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Identifying the asymmetric superposition of fractional orbital-angular-momentum modes via neural networks with a small dataset

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The channel capacity of optical communication can be largely improved by using the orbital angular momentum (OAM) beam because of its inherently infinite dimensions. Identifying the topological charge carried by OAM beams is essential for encoding and decoding the information [1, 2]. Thanks to its ability to tackle a variety of hard tasks (including classifying, identifying, and interpreting massive data), machine learning, particularly convolutional neural networks (CNNs), has been proposed for identifying OAM beams [3–5].

With the increase of the topological charge, the phase singularity and diffraction effect greatly affect the intensity distribution of OAM beams, which increases the difficulty of focusing in free space and coupling in optical fibers [1]. This challenge limits the development of optical communication with high-order OAM. In this case, the superposition of asymmetric fractional OAM modes (i.e., the topological charges of two fractional OAM modes with opposite signs and different magnitudes) can increase the possibility of combining OAM modes, thereby expanding their multiplexing capacity at low topological charges [5]. However, the asymmetric fractional OAM superpositions exhibit more delicate differences between two adjacent modes, which increases the difficulty of distinguishing between them.

In this study, we propose and demonstrate an efficient preparation and identification method for asymmetric fractional OAM superposition using a self-constructed neural network. The method of interfering with plane waves using spherical waves was applied to obtain the datasets, which effectively reduced the complexity of dataset acquisition. The advantage of our method is that the experimental datasets have obvious features, which enables our model in the high-accuracy identification of asymmetric fractional OAM superpositions on small datasets. Furthermore, we obtained arbitrary fractional OAM superposition by conveniently changing the phase holograms on the spatial light modulator (SLM), without extra optical components. A neural network with seven layers was then trained using the experimental datasets. Utilizing this neural network, we completed a 19-class classification task of asymmetric fractional OAM superpositions with a precision of 0.1 and recognition accuracy of 99.34%, only consuming 4560 total datasets. The results demonstrated that this is a useful approach for the accurate, rapid identification of multiplexing OAM in optical information processing.

The experimental setup for generating asymmetric fractional OAM superpositions was shown in Figure 1(a). The light source was an external cavity semiconductor laser (Toptica DL pro) with a wavelength of 895 nm. The power of the laser beam was adjusted using the combination of a half wave plate (HWP) with a polarization beam splitter (PBS). Since polarization is crucial for achieving high modulation efficiency, HWP2 was placed in front of the lens to control the beam's polarization. A 10 mW laser beam with a Gaussian distribution was shaped by Lens1 and Lens2, and injected into the SLM with a small angle to guarantee the modulation efficiency. The SLM in this experiment had a resolution of 1920×1080, with each pixel being 8×8 μm^2.

To generate the asymmetric fractional OAM superpositions, the phase holograms of the superpositions were uploaded on the SLM. After being reflected by the SLM, the Gaussian-distributed beam was modulated into the asymmetric fractional OAM superposition beam. A CCD camera was utilized to capture and record the intensity patterns of the beam, which provided reliable datasets for the subsequent neural network. To construct an abundant dataset, we changed the phase holograms uploaded on the SLM by adjusting the parameters θ_0 and n_{modes} (Appendix A). The parameter θ_0 was varied within the range of 0 to 2π with a step size of 0.1. The n_{modes} was selected for specific val-

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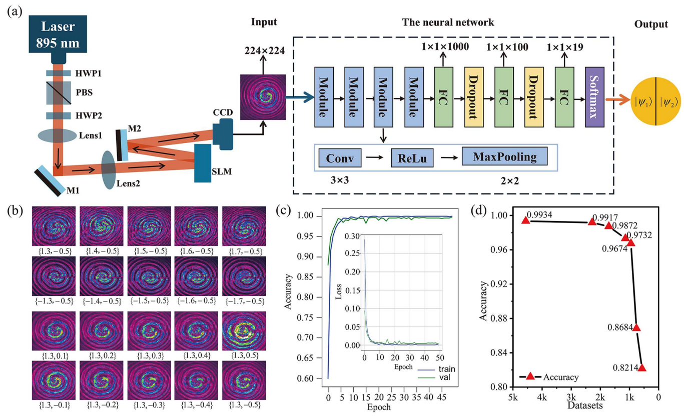

Figure 1 (Color online) (a) Experimental setup; (b) the intensity patterns of the asymmetric fractional OAM superpositions; (c) the accuracy curves and loss function curves of the 19-class classification task; (d) the dependence of accuracy on different numbers of datasets.

ues (10, 12, 14, 16, 18, and 20). As a result, the dataset comprised a total of 4560 images and was divided into three parts: 3192 for training, 912 for validation, and 456 for testing. The theory of asymmetric fractional OAM superpositions and the phase holograms of superpositions can be found in Appendix A.

The intensity patterns of the asymmetric fractional OAM superpositions were shown in Figure 1(b). The patterns had three main features: the gaps of the rings on the left side, the central structure of the pattern, and the malposition between the top and bottom halves of the patterns on the right side. The gap was determined by the fractional part of the plane wave. The central structure of the pattern was determined by the difference between the OAMs of the plane wave and the spherical wave. The malposition was determined by the fractional part of the spherical wave. The larger the fractional part of the spherical wave, the more obvious the malposition. The direction of the malposition was determined by the sign of the spherical wave. When the sign was positive, the upper side shifted to the left, whereas the lower side shifted to the right. Furthermore, the rotation direction of the ring was determined by the wave with the largest absolute value of the topological charge. When the sign was positive, the ring rotated in a clockwise direction. Otherwise, it rotated counterclockwise.

To identify the features of the intensity patterns, we performed a 19-class classification task. The details of the neural network architecture can be found in Appendix B. The accuracies of the training set and the verification set are shown in Figure 1(c). The accuracy curve revealed the fast convergence of the model during the early stages of training. At the fourth epoch, the model achieved 90% accuracy on both the training set and the validation set, which indicated its ability to quickly capture the key features of the dataset. With the increase of iterations, the model's accuracy was further stabilized and ultimately tended to be about 99%. The total time for the whole training process was 951.06 s. The results of the test set demonstrated that the accuracy of the 19-class classification task reached 99.34%, which demonstrated that our method is applicable for superpositions with arbitrary values of topological charges.

A small-scale dataset with distinguishable features can effectively speed up the training and recognition of networks. We present the dependence of accuracy on different numbers of datasets in 19-class classification tasks in Figure 1(d). When the dataset was 2280, the accuracy remained at 99.17%. Even when the dataset was reduced to 760, the accuracy only dropped to 86.84%. This demonstrated that even with a small dataset, the model could achieve a high rate of accuracy.

Conclusion. We have demonstrated the identification of asymmetric fractional OAM superpositions using a self-constructed lightweight neural network. A 19-class classification task achieved an accuracy of 99.34% using 4560 datasets. The results confirmed that our neural network architecture can achieve the high-accuracy identification of asymmetric fractional OAM superpositions on small datasets in a laboratory environment. There are many complex environments in the practical application of optical information processing using OAM. The high-accuracy identification of asymmetric fractional OAM superpositions in complex environments can be achieved by increasing the experimental datasets, introducing a residual connection, and other methods. This work has provided a useful approach for the high-accuracy identification of multiplexing OAM in optical information processing with OAM.

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Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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