Digital holographic imaging and classification of microplastics using deep transfer learning

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We devise an inline digital holographic imaging system equipped with a lightweight deep learning network, termed CompNet, and develop the transfer learning for classification and analysis. It has a compression block consisting of a concatenated rectified linear unit (CReLU) activation to reduce the channels, and a class-balanced cross-entropy loss for training. The method is particularly suitable for small and imbalanced datasets, and we apply it to the detection and classification of microplastics. Our results show good improvements both in feature extraction, and generalization and classification accuracy, effectively overcoming the problem of overfitting. This method could be attractive for future in situ microplastic particle detection and classification applications. © 2020 Optical Society of America

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1. INTRODUCTION

Digital holography allows one to obtain the amplitude and phase information of objects from the holograms recorded by an electronic sensor [1]. It is a powerful tool for use in feature recording and object classification, especially for various imaging tasks in the wild. For instance, Dyomin et al. [2] proposed a fast recognition method of marine particles by identifying morphological features in underwater digital holography. Also, Davies et al. [3] developed an unsupervised holographic system to gain substantial information of natural particles, such as sand grains, bubbles, and diatoms. In recent years, thanks to the rapid development in both computational imaging and artificial intelligence, researchers have started to combine various holographic systems with deep learning algorithms to get significantly better performance [4–6]. Rivenson et al. [7] proposed a neural network-based method to perform phase recovery and holographic image reconstruction from intensity-only measurements with the successful elimination of twin-image and self-interference-related spatial artifacts. Wu et al. [8] demonstrated a method using convolutional neural network (CNN) to accomplish the fast autofocusing and phase recovery with an extension of the depth of field. Wang et al. [9] proposed a one-to-two deep learning framework to optimize the image reconstruction from a digital hologram by simultaneously reconstructing its phase and intensity information. Meanwhile, recognizing the challenges in sectioning in digital holography [10], Ren et al. devised a powerful non-parametric autofocus method [11] and improved the fringe pattern [12] by deep learning, and later also designed an end-to-end deep learning framework that not only can reconstruct low-noise images but also is applicable to phase aberration compensations and twin-image removal [13]. Xu et al. has done some related researches in digital holographic reconstruction [14]. Similarly, Jafarzadeh et al. [15] also presented a CNN with a regression layer to predict the propagation distance from a filtered hologram, and reconstruct single-cell level images. Many of these methods are computationally intensive, and to lighten the burden, Zeng et al. [16] designed a hologram reconstruction process that uses a capsule network, which not only reduces information loss in the pooling operation but can also speed up the computation. We are particularly interested in applying digital holography in the imaging and classification of microplastics, and exploring how deep learning can be harnessed for such applications. Microplastics are generally defined as plastic particles with diameter smaller than 5 mm. It should be noted that analyzing images of microplastics is an increasingly important area, because of the significant pollution problems that they cause [17]. For example, Hufnagl et al. [18] used random decision forests to analyze Fourier transform infrared spectroscopy images of microplastics, and detect them from the viewpoint of chemometrics. Digital holography has also been shown to be an effective imaging modality for this application, especially with the help of machine learning and deep learning [19–22]. However, to obtain a good classification performance, one would need a large number of well-labeled
images or holograms for deep learning network training, which restricts the developments of the deep learning for the related applications.

For us, an important consideration is to achieve microplastics imaging and classification when we only have a small and imbalanced dataset. This is because microplastics are often mixed with minerals, sand and dust particles, shells fragments, microalgae, large microplankton elements, debris, foams and bubbles, bacteria, etc. And it is time-costing and tedious for researchers to collect and filter these samples [17]. Additionally, because microplastic particles often float in water and are relatively dispersed from one another, it is more challenging to obtain microplastics images with a dense distribution (i.e., \( \geq 5 \) microplastics per \( 4 \text{ cm}^2 \)) than images with a sparse distribution (i.e., \( \leq 5 \) microplastics per \( 4 \text{ cm}^2 \)) in the field of vision of an optical system. Hence, in terms of the density of microplastics in an image, we often have an imbalanced distribution.

A common technique to deal with a small and imbalanced dataset is to use data augmentation, where additional images are generated by simple geometric operations, such as resizing and rotating the images [23]. Generative adversarial network [24] (GAN) is another popular approach, which implicitly builds a distribution of the images by training with an adversarial neural network. A third method is to use transfer learning (TL) [25]. The idea is to train a model with a large well-labeled dataset, and then the model is adapted and fine-tuned for the target data. The information extracted by the pre-trained part of deep transfer learning network is fed to the classification part subsequently. During the process of network transfer, the feature extraction capability of the network can be improved. Kim et al. [26] have combined transfer learning with digital holography, and applied it to molecular diagnostics. This is done by connecting a pre-trained VGG19 network to a multilayer perceptron, and one can classify the holograms of biological cells without reconstruction.

In this paper, we propose a digital inline holography system assisted by a specially designed lightweight deep learning network. It consists of compression blocks (Comp), and makes use of transfer learning for microplastics classification. We call the entire network CompNet, which is pre-trained on a well-labeled open-source dataset, and then fine-tuned for our small microplastics dataset using the fine-tuning last-k strategy [27] with a class-balanced cross-entropy loss function. Experimental samples included low complexity synthetic samples and high complexity real beach collected samples. Classification results are evaluated using several metrics that compare some leading methods with our network. In addition, to test the influence of the complexity of the pre-trained dataset and the imbalance ratios of the pre-trained dataset and the target dataset, the network is pre-trained on ImageNet [28], cifar-10 [29], and iNaturalist 2017 [30] datasets, respectively. However, compared with the real underwater detection environment of microplastic particles, the shape and surface roughness of microplastic particles are more uncertain, and further in situ detection and classification of microplastic particles works still need to be explored.

2. METHOD

A. System Setup and Data Collection

In building our imaging system, we would like to avoid bulky optical and mechanical components, so that it can be suitable for out-of-lab uses as a cost-effective and lightweight device. As such, its principle is based on digital inline holography, which is shown in Fig. 1. Compared with off-axis digital holography, the inline setup makes our optical system more robust to mechanical misalignment for the object light and the reference light travel along the same path [1]. The light source is a light-emitting diode (LED) with a 440 nm wavelength and a bandwidth of 24 nm. Instead of using a coherent light source (e.g., a laser), which is commonly used in holography systems, illumination by a LED can reduce the interference of coherent speckle noise [31]. In addition, without the need for lenses to focus light, there is less aberration that could have been introduced by the misalignment between different optical components [32]. The CMOS camera we used in the experiment is Applied Vision Mako G-507 with a pixel size of 3.45 µm and a resolution of 2464(H) × 2056(V). Because of the limitation of the coherence diameter of the light source and the resolution of the optical system, the detection range of our system is about 100 µm ~ 5 mm.

Imaging microplastics by digital inline holography with a partially coherent light source allows us to take full advantage of the rich information embedded in the holograms, which include both amplitude and phase data. Furthermore, compared with other optical images, such as those captured by electron microscopy, holographic images are more suitable for feature extraction and image classification by a neural network [33]. In our experimental setup, the partially coherent light goes through the sample slide and generates the holograms on the imaging plane, which are then recorded by a CMOS camera. The camera is placed on the image plane of the system, resulting in a unit optical magnification.

B. Microplastic Data

The most common plastic materials in the world are low-density polyethylene (LDPE), high-density polyethylene (HDPE),...
polypropylene (PP), polystyrene (PS), and polyethylene terephthalate (PET), which contribute to more than 90% plastic wastes [34] and pollution found in the coastal and marine environment. LDPE and HDPE are the main ingredients of plastic bags and bottles. PS is mainly used to make plastic utensils and food containers. Therefore, we choose LDPE, HDPE, and PS as representatives of the common microplastics to be detected. Moreover, the polyhydroxyalkanoate (PHA), which is a new biodegradable biopolymer plastic material and has been widely used in plastic bags and biomedical packaging materials in recent years [34], is also selected as one of the sample microplastics particles in our experiments.

To simulate the real natural environment, dust particles, such as soil and leaf fragments, are mixed with the microplastics and loaded on a microscope slide. The holograms of samples are obtained by using a microplate and a localization system. The holograms of samples are loaded on a microscope slide. The holograms of samples are mixed with the microplastics and microplastics particles in our experiments. To simulate the real natural environment, dust particles, such as soil and leaf fragments, are mixed with the microplastics and loaded on a microscope slide. The holograms of samples are obtained by using a microplate and a localization system. The holograms of samples are loaded on a microscope slide. The holograms of samples are mixed with the microplastics and microplastics particles in our experiments.
the expressiveness of the data by linear transformation. The parameter $\eta_{i,j}$ is used to prevent the variance from being zero.

Next, the output of the BN goes through a max-pooling step. Each location $(i, j)$ of $g(z_{i,j})$ now considers its local neighborhood and outputs a value that is the maximum within the region. As with many common neural networks, we use a pooling size of $2 \times 2$. Finally, the output feature map of the compression blocks will be flatten to one dimension. After finishing the feature extraction step, four fully connected modules are used for the classification. The first three modules contain a FCL with a length of 1024, 512, and 256, respectively, and each has a ReLU activation function and a dropout layer. The dropout layer is used to reduce the number of parameters and limit overfitting by discarding half of the connections between neurons. The last module of the image classification is a FCL combined with a softmax activation function [40]. The detailed structure of CompNet is shown in Fig. 2(c).

Furthermore, to enhance the feature extraction capability of our network, transfer learning is used during the training process. This is done by first pre-training the CompNet on an open-source image dataset. Then, we fine-tune the last two compression blocks of the pre-trained CompNet on our hologram data. Kim et al. [26] proposed VGG19-PCA-MLP to combine the transfer learning with digital holography for molecular diagnostics. They used a pre-trained VGG19 network as a feature extractor and cascaded it to a multilayer perceptron, which follows the feature extraction technique of the fine-tuning mechanism. In contrast, we adopt a fine-tuning last-k technique in transfer learning, which adjusts the last $k$ (where we set $k = 3$) residual modules of the pre-trained network based on the target dataset. Generally, using the pre-trained model as a feature extractor can reduce the number of parameters and reduce computational power, yet it may result in poor performance because of the dissimilarities between the two datasets. Fine-tuning last-k technique can promote the reuse of the features extracted from the pre-trained dataset, and consider the imbalance ratios of the pre-trained dataset and the target dataset, which helps to improve the generalization capability of the network.

D. Class-Balanced Cross-Entropy Loss

The cross-entropy loss function is widely used as the objective function for classification problems, which can be computed by the following steps. For each sample $k$ in the dataset, the
corresponding ground-truth class is \( c_k \in \{1, 2, \ldots, C\} \), where \( C \) represents the total number of classes. The prediction value of sample \( k \) for each class is \( p = [p_1, p_2, \ldots, p_C]^T \). For every output of the network, we apply a softmax function to represent the predicted probabilities, denoted by

\[
t(p_k) = \frac{\exp(p_k)}{\sum_{b=1}^{C} \exp(p_b)}.
\]

For each sample, the cross-entropy loss function is

\[
L_{CE} = -\sum_{k=1}^{C} c_k \cdot \log t(p_k).
\]

However, for an imbalanced dataset, e.g., one that is long-tailed, the class with the largest sample size may have 10 or 100 times as many samples as the class with the smallest number of samples. Consequently, the results of loss function are more dominant by the classes with more data, and the loss incurred from the samples in those classes with fewer data is omitted. To tackle this, inspired by [43], we introduce a weighting factor to the cross-entropy loss function, called the class-balanced cross-entropy loss. We add a class weighting factor that is related to the effective number \( \theta \) of each class to the cross-entropy loss function, given by

\[
L_{CB} = -\sum_{k=1}^{C} \frac{1 - \theta}{1 - \theta n_k} \cdot c_k \cdot \log t(p_k),
\]

where \( \theta \) is calculated by \( \theta = (N - 1)/N \), with the total number of samples \( N \) in the dataset, and \( n_k \) is the number of samples in the ground-truth class \( c_k \).

### 3. RESULT AND DISCUSSION

The number of trainable parameters of CompNet and some leading networks for classification are shown in Table 1. We also take the value in CompNet as a baseline and normalize the number of parameters in the other networks with it. We can observe that our network has around 5% to 300% fewer parameters to train, except when compared with CNN, which is more suitable for classification with a small dataset. In addition, the lightweight architecture of CompNet makes it more possible to be implemented on a computationally limited portable device.

To evaluate the role of pre-trained architecture, we first train CompNet with randomly initialized weights on the ImageNet [28] dataset, which contains around 1.23 million natural images with 1,000 classes. Since our holograms are monochromatic, we convert those images to gray scale. Then, we freeze the first two compression blocks, where both serve as feature extractors, while extracting features at different depths. The other two blocks are fine-tuned based on our target dataset. The process is shown in Fig. 3. In addition, the class distribution of the target dataset and the sample holograms of each class are shown in Fig. 4.

For comparison, we also train a randomly initialized CompNet on our hologram dataset. While the initialization is random, the parameters in the network will be trained on our dataset, and the network relationship will be fitted according to our during the training process. Moreover, as with the pre-training strategy described above, we randomly split the data into a training set, a validation set, and a test set, with a ratio of 8:1:1. Moreover, for statistical analysis and test for robustness, we repeat all the training process for 10 times with independent data input. In addition, to improve the reliability of the result, we ensure that the test set is never seen previously by the network. All training and testing are performed with an NVIDIA TITAN V GPU and implemented in TensorFlow.

To quantitatively compare the classification performance, we define \( X_{TP} \) as the value of true positive prediction, which is the number of samples that are correctly assigned to the well-classified samples by the network, and \( X_{TN} \) represents the number of correctly predicted mis-classified samples. When the well-classified samples are incorrectly assigned to the prediction results, the sample is considered as a false positive, and the number of them is \( X_{FP} \). When the mis-classified sample mismatches the prediction result, we consider it as a false negative sample, and it has the total number of \( X_{FN} \). The accuracy \( (A) \) is defined by

![Fig. 3. Training policy (parameter frozen or fine-tuned) of the pre-trained network.](image-url)
Fig. 4. Class distribution and sample images of the target dataset.

\[ A = \frac{X_{\text{TP}} + X_{\text{TN}}}{X_{\text{TP}} + X_{\text{TN}} + X_{\text{FP}} + X_{\text{FN}}}. \] (8)

In addition, by defining the sensitivity \( (S_E) \) and specificity \( (S_P) \) as

\[ S_E = \frac{X_{\text{TP}}}{X_{\text{TP}} + X_{\text{FN}}}, \quad S_P = \frac{X_{\text{TN}}}{X_{\text{FP}} + X_{\text{TN}}}, \] (9)

we can further define a quantity known as the G-mean \( (G) \) as

\[ G = \sqrt{S_E \cdot S_P} = \sqrt{\left( \frac{X_{\text{TP}}}{X_{\text{TP}} + X_{\text{FN}}} \right) \left( \frac{X_{\text{TN}}}{X_{\text{FP}} + X_{\text{TN}}} \right)}. \] (10)

When evaluating the performance of the classifier on an imbalanced dataset, the accuracy cannot objectively assess its result. G-mean will give a more reliable evaluation by considering the contribution of each class to the network performance when classifying an imbalanced dataset.

The performances of CompNet and its alternative implementation assisted by transfer learning are shown in Fig. 5. We can observe that in the training process of CompNet, as shown in Fig. 5(a), the value of the loss function \( L_{\text{CB}} \) has a big range of variation. On the other hand, with the assistance of transfer learning, as shown in Fig. 5(b), the loss value of CompNet in the whole training process is more stable. In addition, based on the same training environment and computing devices, the alternative implementation of CompNet assisted by transfer learning costs about 27 s. This compares with CompNet alone, which consumes about 101 s before effective convergence. The use of transfer learning, therefore, saves about 72% training time. In summary, the performance comparisons between CompNet and its alternative implementation assisted by transfer learning conclude that the former increases the feasibility of our method of microplastics detection and classification based on the raw holograms without reconstruction.

To further evaluate the performance of transfer learning on the small and imbalanced dataset, we train the network on datasets with different sizes and distributions. We first train both networks on 533 images, and then reduce the number of data to test the influence of the size of the training set on prediction accuracy. The other experiment is conducted on the dataset with different class distributions, where we use data augmentation to change the distribution among different classes. By rotating and flipping the images, the classes with relatively small sizes are enlarged. To evaluate the performance of GAN and transfer learning for microplastics classification on our small and imbalanced dataset, we design a network based on the architecture of Auxiliary Classifier GAN [44] (AC-GAN) and train it on our dataset. Besides, we also reimplement the VGG19-PCA-MLP network from [26] and train it on our dataset with the best judgements for a fair comparison.

Tables 2 and 3 give the mean value of the prediction performance from 10 repeated independent experiments with the training set of 533 images and 20 images, respectively. The number of test sets for each training is the same, which is 67 images. For fair comparisons, all results for all methods are trained on the same training set and test on the same test set. As shown in Fig. 6, with the reduction of the data size, the performance of the prediction drops as well. However, with the assistance of transfer learning, the accuracy is higher when trained on a small dataset, as shown in Tables 2 and 3. When training with 20 images, both accuracy and the value of G-mean are significantly improved after applying transfer learning, which are higher than 90%. However, for the rest of the methods, they all show a significant decrease in both \( A \) and \( G \) on the small training set. The alternative implementation of CompNet assisted by transfer learning yields a higher \( A \) and \( G \) than those obtained by VGG19-PCA-MLP network proposed in [26], which concludes that the technique of fine-tuning last-k can more fully migrate the feature extractor capability on microplastics classification. Additionally, AC-GAN shows a comparable performance with
CompNet, which suggests that GAN network is less efficient and robust for the feature extraction and generalization on the task of microplastics classification.

In order to further verify the validity and feasibility of the proposed classification method based on transfer learning, we applied it to the detection and classification of microplastics in real samples collected on the beach, as shown in Fig. 7. Compared with the synthetic samples, the types of particles in the real samples, except microplastic particles, are more complex, including several non-biological particles such as gravel, dust particles, minerals, shell fragments, large plastic fragments, leaf fragments, and biological components such as bacteria. In addition, with an electron microscope, it shows that there can be as many as eight microplastic particles in real samples within the field of view of CMOS camera. Therefore, we further expand the number of classes of microplastic classification. In order...
to make a fair comparison with the classification results of the synthetic samples, we also collected 20 holograms as training sets to train different networks, and kept other network training parameters and training platforms the same as those of the synthetic samples. The classification performances on the real sample are shown in Table 4. As we can see, due to the increase in sample complexity, the accuracy of each classification method is generally reduced by 1 to 6 percentage points compared with the synthetic samples, among which the biggest decline occurs in the method proposed by Kim et al. [26]. The reason could be that this method is a deep transfer network built for molecular diagnosis and the target of classification is cells, so it cannot accurately and specifically extract the features of microplastic particle holograms. However, the results in Table 4 show that CompNet based on transfer learning has a better performance in dealing with the classification of microplastic particles with such small training sets, which also demonstrates the effectiveness and feasibility of the classification method proposed in this paper.

To test the feature extraction capability of the alternative implementation of CompNet assisted by transfer learning, we plot the $t$-Stochastic Neighbor Embedding ($t$-SNE) [45] images of our training dataset. The $t$-SNE image is a visual tool to display high-dimensional distributed data in 2D or 3D maps by the processing of dimension reduction. The $t$-SNE plots of the extracted features from the raw holograms, the holograms trained by random initialized CompNet, and holograms trained by CompNet with pre-trained model are shown in Figs. 8(a)–8(c), respectively. As we can see, the features extracted from each class after applying the transfer learning are more segregated than they are in the cases where no transfer learning is applied, suggesting that the pre-trained model of CompNet has improved feature extraction capability of the network.

To test the role of pre-trained model and the generalization capability of feature extraction layers of CompNet, we also pre-train our CompNet on different datasets, including ImageNet, cifar-10 [29], and iNaturalist 2017 [30]. The dataset of cifar-10 contains 10 classes of color images with a size of $32 \times 32$ pixels. For each class, there are 6,000 images. ImageNet and cifar-10 dataset both have balanced distributions but are different in terms of image size, as ImageNet has over 20 times the number of images than cifar-10. iNaturalist 2017 dataset is a long-tailed distributed dataset containing 579,184 real-world images of 5089 classes. We use a parameter $\rho$ to measure the imbalance of the dataset, given by

$$\rho = \frac{\max\{n_k\}}{\min\{n_k\}}, \quad k = 1, \ldots, C. \quad (11)$$

Here, $\max\{n_k\}$ represents the sample size of the most frequent class, and $\min\{n_k\}$ represents the sample size of the least frequent class. The comparisons of the three open-source datasets that we used in this study and our target hologram dataset are shown in Table 5.

For a fair comparison, the target dataset used for fine-tuning is the same for all three pre-trained models. The training of the networks is done using both the class-balanced cross-entropy loss function and the cross-entropy loss function to evaluate the respective performance. As shown in Fig. 9, the accuracy of the

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**Table 4. Classification Performances of Different Methods on Real Samples**

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy ($A$)</th>
<th>G-mean ($G$)</th>
<th>Sensitivity ($S_e$)</th>
<th>Specificity ($S_p$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>0.6801</td>
<td>0.6595</td>
<td>0.6974</td>
<td>0.6831</td>
</tr>
<tr>
<td>CompNet</td>
<td>0.7886</td>
<td>0.8127</td>
<td>0.7922</td>
<td>0.8037</td>
</tr>
<tr>
<td>CompNet (with aug)</td>
<td>0.8127</td>
<td>0.8012</td>
<td>0.8133</td>
<td>0.8009</td>
</tr>
<tr>
<td>Kim et al. [26]</td>
<td>0.7401</td>
<td>0.7329</td>
<td>0.7271</td>
<td>0.7346</td>
</tr>
<tr>
<td>ACGAN</td>
<td>0.7749</td>
<td>0.7376</td>
<td>0.7436</td>
<td>0.7298</td>
</tr>
<tr>
<td>CompNet (with TL)</td>
<td>0.8407</td>
<td>0.8554</td>
<td>0.8567</td>
<td>0.8641</td>
</tr>
<tr>
<td>CompNet (with aug &amp; TL)</td>
<td>0.8878</td>
<td>0.8759</td>
<td>0.8964</td>
<td>0.9032</td>
</tr>
</tbody>
</table>

*a“aug” means augmentation and “TL” means transfer learning.*
CompNet network pre-trained on the iNaturalist 2017 dataset was superior to that of the pre-trained network on ImageNet and cifar-10. We can find that there is a positive relationship between the distribution and imbalance ratio of the pre-trained dataset and the performance of final prediction. In addition, it can be concluded that the feature transferability is less influenced by the size of the pre-trained dataset by comparing the results of ImageNet and cifar-10. When using the traditional cross-entropy loss function, there is no significant improvement on the accuracy compared with the results on CompNet. In conclusion, the experimental results are promising that the features extracted from other natural images with similar distributions can generalize to the holograms and microplastics classification tasks. Transfer learning with class-balanced cross-entropy loss can make up for the poor classification performance of the imbalanced-distributed datasets caused by the difficulties of image collections of certain classes in hologram datasets and some other computation imaging datasets.

4. CONCLUSION

We have proposed and experimentally demonstrated a transfer learning assisted digital inline holography system for microplastics classification, which mainly focuses on the tasks with small and imbalance-distributed dataset. Our method is a robust, computationally minimal and effective tool for automatic microplastics classification and other digital holography and computational imaging modalities, where the collections of well-labeled data for all the classes are difficult. This method also promotes the combination of deep learning and computational imaging and can be implemented on a portable, computationally limited device for out-of-lab use.

The main purpose of this study is to detect and monitor the concentration of microplastic particles, so the classification in this paper is based on the number of microplastic particles. In future studies, the classification of microplastic particulate materials and types can be further explored. In addition, in order to better detect the true distribution of microplastic particles in the ocean, an underwater holographic imaging experiment is also a direction for further research in the future. The classification method based on transfer learning proposed in this study can also be further applied to the underwater holograms of microplastic particles.

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