Digital holographic microplastics detection and characterization in heterogeneous samples via deep learning

Yanmin Zhu[a], Chok Hang Yeung[b,c], and Edmund Y. Lam[*,a]

[a]Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam, Hong Kong SAR, China
[b]Department of Civil Engineering, The University of Hong Kong, Pokfulam, Hong Kong SAR, China
[c]Centre for Water Technology and Policy, The University of Hong Kong, Pokfulam, Hong Kong SAR, China

ABSTRACT

Detecting and quantifying microplastic particles have become important problems in environmental monitoring in recent years. In the natural environment, microplastic and nanoplastic particles are often mixed with large pieces of plastic, microalgae, microorganisms, and leaf fragments, etc., making them difficult to be distinguished. In addition, the microplastics themselves are made of different materials and have various shapes. As a result, the conventional classification methods based mostly on morphological characteristics cannot accurately classify microplastics in a complex environment, which brings great challenges to their detection and analysis. We have developed a classification and detection method based on digital holographic imaging and deep learning, which effectively classifies the types of microplastic particles by using the holographic interference fringe features of microplastic particles. With heterogeneous samples containing microplastic particles, microalgae and other substances, we are able to demonstrate the strength of our technique in the detection and characterization of the microplastics. Indeed, the results show that the deep learning network can automatically extract the features of holographic images of different particles in such samples, and delineate with good sensitivity the feature differences in the digital holograms that are caused by optical path differences introduced by various kinds of particles. Furthermore, this holographic feature-based classification is not affected by material morphological characteristics and has good robustness.

Keywords: Digital holography, deep learning, microplastic detection, microplastic characterization

1. INTRODUCTION

Plastic products that are widely used in all aspects of human life not only bring convenience to human life, but also produce a lot of pollution that cannot be ignored. Among them, the pollution caused by microplastic particles with a diameter of less than 5mm has attracted people's attention in recent years.[1] Microplastic particles can be produced by the degradation of large plastic waste or originally exist in industrial products and be directly discharged into the natural environment, such as plastic waste dumped in towns, agriculture and industry, aquaculture, and plastic particles produced during ship transportation. And they exist in products containing cleaning microbeads, such as facial cleansers, toothpaste and industrial raw materials containing plastic and resin particles. In addition, plastic microfibers generated during the washing process of artificial synthetic fiber textiles are also one of the main sources of microplastic particles.[2] Microplastic particle pollutants may be further degraded into nanoplastic particle pollutants and more difficult to be identified in the natural environment. Because of its small size, microplastic particles are easily swallowed by organisms to enter the food web and accumulate layer by layer along the food chain, ultimately threatening the life and health of higher organisms.[3] Since microplastic particles are mainly composed of polyethylene (PE), polypropylene (PP), polystyrene (PS), etc., the biological toxicity produced by them may have a long-term impact on the growth and

Further author information:
Edmund Y. Lam: E-mail: elam@eee.hku.hk, Telephone: +852 2241 5942, Fax: +852 2559 8738

Twelfth International Conference on Information Optics and Photonics,
edited by Yue Yang, Proc. of SPIE Vol. 12057, 120573G

development, behavioral activities, and gene expression of organisms. In addition, the plastic particles in the soil may adsorb heavy metals and pathogenic bacteria in the soil solution and the surrounding soil environment, and affect soil animals, soil microbial communities, and soil material circulation.[4]

Because microplastic particles are small in size and often mixed with other substances in the natural environment, such as microorganisms, microalgae, broken glass, soil, etc., it is difficult to detect them. At present, the commonly used methods include microscopic counting, scanning electron microscope (SEM), Raman spectroscopy, Fourier-transform infrared spectroscopy (FT-IR).[5] The microscopic counting method has low analysis cost and relatively simple operation. But it can only observe the morphology of microplastic particles, and cannot analyze its composition. SEM has relatively high resolution, and it is also mainly used for surface morphology identification of microplastic particles. Raman spectroscopy can accurately analyze the molecular skeleton of the material and determine its chemical composition by identifying the characteristic Raman spectrum of the plastic. Raman spectroscopy is suitable for the analysis of particles with a diameter between 1 and 20 microns, but the presence of microbial particles and some organic and inorganic impurity particles will greatly interfere with the accuracy of its detection. The FT-IR method analyzes the type of material by identifying the functional groups of the sample. It is impossible to analyze small diameter and opaque particles. In general, all of the above-mentioned methods require manual analysis by researchers with professional background, and require preliminary sample preparation such as filtering, screening, and staining of samples, which takes a long time and is expensive to analyze, so it is not suitable for fast and efficient detection of large quantities of microplastic particles.

In recent years, digital holography has been applied to the detection and analysis of microplastic particles.[6–9] Digital holography is a non-contact optical detection technology with fast imaging speed and high resolution, which forms coherent fringes through the spatial coherence of the reference light and the object light carrying sample information. The refractive index and optical path difference information contained in this specific coherent fringe can be used to analyze the surface morphology and material characteristics of the sample. The rapid development of artificial intelligence technologies such as deep learning and machine learning has greatly improved the imaging performance of digital holography in terms of auto-focusing,[10] super-resolution imaging,[11] image reconstruction,[12] and phase retrieval,[13] etc. It provides the possibility for digital holography to detect and identify microplastic particles. For example, a lightweight classification network, called holographic-classifier convolutional neural network, combines digital holography with deep learning in order to fully extract the spatial feature information carried in the hologram, and perform fast and accurate classification.[14] Its superior classification ability has been verified on microplastic particles and open source holographic datasets. In addition, in view of the small amount of data and the unbalanced distribution of categories in the holographic dataset, we have also proposed a holographic image classification method based on transfer learning.[15] The network is pre-trained on the public dataset and a part of the parameters are fixed. This method effectively improves the accuracy and robustness of the holographic image classification problem on small datasets. This method can also be applied to the classification of other datasets with similar distribution characteristics. In the above two studies, the classification method was applied to holograms containing different numbers of microplastic particles, mainly used for quantity measurement and concentration analysis of microplastic particles in a certain volume. For the specific types of microplastic particles, no further statistics have been made. In terms of type analysis of microplastic particles, Bianco *et al.* performed a feature extraction method on holographic images, and used machine learning to classify a novel set of distinctive holographic features, thereby completing the identification of microplastic particles.[8] However, it still needs to manually extract the features of the holographic image of the microplastic particles, and need to evaluate the representativeness and effectiveness of the feature in the hologram.

In this work, we describe a method for detecting and classifying microplastic particles based on digital holography and deep learning for heterogeneous samples. This method can identify microplastic particles from environmental particles in the sample, such as microalgae, soil particles, and broken leaf particles. In the next section, we introduce the optical system and classification network used in this method. The third section shows the experimental performance and data analysis of this method on the microplastic dataset. And we give a brief conclusion in the last section.

2. MATERIALS AND METHODS

The heterogeneous samples containing microplastic particles are collected from three natural environments, including gravel, microalgae, microplastic particles, soil particles, broken leaves, etc. Among them, sample pictures of different shapes of microplastic particles collected by a dissecting microscope mounted with CCD camera. After collection, the sample is placed in a petri dish and stored upright in a refrigerator at 4 °C. In order to simulate the water environment, we take the original sample and place it in a petri dish filled with distilled water, and place it horizontally on the observation platform for experimental observation. The diameter of the microplastic particle sample used in this experiment ranges from 180 to 400 µm.

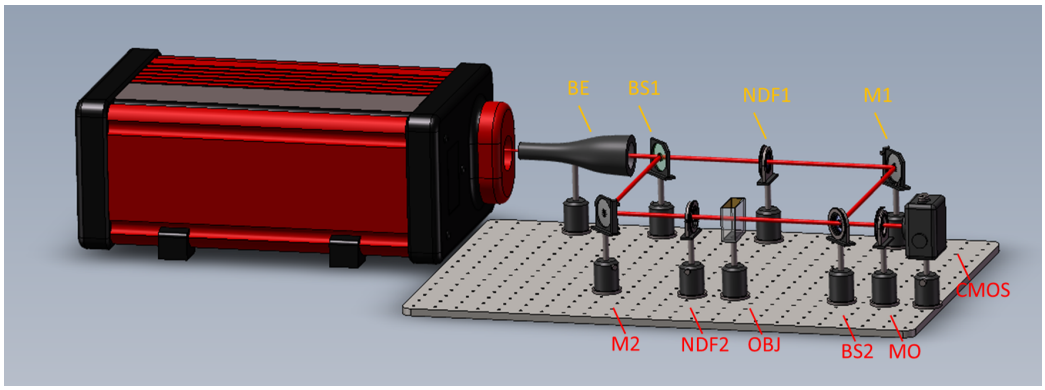


Figure 1. The diagram of the digital holographic optical system.

An optical system with a basic frame of the Mach–Zehnder interferometer is used in this method, as shown in Figure 1. A beam of coherent light with a wavelength of 632.8 nm is emitted from the laser, passes through a beam expander (BE) and is expanded by the beam splitter (BS1) into reference light and object light with equivalent light intensity. The light intensity of the beam light can be further adjusted more precisely through the neutral density filters (NDF1 and NDF2) in their optical paths. After being reflected by the mirror (M2), the object light carrying the sample information and the reference light are merged and spatially coherent at the second beam splitter (BS2), and the coherent fringes generated by them are transmitted to the photosensitive surface of the CMOS camera (Allied Vision Mako G-507). In order to observe the coherent fringes of the sample more accurately, a 10× objective lens is placed 10 mm in front of the camera.

The classification of images is carried out using the holographic-classifier convolutional neural network (HC-CNN),[14] which is specially designed for holographic image classification. The network can deeply extract the spatial shape information contained in the holographic coherent fringes in order to identify and classify the object types according to the characteristics of rich information and small datasets of holographic images. The HC-CNN network is a lightweight classification network, and its classification performance has been verified in the number counting and density analysis of microplastic particles.[9] The detailed structure of HC-CNN is shown as Figure 2.

3. RESULT AND DISCUSSION

The dataset contains 1000 holographic images of the heterogeneous samples manually labeled by researchers with relevant professional backgrounds using Raman spectrometers and scanning electron microscopes. The original holographic images are collected by the optical system and recorded by the CMOS camera. Then, the images are processed by auto-focusing algorithm[10] and reconstructed to the wavefront, and resized to 128 × 128 pixels. The dataset input to the network is divided into training set, validation set and test set at a ratio of 8:1:1. The network is implemented with TensorFlow and runs on the Nvdia Titan V GPU platform. The Adam optimizer is used to update the gradient with a learning rate of 0.0001. The classification performances are evaluated in

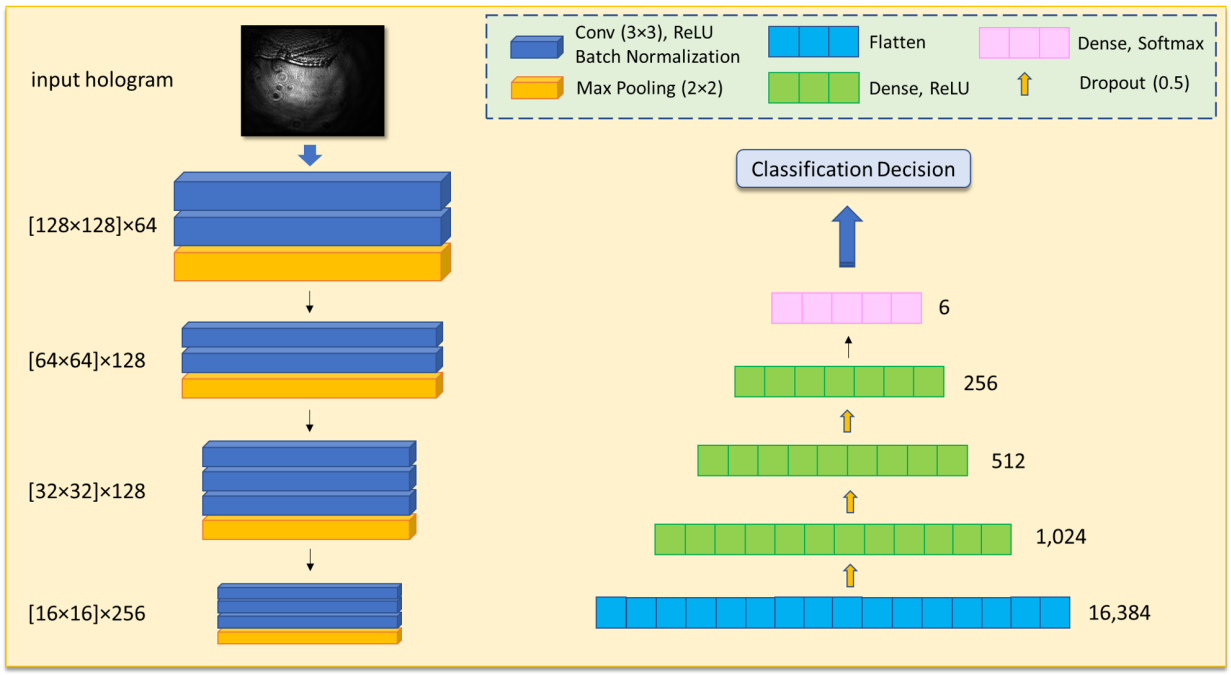
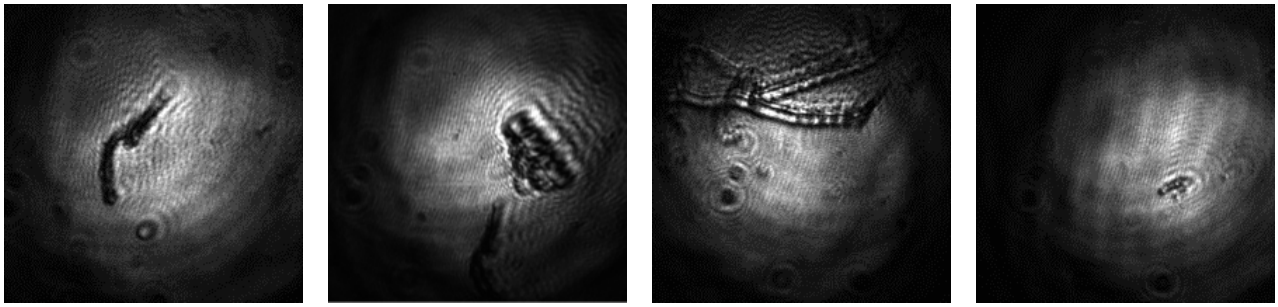


Figure 2. The network structure of HC-CNN for microplastic classification and characterization.



(a) (b) (c) (d)

Figure 3. Example holographic images of the heterogeneous samples: (a) microplastic fiber; (b) microplastic pallet; (c) microalgae; (d) microplastic fragment.

terms of accuracy (A), precision (P), recall rate (R) and F1-score (F_1), defined as follows:

$$A = \frac{X_{TP} + X_{TN}}{H}, \quad P = \frac{X_{TP}}{X_{TP} + X_{FP}}, \quad R = \frac{X_{TP}}{X_{TP} + X_{FN}} \quad \text{and} \quad F_1 = \frac{2PR}{P + R}, \tag{1}$$

where X_{TP} is the output results correctly predicting the well-classified samples, X_{TN} is the output correctly predicting the mis-classified samples, X_{FP} is the output incorrectly predicting the well-classified samples and X_{FN} is the output incorrectly predicting mis-classified samples. H represents the number of holograms in the test set. We select several example holographic images containing different types of microplastic particles and environmental particles in the dataset, which are shown in Figure 3. Then, a classification test is conducted on this dataset. In addition to using the HC-CNN network, we also selected several commonly used classification networks for analogy experiments, so as to more objectively evaluate the performance of the HC-CNN network on the classification and characterization of microplastic particles. The results are shown in Table 1. In order to ensure the fairness of the experiments, all classifications are performed on the same dataset and use the same hardware platform.

As shown in Table 1, the HC-CNN network has achieved good performance in accuracy, precision, recall

Table 1. Classification performances of MLP, VGG-16, CNN, ResNet and HC-CNN.

Methods	A	P	R	F_1
MLP[16]	0.5234	0.5391	0.6435	0.6630
VGG-16[17]	0.8125	0.7931	0.7767	0.7960
CNN	0.9011	0.9107	0.8963	0.9074
ResNet[18]	0.9201	0.9125	0.8963	0.9123
HC-CNN	**0.9620**	**0.9544**	**0.9677**	**0.9432**

rate and F_1 value, especially that the accuracy rate reached 96%. Compared with the performance of several mature classification networks, there are obvious improvements. In addition, the metric F_1 can reflect the classification situation when the accuracy and recall rate cannot correctly evaluate the classification performance in some special cases. We see that the F_1 value of the HC-CNN network classification test is also 3% higher than the rest of the best-performing ResNet network. It can be explained that, in the holographic image classification of microplastic particles, the HC-CNN network can better perform feature extraction on the hologram of microplastic particles for their identification and characterization. Using this method, we can separate the microplastic particles in the heterogeneous sample from other environmental particles, and efficiently obtain the types of microplastic particles. It eliminates the need to manually distinguish each sample, and takes advantage of the specificity of the holographic fringes to accurately and efficiently identify the microplastic particles in the heterogeneous sample.

4. CONCLUSION

In this paper, we described a method based on deep learning and digital holography to classify and identify plastic particles in heterogeneous samples. Experiments have verified that this method can identify the microplastic particles from other environmental particles. This method provides an effective way for the detection of microplastic particles in the natural environment, and can be used to help detect and monitor microplastic particle pollution. In terms of the identification of microplastic particles, compared with the previous researches about the quantitative statistics and analysis based on the number of microplastic particles, the scope of research has been broadened. This method makes full use of the advantages of digital holography in spatial imaging recording[19,20] and is expected to be applied to real-time microplastic pollution monitoring in the natural environment in the future.

ACKNOWLEDGMENTS

The work is supported in part by the Research Grants Council of Hong Kong (GRF 17201818, 17200019, 17201620), the University of Hong Kong Interdisciplinary KE Project Fund (KE-ID-2018/19-17) and Environment and Conservation Fund (ECF Project 109/2019). The authors also acknowledge the support of Dr. Hau Kwan Lo for the microplastic particle image collection.

REFERENCES

[1] Law, K. L. and Thompson, R. C., "Microplastics in the seas," *Science* **345**, 144–145 (July 2014).

[2] De Falco, F., Di Pace, E., Cocca, M., and Avella, M., "The contribution of washing processes of synthetic clothes to microplastic pollution," *Scientific Reports* **9**, 1–11 (April 2019).

[3] Lim, X., "Microplastics are everywhere — but are they harmful?," *Nature* **593**, 22–25 (May 2021).

[4] Peeken, I., Primpke, S., Beyer, B., Gütermann, J., Katlein, C., Krumpen, T., Bergmann, M., Hehemann, L., and Gerdts, G., "Arctic sea ice is an important temporal sink and means of transport for microplastic," *Nature Communications* **9**, 1–12 (April 2018).

[5] Shim, W. J., Hong, S. H., and Eo, S. E., "Identification methods in microplastic analysis: A review," *Analytical Methods* **9**, 1384–1391 (November 2017).

[6] Bianco, V., Pirone, D., Memmolo, P., Merola, F., and Ferraro, P., "Identification of microplastics based on the fractal properties of their holographic fingerprint," *ACS Photonics* **8**, 2148–2157 (July 2021).

[7] Zhu, Y., Yeung, C. H., and Lam, E. Y., "Automatic detection of microplastics by deep learning enabled digital holography," in [*Digital Holography and Three-Dimensional Imaging*], HTu5B–1, Optical Society of America (June 2020).

[8] Bianco, V., Memmolo, P., Carcagnì, P., Merola, F., Paturzo, M., Distante, C., and Ferraro, P., "Microplastic identification via holographic imaging and machine learning," *Advanced Intelligent Systems* **2**, 1900153 (February 2020).

[9] Zhu, Y., Yeung, C. H., and Lam, E. Y., "Holographic classifier: Deep learning in digital holography for automatic micro-objects classification," in [*2020 IEEE 18th International Conference on Industrial Informatics*], **1**, 515–520 (July 2020).

[10] Ren, Z., Xu, Z., and Lam, E. Y., "Learning-based nonparametric autofocusing for digital holography," *Optica* **5**, 337–344 (April 2018).

[11] Ren, Z., So, H. K.-H., and Lam, E. Y., "Fringe pattern improvement and super-resolution using deep learning in digital holography," *IEEE Transactions on Industrial Informatics* **15**, 6179–6186 (April 2019).

[12] Ren, Z., Xu, Z., and Lam, E. Y., "End-to-end deep learning framework for digital holographic reconstruction," *Advanced Photonics* **1**, 016004 (January 2019).

[13] Song, L. and Lam, E. Y., "Phase retrieval with data-driven dual alternating direction method of multipliers for coherent diffraction imaging," in [*OSA Topical Meeting in Novel Techniques in Microscopy*], NTu1C–2 (April 2021).

[14] Zhu, Y., Yeung, C. H., and Lam, E. Y., "Microplastic pollution monitoring with holographic classification and deep learning," *Journal of Physics: Photonics* **3**, 024013 (April 2021).

[15] Zhu, Y., Yeung, C. H., and Lam, E. Y., "Digital holographic imaging and classification of microplastics using deep transfer learning," *Applied Optics* **60**, A38–A47 (February 2021).

[16] Bourlard, H. and Kamp, Y., "Auto-association by multilayer perceptrons and singular value decomposition," *Biological Cybernetics* **59**, 291–294 (September 1988).

[17] Simonyan, K. and Zisserman, A., "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556* (2014).

[18] Szegedy, C., Ioffe, S., Vanhoucke, V., and Alemi, A. A., "Inception-v4, inception-resnet and the impact of residual connections on learning," in [*Thirty-first AAAI conference on Artificial Intelligence*], (Feburary 2017).

[19] Ren, Z., Chen, N., and Lam, E. Y., "Automatic focusing for multisectional objects in digital holography using the structure tensor," *Optics Letters* **42**, 1720–1723 (May 2017).

[20] Ren, Z. and Lam, E. Y., "Edge-preserving autofocusing in digital holography," in [*Digital Holography and Three-Dimensional Imaging*], W2A–29, Optical Society of America (May 2017).