrestrial environment: sources (with a specific focus on personal care products), fate and effects,” Environ. Sci. Eur. **28**, 1–25 (2016).
2. J. Huang, Y. Zhu, Y. Li, and E. Y. Lam, “Snapshot polarization-sensitive holography for detecting microplastics in turbid water,” ACS Photonics **10**, 4483–4493 (2023).
3. L. Huang, R. Luo, X. Liu, and X. Hao, “Spectral imaging with deep learning,” Light. Sci. & Appl. **11**, 61 (2022).
4. W. J. Shim, S. H. Hong, and S. E. Eo, “Identification methods in microplastic analysis: a review,” Anal. methods **9**, 1384–1391 (2017).
5. Y. Zhu, Y. Li, J. Huang, and E. Y. Lam, “Smart polarization and spectroscopic holography for real-time microplastics identification,” Commun. Eng. **3**, 32 (2024).