Edge-Preserving Autofocusing in Digital Holography

Zhenbo Ren, Edmund Y. Lam*

Imaging Systems Laboratory, Department of Electrical and Electronic Engineering, The University of Hong Kong, Pokfulam, Hong Kong

**elam@eee.hku.hk*

Abstract: In digital holography, it is essential to know the axial position of the recorded object for reconstruction. Here we propose an autofocusing algorithm using structure tensor to determine the focal distance and to extract the edge information.

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1. Introduction

Digital holography (DH) is a significant imaging technique that can record the wavefront information, including the amplitude and the phase, of a three-dimensional (3D) object in a noninvasive way as a 2D hologram. With the hologram, one can reconstruct the object using algorithms like back-propagation or inverse imaging to achieve optical sectioning [1], extended focused imaging [2], or 3D imaging [3] etc numerically. Due to the advantages, DH has been applied to many areas such as microscopy [4] and particle tracking [5].

However, in the reconstruction, an essential parameter one has to know is the exact position of the recorded object. Although some autofocusing methods have been proposed before [6–8], most of them deal with one-sectional object, where there is no defocus noise. For multiple-sectional case, the severe defocus noise makes this problem challenging. In this paper, we propose a new autofocusing algorithm based on the structure tensor. Apart from detecting the focal planes, the edge information of each section can be extracted with the intermediate tensor image. The performance of the proposed method is verified using simulation and experimental data.

2. Imaging Formulation of DH System

Normally, the DH system makes use of the interference of two beams originating from the same source. A typical implementation, optical scanning holography (OSH) shown in Fig. 1, is modified from the Mach-Zehnder interferometer. Two laser beams with carrier frequencies ω and $\omega+\omega_0$ ($\omega_0 \ll \omega$) interfere at the object plane and raster scans the object by a 2D scanner. By using of heterodyne detection, a complex hologram is then obtained.

In the viewpoint of signal processing, the OSH system is linear and time-invariant. Mathematically, the complex hologram $g(x,y)$ is the convolution result of the object $\sum_i^N o(x,y;z_i)$, N is the total number of sections, and the point spread function (PSF) $h(x,y;z)$, denoted as $g(x,y) = \sum_i^N o(x,y;z_i) * h(x,y;z_i)$. In the reconstruction, the conjugate PSF $h^\dagger(x,y;z_r)$ at distance z_r is used to convolve with the hologram to get the section at the corresponding position, denoted as $u(x,y;z_r) = g(x,y) * h^\dagger(x,y;z_r) = \sum_i^N o(x,y;z_i) * h(x,y;z_i - z_r) = o(x,y;z_r) + \sum_{i\neq r}^N o(x,y;z_i) * h(x,y;z_i - z_r)$. The second term here is the so-called "defocus noise", which brings difficulty in autofocusing.

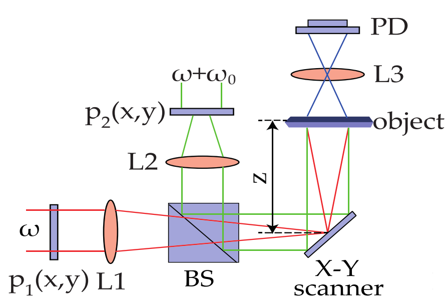

Fig. 1. OSH system. BS: beam splitter; L1, L2 and L3: lens; $p_1(x;y)$ and $p_2(x;y)$: pupil; X-Y scanner: active 2D scanner; Object: the object to be recorded; PD: photodetector; ω and ω_0: initial carrier frequency of laser and shifted frequency.

3. Proposed Method

In communities of image processing and computer vision, structure tensor, also referred to as the second-moment matrix, is a widely used tool for problems like corner detection, interest point detection, and feature tracking. It is a matrix derived from the gradient of a function or an image, and summarizes the predominant directions of the gradient in a specified neighborhood of a point, and the degree to which those directions are coherent [9].

For an image $u(\boldsymbol{x})$, the 2D structure tensor at pixel $\boldsymbol{x}$ can be written as

$$\begin{aligned} \boldsymbol{S}(\boldsymbol{x}) &= G(\boldsymbol{x}) * \left[\nabla u(\boldsymbol{x}) \cdot \nabla u(\boldsymbol{x})^T\right] \\ &= G(\boldsymbol{x}) * \begin{bmatrix} u_x^2(\boldsymbol{x}) & u_x(\boldsymbol{x})u_y(\boldsymbol{x}) \\ u_x(\boldsymbol{x})u_y(\boldsymbol{x}) & u_y^2(\boldsymbol{x}) \end{bmatrix}, \end{aligned} \tag{1}$$

where $\nabla u(\boldsymbol{x}) = (u_x(\boldsymbol{x}), u_y(\boldsymbol{x}))^T$ is the 2D spatial gradient, and $G(\boldsymbol{x})$ is a non-negative and rotationally symmetric convolution kernel that performs the weighted averaging in a window.

The 2D structure tensor $\boldsymbol{S}(x)$ at an image point $\boldsymbol{x}$ is a symmetric and semi-positive-definite matrix, such that it has two positive eigenvalues, which lead to the importance of this concept. Let λ^+ and λ^- be the larger and smaller eigenvalues of matrix $\boldsymbol{S}(x)$, and θ^+, θ^- be the corresponding unit eigenvectors, thus we have $\lambda^+ \geq \lambda^- \geq 0$. The structure tensor measures the geometry of image structures in the neighborhood of each point. Its eigenvectors $\boldsymbol{\theta}^+$ and $\boldsymbol{\theta}^-$ describe the orientation of maximum and minimum vectorial variation of $u(\boldsymbol{x})$, and its eigenvalues λ^+ and λ^- describe measures of these variations. Therefore the eigenvalues of the structure tensor offer a rich and discriminative description of the local geometry of the image.

Based on the principles explained above, we formulate a novel autofocusing algorithm using the structure tensor and its eigenvalues. For an image $u(\boldsymbol{x})$ in a stack of images $u(\boldsymbol{x})$, at each pixel $\boldsymbol{x}$ we compute the structure tensor $\boldsymbol{S}(\boldsymbol{x})$ within a window function $G(\boldsymbol{x})$, the size of which is defined accordingly. With the two positive eigenvalues of the structure tensor matrix, we then define a 2D vector $\boldsymbol{\lambda} = [\lambda^+, \lambda^-]^T$. Considering a general case of a vector norm, we compute the ℓ_p-norm ($p \geq 1$) as $\|\boldsymbol{\lambda}\|_p$. Thus the proposed metric is defined as

$$\begin{aligned} M_p(u) &= \int_{-\infty}^{+\infty} \|\boldsymbol{\lambda}(\boldsymbol{x})\|_p d\boldsymbol{x} \\ &= \int_{-\infty}^{+\infty} \left[\left(\lambda^+(\boldsymbol{x})\right)^p + \left(\lambda^-(\boldsymbol{x})\right)^p \right]^{1/p} d\boldsymbol{x}. \end{aligned} \tag{2}$$

4. Results

As discussed above, the proposed method is a measure of image sharpness and can be used to autofocus the in-focus plane for multiple sections. We first simulate an opaque three-sectional object composing of a circle, a rectangle and a triangle on each section at $z_1 = 10$ mm, $z_2 = 11$ mm, and $z_3 = 12$ mm, as shown in Fig. 2a. The focusing value is computed in a propagation interval of $[9.5, 12.5]$ mm with a step size of 0.06 mm and for comparison, the value is normalized to $[0, 1]$. The autofocusing results using the proposed and other four methods (variance, entropy, ℓ_1 gradient, image power) are given in Fig. 2b and Fig. 2c. As can be seen, in Fig. 2b three peaks present the positions of the individual sections, while in Fig. 2c there is no useful information about their axial distances. Fig. 2(d-f) give the edge detection images.

Then we test our method using experimental data. Detailed description about the parameters of the setup and the recorded object can be found in [10]. In this experiment, the object contains two sections “S” and “H”. The searching range is $[7, 12.5]$ mm with the same interval. Fig. 3 presents the autofocusing result and edge detection images. Two maximums denote the focal planes of the individual sections, while other metrics in Fig. 3b cannot locate the positions. Fig. 3c and Fig. 3d give the edge detection.

5. Conclusion

In this paper, a novel autofocusing algorithm based on structure tensor is proposed. This method outperforms in finding the position of the object for scenarios like multiple sections with non-overlapping and overlapping regions. Additionally, the tensor image at the extracted position presents the detected edge image of the corresponding section.

Acknowledgments

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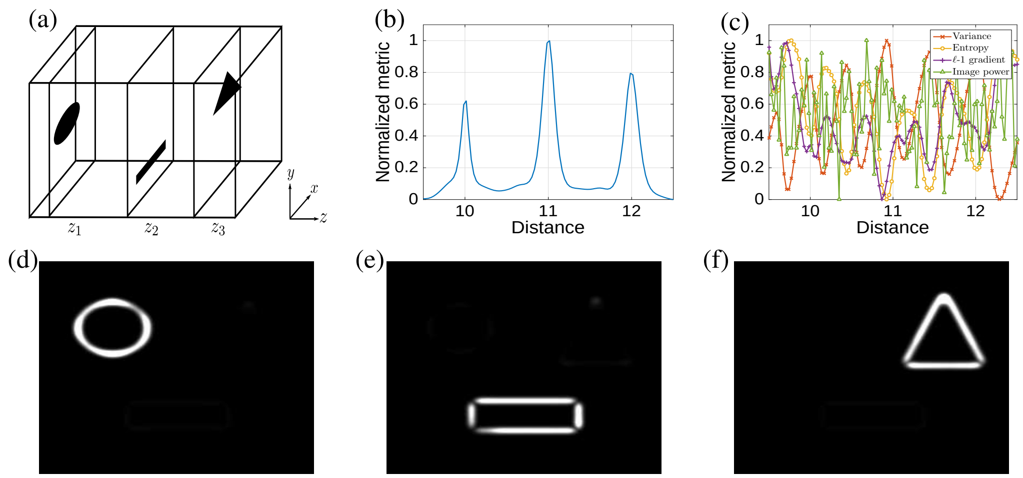

Fig. 2. (a) A 3D object with three sections. The autofocusing detection results using (b) the proposed algorithm and (c) other four metrics. (d-f) Edge detection results. Unit: mm.

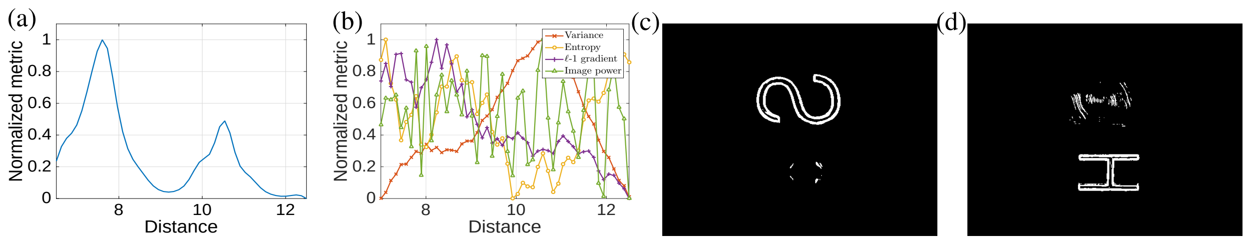

Fig. 3. (a) Autofocusing result using the proposed algorithm. (b) Autofocusing results using the other four metrics. (c-d) Edge detection results. Unit: mm.

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