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Research on Identification and Classification Methods for Soil Microplastics in Hyperspectral Detection

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Abstract

The pollution of microplastics in the environment has attracted worldwide attention, and research and reports on microplastic pollution in soil have gradually increased in recent decades. Currently, microplastic particles can be accurately detected through Raman spectroscopy or Fourier-transform infrared spectroscopy, allowing for individual particle analysis and visual identification of suspicious microplastic particles. However, analyzing a large number of particles using spectroscopic detection techniques is time-consuming, thus there is an urgent need to develop a new detection technology for rapidly and accurately determining and mapping the distribution of microplastics in soil. In this study, hyperspectral imaging technology was employed as a detection method to directly and effectively identify and classify microplastic pollutants in soil. The experimental setup utilized a hyperspectral imaging system with a wavelength range of 400-1000 nm. The experimental results demonstrate that hyperspectral imaging technology is a promising method for detecting microplastics, as it enables direct identification and visualization of microplastic particles on the surface of soil.

Keywords

Microplastics; Marine Pollution; Image Detection; Hyperspectral.

1. Introduction

Microplastic pollution in soil is widespread, but research on microplastics in terrestrial ecosystems is still limited [1,2]. Studies estimate that 100,000-70,000 tons of microplastics are released into the soil environment annually in Europe and North America, surpassing the total amount of microplastics floating on the ocean surface [3]. In the suburban farmland and vegetable fields of Shanghai, China, the abundance of microplastics with particle sizes ranging from 20 μm to 5 mm in the shallow layer (0-6 cm) of soil is approximately 62.50 particles/kg soil, with microplastics smaller than 1 mm accounting for around 50% of the total [4]. In a study of soil in the riparian forest buffer zone and planting area of the Chaihe River Basin in the southern Dianchi Lake Basin of China, plastics (0.05-10 mm) were found in all fifty soil samples, with an average abundance of 18,760 particles/kg soil, and 95% of the plastic particles had a size smaller than 1 mm [5]. Microplastics in terrestrial ecosystems include primary microplastics, which are small-sized plastic materials directly discharged from industrial production, and secondary microplastics formed through the weathering and degradation of larger plastic fragments under natural conditions, such as weathering and UV radiation [1].

The polymer properties in the soil environment are stable and not easily degraded, and these smaller plastic fragments can have long-lasting effects on the soil for several years or even decades [6]. The influx of a large amount of microplastics into the soil, without proper regulation, can alter the soil structure and physicochemical properties, affecting the transport of water, inorganic salts, and other nutrients, and posing a significant threat to the safety of terrestrial soil systems. Aged microplastics exhibit stronger adsorption capacity for metals [7] and have a large specific surface area, making them prone to adsorb toxic pollutants in the soil environment, such as persistent organic pollutants and heavy metals.

This chapter collected plastics from the soil environment and prepared simulated soil microplastic samples in the laboratory using fresh leaves, withered leaves, rocks, and extracted microplastics. Hyperspectral images of these samples were obtained. The aim of this study is to directly identify and locate microplastics in the soil using hyperspectral imaging technology and visualize their distribution.

2. Materials and Methods

2.1. Experimental Instruments

Instruments:

Hyperspectral imaging device (Headwall Photonics Inc, VNIR-A, USA), ENVI 4.6 software (Research system, Inc., Boulder, Co., USA), halogen lamp (model: LOWEL PRO-LIGHT), micro-Raman spectrometer (inVia-Reflex, Renishaw Inc., UK), fluorescence microscope (NOVEL, Yongxin Optical, N-300 M), vacuum oven (Senxin, DZG-6050, China).

Hyperspectral Imaging System:

The hyperspectral imaging system consists of a CCD camera and a digitally controlled pan-tilt platform for image acquisition. The system is compact, lightweight, portable, easy to operate, and has low requirements for working conditions, making it suitable for spectral acquisition of soil samples in the field. In the laboratory, when collecting hyperspectral data, the lighting intensity is insufficient, and a close-range 250 W tungsten-halogen lamp is used as the light source. After acquiring hyperspectral images of the soil microplastic samples, hyperspectral images of polytetrafluoroethylene (PTFE) whiteboards with 99% reflectance are also collected. The whiteboard images are used for calibration to reduce experimental errors caused by uneven illumination. The wavelength range of the hyperspectral device for spectral data collection is 400-1000 nm, with a total of 329 bands, covering the entire visible light region and part of the near-infrared region, which has high recognition capability for terrestrial green vegetation. Therefore, it is easy to distinguish microplastics from field plants on hyperspectral images. In the laboratory, the acquisition time for a single hyperspectral image of a simulated field soil microplastic model sample is approximately 30 s, with an exposure time of 38 ms and a frame period of 39 ms.

2.2. Sample Collection

The soil samples used in this study were collected from agricultural areas near the Quzhou West Exit of Quzhou City, Zhejiang Province, China. The soil surface in this area contains a considerable amount of weathered and semi-weathered plastic debris.

As shown in Figure 1, weathered plastic fragments were found in the agricultural area near the highway, and the plastic fragments along with the top 5 cm layer of soil in the vicinity were collected. The collected samples were placed in bags and brought back to the laboratory for storage. The collected soil samples containing plastic debris had a total mass of 3 kg, and they were divided into two groups. One group of soil samples was subjected to extraction using saturated NaCl solution to isolate microplastics for compositional analysis, while the other group of samples was used to establish the method for identifying soil microplastics using hyperspectral imaging technology.

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Fig 1. Soil samples collected from farmland near the highway

2.3. Extraction and Identification of Microplastics

Microplastics typically have a lower density than soil and gravel, while saturated saltwater has a density between the two materials. Therefore, density separation methods are commonly used in research to extract microplastics from soil and sediment. By utilizing saturated saltwater, the denser soil and gravel particles settle at the bottom, while the lighter microplastics float on the surface of the saltwater [8]. In this study, a density separation method was employed to extract microplastics from the soil.

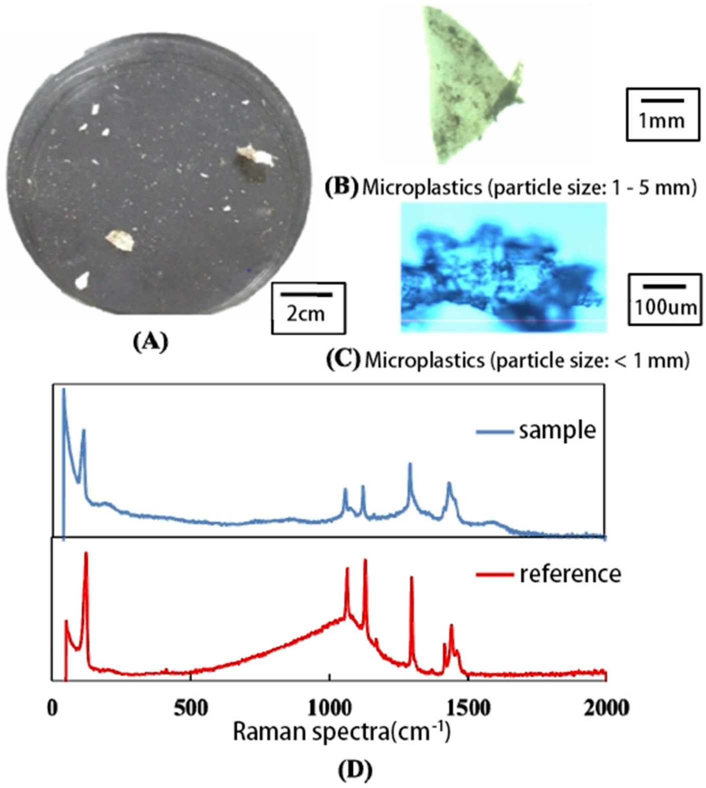

Fig 2. Morphological and chemical properties of the extracted MPs
(A) MPs in the petri dish; (B) MPs under the microscope; (C) MPs under the fluorescence microscope; (D) Raman spectra of the extracted MPs and PE reference

Approximately 30 g of soil sample containing microplastics was weighed and placed in a beaker. A sufficient amount of saturated NaCl solution was added, and the soil and solution were mixed thoroughly using a glass rod. The mixed solution was allowed to settle at room temperature for 12 hours until the soil completely settled, resulting in a clear layering of the solution. The uppermost layer consisted of suspended microplastics and similar materials. Using a clean stainless steel needle (23 cm long, 3 mm in diameter), visible floating particles from the suspended layer were carefully picked and transferred to a glass Petri dish filled with deionized water (Figure 2 A). The mixing and settling process was repeated 3-4 times, with the floating particles from the solution surface being picked out, until no visible floating particles were observed. The extracted material in the Petri dish was examined under an optical microscope (Figure 2 B) to remove non-microplastic impurities. The remaining microplastic-like particles were analyzed for their chemical properties using near-infrared spectroscopy and micro-Raman spectroscopy.

2.4. Sample Preparation

Statistical results of microplastics in the Chinese rivers of Oujiang, Jiaojiang, and Minjiang estuaries have shown that microplastics with particle sizes ranging from 0.5 mm to 5 mm account for over 90% of all collected microplastics [9]. In this study, the detected particle size range of microplastics was also set between 0.5 mm and 5 mm. Moreover, to investigate the influence of microplastic particle size on the classification and identification results using hyperspectral imaging technology, the microplastic samples were limited to the particle size range of 1 mm to 5 mm. Additionally, white and black microplastics collected from soil samples were used to study the impact of microplastic color on the classification of microplastics using hyperspectral imaging technology.

The larger white and black plastic fragments extracted from the soil were manually cut into microplastic sizes. Stainless steel sieves with apertures of 1 mm and 5 mm were used to classify the microplastics by particle size, resulting in microplastics within the desired size range: 1 mm to 5 mm. To simulate the environmental presence of microplastics in field soil, a certain quantity of fresh leaves, dried branches, withered leaves, and stones were collected from the environment to create a simulated complex soil environment in the laboratory. Before creating the microplastic samples in the soil environment, the soil was dried in a vacuum oven at a temperature of 80°C for 8 hours to remove soil moisture, preventing changes in soil moisture during the experiment from affecting the identification of microplastics.

White microplastics (1 mm to 5 mm), black microplastics (1 mm to 5 mm), rocks, withered leaves, fresh leaves, and dried branches were mixed and randomly distributed on the surface of the dry soil. A total of 10 samples were prepared for each type of material, and hyperspectral images of the samples were subsequently acquired.

3. Data Analysis

During the acquisition of spectral image data by the hyperspectral imaging system, noise signals are simultaneously collected, resulting in a large amount of redundant and highly similar information. To improve the stability and robustness of the identification model, reduce the amount of hyperspectral data, and obtain a robust model, principal component analysis (PCA) was applied as a preprocessing step to the original hyperspectral data before developing the classification model. Several representative components, including fresh leaves, withered leaves, rocks, dried branches, white microplastics, black microplastics, and dried soil, were selected to simulate the presence of microplastics in a field soil environment model in the laboratory. A portion of each component was chosen from the hyperspectral images as regions of interest (ROIs) to construct the training set for the microplastic identification model. Two supervised classification methods, namely MD (Mahalanobis Distance) and SVM (Support

Vector Machine), were used to simulate calculations on the training set and create different microplastic identification models to recognize microplastics from the complex soil environment in the hyperspectral images.ENVI (The Environment for Visualizing Images) software is commonly used for data processing of hyperspectral images, providing various data processing techniques such as image enhancement, information extraction, data fusion transformation, and image classification for the analysis of experimental data. The hyperspectral data analysis in this experiment was performed using ENVI 4.6 software.

4. Results and Discussion

4.1. Analysis of Microplastics in Soil Samples

The soil samples collected in the field were soaked and left to settle in a saturated saltwater solution for a sufficient period of time. Impurities such as sediment and stones settled at the bottom of the beaker, while microplastics with lower density floated on the surface of the saturated saltwater solution. Microplastics and similar materials floating on the surface of the saturated NaCl solution were individually picked out using visual inspection and placed in clean glass petri dishes, as shown in Figure 2(A). The extracted material in the glass petri dish was observed under a low-power optical microscope, and microplastic fragments were selected one by one, as shown in Figure 2(B) and (C). The spectral information of the microplastic fragments was obtained using a Raman spectrometer, and the type of microplastic was determined by comparing the Raman spectra with those of pure plastics. The Raman spectra were recorded in the range of 50-2000 (cm-1), as shown in Figure 2(D). A comparison revealed that the experimentally measured Raman spectra of the microplastics were consistent with the known standard Raman spectra of polyethylene (PE) plastics, indicating that the extracted microplastics from the soil samples belonged to PE microplastics. The peaks at 1420, 1443, and 1464 (cm-1) on the Raman spectra corresponded to the bending, bending, and vibration of the CH2 group, respectively [10]. The peaks at 1070 and 1138 (cm-1) corresponded to the stretching of the C-C bond, while the peaks at 1177 and 1298 (cm-1) were due to the vibration and twisting of the CH2 group [11].

4.2. Hyperspectral Image Analysis

A simulated hyperspectral image of microplastic samples in a field soil environment is shown in Figure 3 (A), where microplastics are randomly distributed on the soil surface along with fresh leaves, withered leaves, rocks, and dried branches. In the hyperspectral image, the X and Y axes represent two perpendicular directions in the planar image space of the soil samples, while the Z axis represents the spectral wavelength range of each pixel in the spatial image. Seven different materials used in the experiment are marked with different colors on the image: yellow (white microplastics), light blue (black microplastics), blue (withered leaves), magenta (dried branches), green (rocks), red (fresh leaves), and brown (soil). Fifty to 200 pixels for each material were selected as regions of interest (ROIs) on the hyperspectral image for training the two supervised classification methods, as shown in Figure 3 (B).

Each pixel in the ROI has a spectral curve within the spectral space. By calculating the average of the spectral curves in the ROI for each material, their characteristic spectral curves were obtained in the visible and near-infrared spectral range of 400-1000 nm, as shown in Figure 3 (C). The spectral feature curves of fresh leaves exhibit the most distinct differences compared to other materials. This is because chlorophyll contained in fresh leaves is highly sensitive to the visible light region, allowing both classification models to easily identify fresh leaves in the samples. White PE microplastics exhibit the highest reflectance when the wavelength value is below 675 nm, while black PE microplastics show the lowest reflectance across the entire spectral range of 400-1000 nm. The spectral curves of soil and rocks show similar trends, but rocks have higher reflectance throughout the entire spectral range. Among all the materials, except for fresh leaves, there are no significant differences in the spectral curves between the other materials.

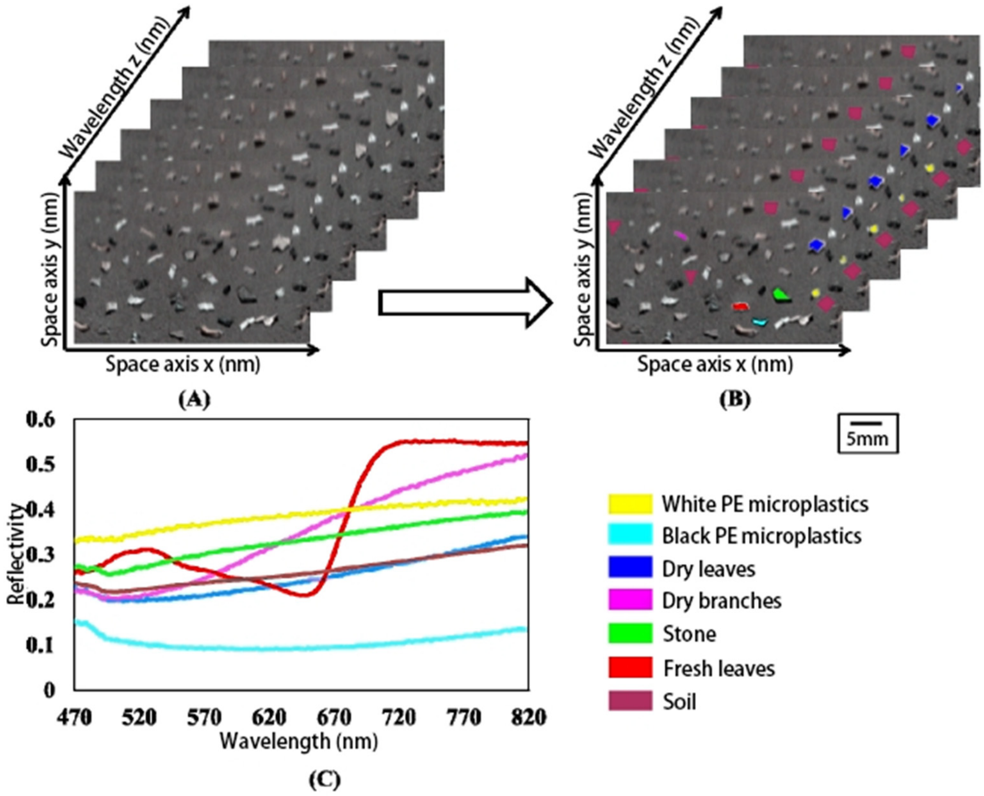

Fig 3. (A) Hyperspectral imaging of soil covered with MPs and other materials; (B) ROIs of each type material; (C) Obtained spectra from ROIs of each type material

4.3. Classification Results of 1-5 mm Polyethylene Microplastics in Particle Size

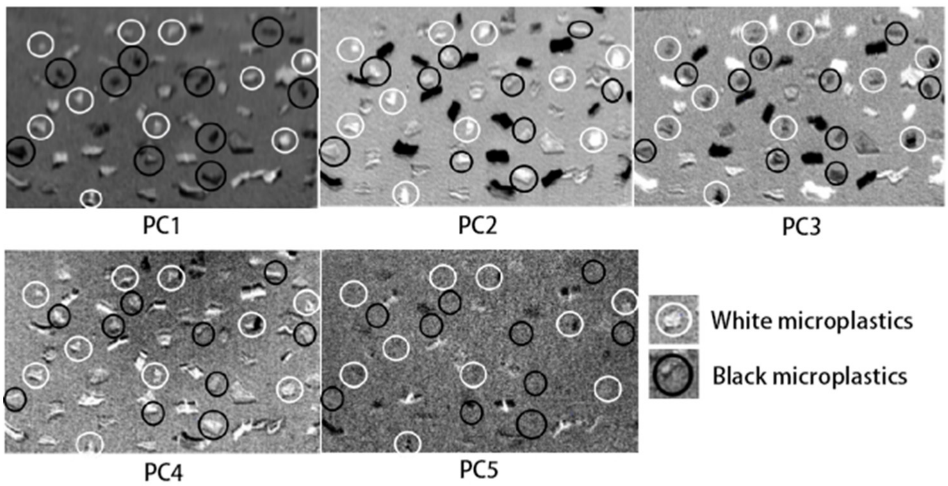

Fig 4. First five principal components (PCs) of a soil sample covered with MPs (1-5 mm)

To remove redundant information from the original hyperspectral image and improve the signal-to-noise ratio of the data, smoothing and principal component analysis (PCA) were used as preprocessing methods for the raw spectral data. Through PCA, most of the information from the original hyperspectral data was concentrated in the first few principal components (PCs). In this study, the first five principal components were used to establish the model for microplastic identification and classification. The first five principal components are shown in Figure 4, where the clarity of the five images gradually decreases, indicating a reduction in the

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amount of information contained in each successive principal component. The subsequent principal components contain a significant amount of noise and cannot be used for model analysis.

5. Conclusion

This study investigated the detection method of directly identifying microplastics on the soil surface using hyperspectral imaging technology. To examine the effect of microplastic particle size on the identification of microplastics using hyperspectral imaging, the study focused on detecting microplastics in the particle size range of 1-5 mm. Sensory regions of each environmental material were extracted from the hyperspectral images, and their average spectra were calculated. The results demonstrate that hyperspectral imaging technology has great potential for detecting microplastics on the complex soil surface, even without the need to extract microplastics from the soil environment.

Acknowledgments

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References

[1] Liu H, Yang X, Liu G, et al. Response of soil dissolved organic matter to microplastic addition in Chinese loess soil [J]. Chemosphere, 2017, 185: 907-917.

[2] Rillig M C. Microplastic in terrestrial ecosystems and the soil? [J]. Environmental Science & Technology, 2012, 46(12): 6453-6454.

[3] Nizzetto L, Futter M, Langaas S. Are agricultural soils dumps for microplastics of urban origin? [J]. Environmental Science & Technology, 2016, 50(20): 10777-10779.

[4] Liu M, Lu S, Song Y, et al. Microplastic and mesoplastic pollution in farmland soils in suburbs of Shanghai, China [J]. Environmental Pollution, 2018, 242: 855-862.

[5] Zhang G S, Liu Y F. The distribution of microplastics in soil aggregate fractions in southwestern China [J]. Science of The Total Environment, 2018, 642: 12-20.

[6] Briassoulis D, Babou E, Hiskakis M, et al. Analysis of long-term degradation behaviour of polyethylene mulching films with pro-oxidants under real cultivation and soil burial conditions [J]. Environmental Science and Pollution Research, 2015, 22(4): 2584-2598.

[7] Turner A, Holmes L A. Adsorption of trace metals by microplastic pellets in fresh water [J]. Environmental Chemistry, 2015, 12(5): 600-610.

[8] Nuelle M, Dekiff J H, Remy D, et al. A new analytical approach for monitoring microplastics in marine sediments [J]. Environmental Pollution, 2014, 184: 161-169.

[9] Zhao S, Zhu L, Li D. Microplastic in three urban estuaries, China [J]. Environmental Pollution, 2015, 206: 597-604.

[10] Kim J, Kim Y, Chung H. Direct on-line Raman measurement of flying solid samples: Determination of polyethylene pellet density [J]. Talanta, 2011, 83(3): 879-884.

[11] Oßmann B E, Sarau G, Schmitt S W, et al. Development of an optimal filter substrate for the identification of small microplastic particles in food by micro-Raman spectroscopy [J]. Analytical and Bioanalytical Chemistry, 2017, 409(16): 4099-4109.