Zero-shot learning for holographic context analysis in microplastics probing

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Abstract: A zero-shot learning method with attribute embedding is developed for holographic image analysis and microplastics probing. Experimental results show its efficacy in identifying the unknown microplastics and alleviating the need for manual dataset class annotation.

1. Introduction

Zero-shot learning (ZSL) is an emerging deep learning method whose networks have strong inference capabilities [1]. The side information, such as attributes and texts, are used to assist network training. ZSL-based methods show superior performance on the recognition and classification of unknown objects, especially when the dataset is limited for network training.

Microplastics (MPs), as a kind of fine particulate matter, are abundant in the natural environment. MP pollution has attracted public attention in recent years [2]. Because of the different natural processes involving these plastic fragments, there is also a great deal of uncertainty in the appearance of MP particles. Researchers have endeavored to identify MPs in various situations with learning-based imaging methods, such as digital holography [3, 4], Raman spectroscopy [5], etc. However, most current methods are limited to the identification of known MP classes that have appeared during the network training stage [6].

In this study, we develop a ZSL method for holographic context analysis and demonstrate its effectiveness in MP particle probing and pollution assessment. We describe the morphological and textural characteristics of MPs with attributes, and embed the attributes into the image feature space by a mapping function to assist the network training. With this strategy, the network can identify the MPs from natural samples only depending on their character description, even though they are from the unknown MP classes.

2. Method

We demonstrate the working principle of our method in Fig. 1. Holographic images are represented as feature vectors in the image feature space $\mathbb{I}$. For each seen MP image class, there is a set of text attributes A_i to describe its morphological and texture characteristics. The attributes are coded as vectors and embedded in the semantic space $\mathbb{T}$. A trainable mapping function $g(\cdot)$ is used for the space projection and to transfer A_i from $\mathbb{T}$ to $\mathbb{I}$. In the

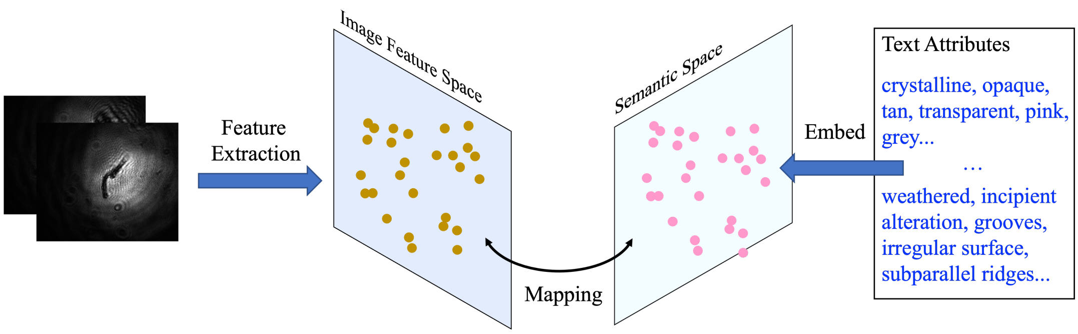

Fig. 1. Schematic demonstration for our ZSL method.

image feature extraction step, an attention mechanism is adopted to scale the weights of different image regions. Inspired by [7], a spatial attention map and a channel attention map are computed in the spatial dimension and the channel dimension. Furthermore, we introduce the Kullback-Leibler (KL) divergence [8] as one part of the loss function, which is combined with the mean squared error function, to guide the convergence of the ZSL network. The combined loss function is given by

$$L = L_{\mathrm{MSE}} + \beta L_{\mathrm{KL}}, \tag{1}$$

where β is the balancing factor for the two terms.

3. Experiment

The source images in our dataset are captured by a specially designed off-axis digital holographic system [9], which can record high-quality holographic images with different polarization states in a single shot. In the network training, the seen classes are labeled according to the object categories, including fiber, fragment, film, sand, shells and bones. In the test dataset, apart from the seen classes, three unseen classes are also involved, which are foam, glasses, and others. The unseen classes are used to test the derivation ability of the network, which is relatively poor for learning-based methods without the assistance of attributes [1]. We show the experimental results in Fig. 2. When the test dataset does not contain unseen classes, the accuracy achieved by the learning-based method, i.e., the method without attributes, is comparable to our method. As the number of unseen classes increases, the accuracy of our method shows a moderate downward trend, while the learning-based method performs a significant drop in its accuracy.

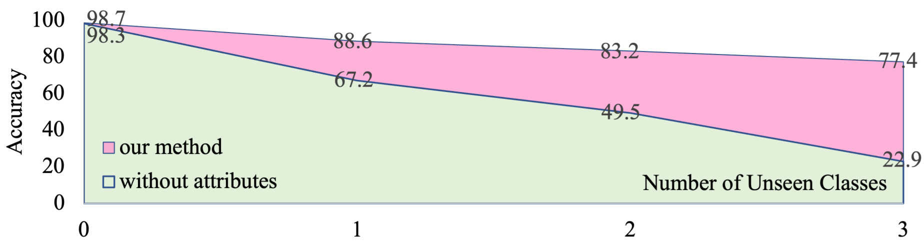

Fig. 2. Classification accuracy with the number of unseen classes in the test dataset.

4. Conclusion

In this paper, a zero-shot learning method is developed for holographic context analysis. Experimental results demonstrate its feasibility on MP probing and use for MP pollution assessment.

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