Differential Interference Contrast Phase Edging Net: an all-optical learning system for edge detection of phase objects

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Edge detection for low-contrast phase objects cannot be performed directly by spatial difference of intensity distribution. In this work, an all-optical diffractive neural network (DPENet) based on the differential interference contrast principle to detect the edges of phase objects in an all-optical manner has been proposed. Edge information is encoded into interference light field by dual Wollaston prisms without lenses and light-speed processed by the diffractive neural network to obtain the scale-adjustable edges. Results show that DPENet achieves F-scores of 0.9293 (MNIST) and 0.9356 (NIST) and enables real-time edge detection of biological cells, achieving an F-score of 0.7547.

Keywords: diffractive neural network, edge detection, phase objects.

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1.Introduction

Edge detection is one of the common data processing methods and core problems in the field of machine vision, which has a wide range of applications in object detection[1], image segmentation[2], data compression[3], microscopic imaging[4] and object suggestion generation[5]. Edges can be extracted by the spatial differentiator (SD) and reflect the key information in the image more efficiently[6]. In the biomedical field, intensity changes of phase objects such as biological tissues and cells are usually weak[7]. To more clearly and directly reflect the morphological boundary and structural characteristics of phase objects, it is of great significance to develop edge detection technologies for phase objects.

As a common method of phase imaging, Differential Interference Contrast (DIC) technology can produce a relief effect for observing phase objects[8,9]. However, the beam splitter prism can only be set in one direction to image and the relief effect only enhances the one-dimension edge. The differential interferometric imaging spectrometer can also record the phase information of the object, but the collected interference fringes need to be unwrapped to image[10]. To further detect the edge of the imaged object, the SDs need to be processed by digital or analog means.

Optical analog computing performs large-scale data processing at the speed of light and becomes a powerful tool to replace digital signal processing[11,12]. At present, optical SDs based on Surface Plasmon Polariton (SPP) resonance [13], Brewster Angle Effect[14], Anisotropic Crystal Birefringence[15] and Optical Spin Hall Effect[16] were only able to detect one-dimension edges of objects. The transfer function of nanophotonic material was regarded as Laplacian operator to realize two-dimension SD[17]. However, due to the crosstalk of incident light with different polarization directions, the edges with enough resolution were obtained only by working at the terahertz frequency. Moreover, the above methods to simulate differential operators are only effective for intensity objects, but for low contrast phase objects. Diffractive deep neural network (D²NN) is an all-optical neural network framework based on holographic technology and provides new ways to solve these problems[18-20].

Here, we proposed a diffractive neural network (Differential Interference Contrast Phase Edging Net, DPENet) based on differential interference contrast principle to detect the edge of phase objects in an all-optical manner. In the simulation, the phase object is divided into incident light and reference light by dual Wollaston prisms (DWP). Differential interference is accomplished by polarized light in the same direction by the polarizers. The diffractive neural network processes the original differential signal to obtain the edge image of the corresponding phase object. The scale of the edge can be changed by adjusting the air gap of the DWPs during detection. MNIST and NIST datasets were simulated to verify the performance of edge detection and generalization of the system. The F-score obtained on MNIST and NIST datasets is 0.9293 and 0.9356 respectively, and the highest imaging resolution can reach 420 nm. In addition, we also verified the application of DPENet in the field of biological imaging, which can detect the edge of biological cells and achieve the maximum F-score of 0.7547.

2.Principle

The structure of DPENet is shown in Fig. 1(a). DPENet is mainly composed of two parts. One part is a SD for the input phase object, and the other part is an all-optical D²NN processing module. The schematic diagram of...
integrating D²NN with traditional DIC microscope for edge detection is shown in Fig. 1(b). In the DPENet, the DIC module is changed to SD for lens-less imaging to reduce the size of the system.

Fig. 1. (a) The schematic diagram of DPENet. The DPENet consists of two parts: spatial differentiator and all-optical processor. POL: polarizer; DWP: dual Wollaston prisms; QWP: 1/4 wave plate. (b) The edge detection system based on DIC microscope. (c) The ray tracing diagram of dual Wollaston prisms. α: structural angle of prism; γ: refraction angle. (d) Schematic diagram of forward and back propagation of a three-layer D²NN.

In the SD part, the phase object is entered with coherent light. All polarizers are oriented at a 45° angle with respect to the horizontal direction. The polarized light is split into ordinary light and extraordinary light with perpendicular directions by dual Wollaston prisms. The ray tracing diagram of the beam splitter that incorporates dual Wollaston prisms is illustrated by Fig. 1(c). Due to the birefringence property of the Wollaston prism, the ordinary light and extraordinary light are split into two parallel beams in the same direction as the incident light. The distance of splitting beams d can be expressed as[23]:

\[ d = \frac{\tan (\gamma_o - \alpha) + s \tan \gamma_{o2}}{1 - \tan \tan (\gamma_o - \alpha)} + \frac{\tan (\alpha - \gamma_o) + s \tan \gamma_{o2}}{1 + \tan \tan (\alpha - \gamma_o)} \]  

(1)

where \( \alpha \) is the structural angle of Wollaston prism, \( \gamma_o \) and \( \gamma_{o2} \) respectively represent the refraction angles of ordinary light and extraordinary light at the \( r \)th interface, \( l \) is the thickness of the Wollaston prism, and \( s \) is the thickness of the air gap between two prisms. The scale of the spatial difference can be changed by adjusting the distance of the splitting beams and the resolution of the edge detection will be controllable.

Two orthogonally polarized lights are normalized to the uniform direction by the polarizer to produce interference. When multi-channel optical signals interfere, the superimposed optical field received by the detector can be expressed as[23]:

\[ U_{out} = |Ae^{j\varphi_1} + Ae^{j\varphi_2} + \ldots + Ae^{j\varphi_N}|^2 \]

\[ = 2A^2\sum_{i=1}^{N}\sum_{j>i}>\cos(e^{j\varphi} - e^{i\varphi}) + A^2N \]  

(2)

where \( A \) is the amplitude of the input signals, \( \varphi \) is the phase of the input signal, and \( N \) is the number of input light channels.

When the system is used as a one-dimension (two-dimension) differentiator, spatial difference can be accomplished by setting the DPWs in one (orthogonal) direction(s). The input complex optical filed is divided into incident light and reference light, and the edge information will be encoded into the interference light field.

The edge information will be enhanced and the overlapping part will be suppressed, when the incident light and reference light with a phase difference are spatially differentiated. The total phase difference can be divided into the phase difference introduced by dual Wollaston prisms and the 1/4 wave plate. The phase difference of the DWP can be expressed as[23]:

\[ \theta_{DWP} = \frac{2\pi}{\lambda} \left( n_o - n_e \right) + \frac{n_o}{\cos (\gamma_o - \alpha)} - \frac{n_e}{\cos (\alpha - \gamma_o)} \]

\[ + \left( \frac{1}{\cos \gamma_o} - \frac{1}{\cos \gamma_o} \right) s \]

(3)

where \( n_o \) and \( n_e \) are the refractive indices of the birefringent crystal to ordinary light and extraordinary light, respectively.

The D²NN is used as an all-optical signal processor to modulate the phase and amplitude of the original differential signal and obtain clear edges. Schematic diagram of forward and back propagation of a three-layer D²NN is demonstrated by Fig. 1(d). Each neuron is regarded as a new secondary wave source propagating by diffraction between layers. Its spatial diffractive propagation model is expressed by the Rayleigh-Sommerfeld diffraction equation in the far field[23]:

\[ w(r) = \frac{x - x_i}{r} \left( \frac{1}{2} + \frac{1}{j} \right) \exp \left( \frac{jmr^2}{\lambda} \right) \]

(4)

where \( i \) represents the \( i \)th pixel of a given layer of the system located at position \( (x_i, y_i) \), \( \lambda \) is the operative wavelength, \( r = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} \) and \( j = \sqrt{-1} \). The diffractive propagation of signal in optical differentiator is also defined by Eq. (4).

The ground truth of the edges for training and evaluation are obtained by the traditional edge-extraction canny operator. The loss function is defined to evaluate the cross entropy (CE) between the intensity distribution of the outputs and the objects on the detection plane. The "Adam" optimization algorithm, which is adapted according to the optimization method based on stochastic gradient, is used to minimize the loss function. The network has a learning rate of 0.01 with a decay of 0.1 for every 2 epochs and a batch size of 8. It is implemented using Python version 3.7.11 and TensorFlow framework 1.15(Google Inc.), and runs on a desktop computer (Nvidia Tesla T4 graphics processing unit, Intel Xeon Gold 5218 CPU, 16 cores, 256GB RAM on Microsoft Windows 10).
The green laser with a wavelength of 532 nm is used as the input light source of DPENet. The pixel size is set to 420 nm and the propagation distance between layers is 40λ. The output of the SD is discretized by the D2NN processor to a resolution of 200×200 to match the model.

Fig. 2. (a) Convergence plots of DPENet and ANN. (b) The intensity of each layer of D2NN processor. The complex light field is directly phase-only modulated by D2NN, but only the intensity distribution of each layer is shown. (c) The phase parameters of each layer D2NN obtained by training.

Fig. 2(a) compares the ANN (intensity input) and DPENet (complex light field input) of the same structure. The results show that DPENet can directly process the complex light field to get the edge without additional detector. However, the ANN with intensity input needs to detect the intensity before working, and the convergence effect is obviously worse than that of complex light field input. In DPENet, the interference light field of spatially differential signal obtained by SD contains the edge information of the phase targets, and it needs to be processed to get a clear edge image by D2NN. Fig. 2(b) and (c) show the processing flow of the interference light field emanating from the SD in a 5-layer phase-only D2NN. It should be noted that D2NN directly processes complex light fields, and figures only show the intensity distribution after each layer of processing.

To demonstrate the edge detection capability of DPENet, the performance of the one-dimension and two-dimension edges was tested by using MNIST of 10 classes and NIST of 52 classes. The dataset for the MNIST includes 60,000 data for training and another 10,000 for testing. The NIST dataset contains 124,800 training data and 20,800 testing data, including 26 handwritten English letters in capital and lowercase letters. For all results, the same evaluation system including PR curves and F-scores was adopted.

In Fig. 3(a), the results of one-dimension and two-dimension edges of the MNIST dataset with perpendicular directions are displayed. The DPENet is highly sensitive to such tiny one-dimensional edges. It is observed that the edge is also detected in the tilt direction due to the resizing and discretization of the object, which causes the sloping edge to appear as a ladder shape in both horizontal and vertical directions. The F-score of the horizontal and vertical edges can reach 0.8966 and 0.9293, respectively. Fig. 3(b)–(e) show the results of two-dimension edge detection of NIST by DPENet. The results show that DPENet can also directly perform two-dimension edge detection of phase objects.

Moreover, DPENet can detect the two-dimension edges with different resolutions, including thicker strokes (upside) and thinner strokes (downside). Fig. 3(f) shows the PR curves of DPENet using each of MNIST and NIST. For MNIST and NIST edge imaging, the maximum F-score can achieve 0.9293 and 0.9356, respectively. It is worth noting that since DPENet is a data-driven all-optical deep learning paradigm, the large amount of training data makes the DPENet highly generalized. The testing results of the MNIST dataset can be detected directly after the model has been trained with the NIST dataset, and the model does not need to be retrained.

Fig. 4 Statistics of edge results at different spatial differential scales of inputs: (a) 1 pixel (b) 2 pixels (c) 4 pixels (d) 6 pixels; (e) Resolution of edge imaging with different scales.

Fig. 4(a)-(d) shows the statistics of edges at different spatial differential scales of inputs with SDs dislocated by 1, 2, 4, and 6 pixels. The scale of edge detection can be directly adjusted by changing the air gap of the double Wollaston prisms. In the limit state with no gap, the differential dimension of space reaches the minimum. As the gap increases, the incident light and the reference light become more separated, resulting in thicker edges. This property is particularly significant when the size of the observed object is uncertain. A thick edge is not suitable for small
objects since it fails to reflect details, whereas a thin edge is not conducive to observing large objects due to the low contrast. Therefore, the scale of edge detection can be freely adjusted according to the target object. Notably, there is no need to retrain DPENet for this conditioning process. After training the DPENet, the scale of edges can be controlled by directly adjusting the gap. Fig. 4(e) shows the resolution of the same position in Fig. 4(a)-(d), with the red line representing the full width of half wave (approximately 1-4.5 pixels). Statistical analysis shows that DPENet can achieve a highest resolution of about 420 nm (single pixel).

To demonstrate the application of DPENet in edge detection of biological tissue, pathological section images from the National Cancer Institute GDC data Portal consisting of 4500 training images and 1000 testing images has been used. Some measures were taken to extend the training data set to ensure the training effect, such as different directions of inversion and elastic deformation for dataset.

![Fig. 5 The results of edge extraction of pathological sections. (a) Type 1: Normal edge detection results. (b) Type 2: Wrong edge detection results. (c) Type 3: Missed edge detection results.](image)

Fig. 5 shows the edges of pathological sections. Unlike the Canny operator, DPENet can detect the edge of the phase object (Type 1) without staining cells and obtain results comparable to the detection results of the Canny operator. As expected, the edges show the boundaries of the cell nucleus and reveal their shapes and positions. DPENet can also reliably carry out selective edge detection in case of error detection and missing detection that may occur with traditional edge operators. For the type 2, the regions marked with red boxes are not real nucleus. DPENet does not generate misjudgments for error checks compared with Canny operator. For the type 3, DPENet can detect the region where the gradient of phase changes inconspicuously, and successfully reflects the morphologic characteristics. To quantitatively evaluate the results, maximum F-score could be reached 0.7547.

3. Conclusion

In conclusion, we proposed a scale-adjustable edge detection system DPENet for phase objects in an all-optical manner and simulated the optical SDs and the DNN. Different from the traditional optical calculation methods, only analogizing differential operator cannot detect the edge of the undyed phase objects. DPENet can detect the edge information of phase targets by interference difference and uses passive diffractive layers as optical processing device to ensure the high-speed operation and transmission efficiency of edge detection. No lens or imaging system is used in the whole system, which successfully reduces the complexity of the device. Compared with the ANNs, our proposed system does not need to collect the intensity distribution in advance, but directly modulate the complex light field to enable real-time online edge detection of phase objects.

References
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