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Rapid identification of microplastics through spectral reconstruction from RGB images

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Abstract: We propose a method to generate hyperspectral bands and extract spectral signatures from RGB images. Experimental results validate its efficacy in streamlining microplastic identification through comprehensive spectroscopic analysis and reducing imaging time requirements. © 2024 The Author(s)

1. Introduction

Microplastics (MPs) pose a significant environmental challenge due to their widespread presence in various ecosystems and their harmful effects on wildlife and human health [1, 2]. Hyperspectral imaging (HSI), a sophisticated technique capturing high-resolution spectral data over a wide range of wavelengths, shows promise in distinguishing MPs from other materials based on their unique spectral signatures [3]. However, conventional HSI devices often suffer from portability constraints, time-intensive imaging processes, high costs, and complexity, hindering their broad adoption and efficacy in rapid MP identification for industrial, commercial and end-user applications. Consequently, current efforts aim to reconstruct hyperspectral (HS) images from visible (RGB) images.

In this study, we employ a deep learning-based approach to reconstruct spectral information from RGB images for MP identification, involving the determination of an inverse response function as a reverse process of HSI [4]. Leveraging learned mapping relations, the method generates 31 HS bands spanning 400–700 nm by recovering lost spectral data from a given RGB image. Moreover, a 3D convolutional neural network (CNN) model is deployed to process the resulting spectral data cube and differentiate MPs from other materials. Our proposed approach offers a convenient and cost-effective means of obtaining HS images, potentially expediting the detection of MPs in environmental samples compared to conventional spectroscopic methods.

2. Methods and materials

The RGB images captured alongside their corresponding ground truth HS images from the samples undergo calibration using a standard whiteboard to eliminate the effects of the illumination spectrum. As illustrated in Fig. 1, a CNN-based network architecture is employed for precise spectral reconstruction from RGB images. RGB images consist of 3 channels, while HS images contain 31 channels. The process at each level comprises inter-level integration, artifact reduction, and global feature extraction [4]. Parameters of the spectral reconstruction model are fine-tuned to minimize the losses, quantified as discrepancies between ground truth and estimated values measured by a specified loss function. Following model training, evaluations are conducted based on desired metrics [5].

The reconstructed spectra are subsequently utilized for material classification, employing a 3D CNN model to identify various material types based on their spectral signatures. Each layer incorporates volumetric kernels conducting convolutions simultaneously across the width, height, and depth axes of the input. The architecture processes 3D voxel input data, generating 3D feature maps that progressively reduce into 1D feature vectors throughout the layers. Model performance is assessed using metrics such as accuracy, confusion matrix, and Kappa value. The samples encompass six types of plastics exhibiting variability in the visible spectrum: polyamide (PA), polyethylene (PE), polyhydroxyalkanoates (PHA), polylactic acid (PLA), polyoxymethylene (POM), and polypropylene (PP). Additional non-plastic materials, including soil, stone, and leaves, are included in the control group to enhance sample diversity, with the labeling of different samples manually annotated.

3. Results and discussion

Fig. 2(a) illustrates the hypercube, representing the generated HS images, with each spectral image containing information from 31 bands spanning the range of 400 nm to 700 nm, at a spectral resolution of 10 nm. The spectral reconstruction runtime for each image is approximately 3.7 seconds, representing a notable improvement over conventional HSI devices. Visible spectra of various materials are depicted in Fig. 2(b), revealing distinct spectral signatures for different types of MPs and other environmental materials, facilitating further classification.

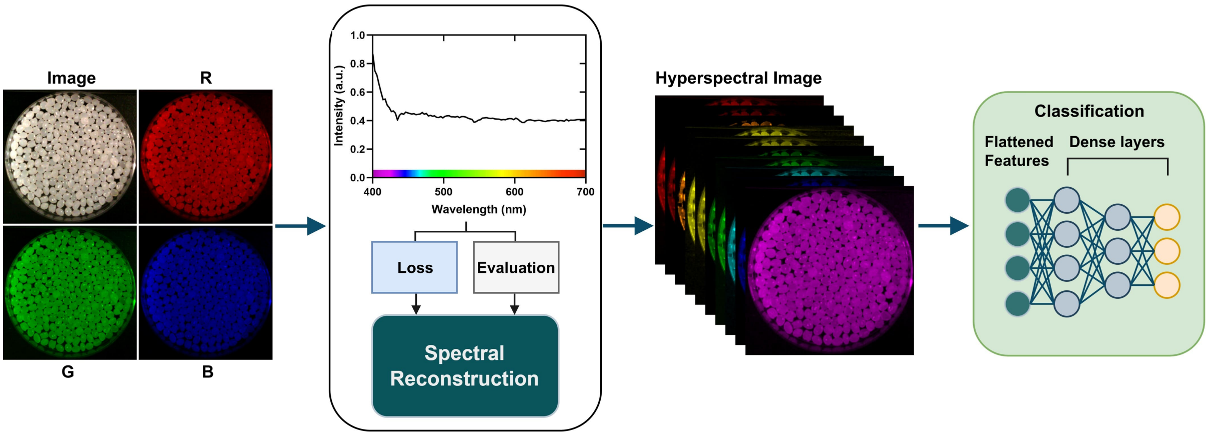
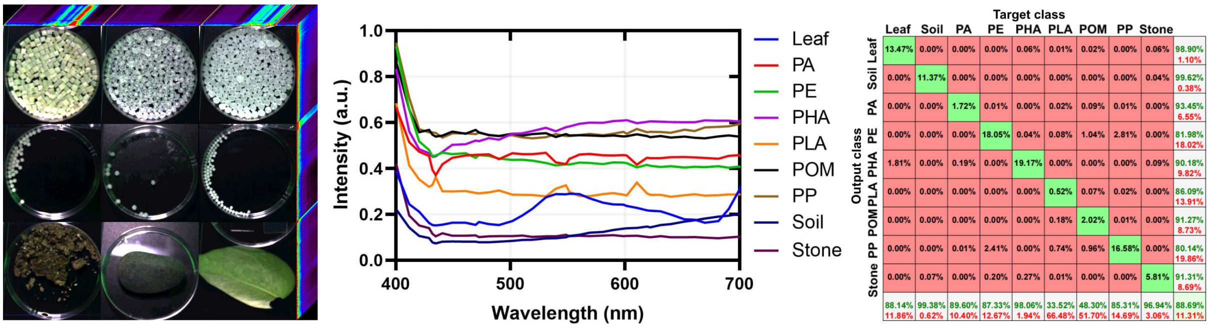


Fig. 1. The pipeline for MP material identification involves spectral reconstruction training and evaluation using ground truth data, followed by classification of the generated HS data cube using a 3D CNN architecture.



(a) (b) (c)

Fig. 2. (a) The generated hypercube (spanning 400–700 nm) arranged with materials from left to right and top to bottom, including PHA, PP, PE, PA, PLA, POM, Soil, Stone, and Leaf. (b) Spectra extracted for different material types. (c) Confusion matrix illustrating classification results.

The confusion matrix presented in Fig. 2(c) demonstrates the classification results. The 3D CNN model exhibits promising performance in accurately identifying MPs based on their reconstructed spectral signatures. Among the evaluated models, the 3D CNN model shows superior performance, achieving overall accuracy rates exceeding 89.1% for MP identification and classification of their types, significantly surpassing single RGB-based identification. Additionally, the model demonstrates a high Kappa value of 0.81, indicating their effectiveness in minimizing false positives and false negatives.

In conclusion, the results of this study underscore the potential of computational spectral reconstruction for the rapid identification of MPs in environmental samples. This method holds promise for advancing MP spectroscopic analysis and aiding in the development of effective detection strategies.

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