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Photoelastic Dispersion Coefficient by Holographic Reconstruction with Neural Networks and the Fresnel Method

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***Abstract*—Here we report the characterization of the photoelastic dispersion coefficient using digital holography with two distinct reconstruction methods: one based on the Fresnel method and the other utilizing convolutional neural networks (CNN). The CNN was trained with reconstruction from the Fresnel method and was able to provide reconstructions with an average Mean Squared Error of 0.006.**

***Keywords*—Holography, Photoelasticity, Neural Network, Fresnel method, Dispersion coefficient.**

I. Introduction

The photoelastic dispersion coefficient is used to describe the photoelastic material. Its characterization is essential for understanding the relationship between optics and mechanical properties [1]. Photoelasticity for the study of materials presents several advantages, such as the non-destructive nature of the technique and straightforward calculations that yield the material's properties [1-2]. These properties, however, are mainly obtained indirectly and rely on many approximation conditions to yield accurate results [1,3]. The use of polarized digital holography for the study of photoelastic materials brings the advantage of a more sophisticated and precise technique that is capable of presenting properties, such as the phase difference and index of refraction in a direct way [3–5]. The downside of this approach stems from the requirement for a larger dataset and the use of a more complicated reconstruction algorithm.

A prominent approach is to make use of convolutional neural networks (CNN) to, from a single input image, obtain the stress map from a photoelastic sample under tension [6], or even obtain the holographic phase retrieval from a single input hologram. The latter is especially useful for in-line holographic microscopy, but can also be used in off-axis configurations [7,8].

In this work, we present a convolutional neural network to perform the holographic reconstructions of a photoelastic sample. We then, calculate the dispersion coefficient of a test sample and compared it with the results obtained by the traditional Fresnel method for reconstruction.

II. Experimental set-up

The holographic setup was based on a Mach-Zender interferometer and employed a linear transmission polariscope in the object arm of the interferometer. As shown in Fig. 1, the light from a He-Ne laser (15 mW; 632 nm), after passing through a spatial filter (SF) consisting of a 10x objective lens, one 10 µm pinhole, is collimated by a plane-concave lens (L). The laser is then divided by a 50/50 beam splitter (BS1). In the reference path, a linear polarizer (P3) is used to set the polarization to be the same as at the end of the object path.

To observe the fringe patterns, the photoelastic sample (S) is placed between two crossed polarizers (P1 & P2), in the object path. Both paths are then combined, at the second beam splitter (BS2), and are sent to a CCD camera, where the interference pattern is recorded.

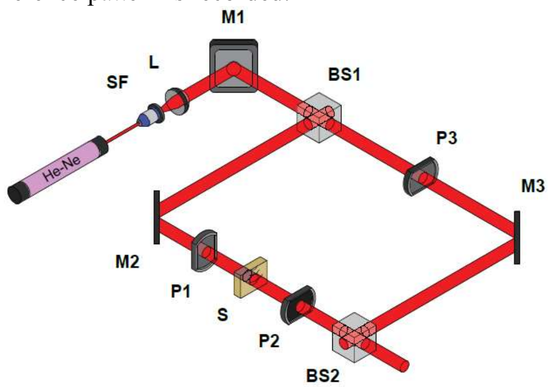

Fig. 1. Holographic set-up. SF: spatial filter; L: plane-concave lens; M1,2,3: Mirrors; P1,2,3: Polarizers; BS1,2: 50/50 beam splitters.

III. Holographic Reconstruction

Loads ranging from 40g to 590g were applied to test samples, with a 50g increment, and, for each load of each sample, a reconstructed phase map was created. The sample was set in a position where the isoclinic fringes could be mainly avoided. The Fresnel method was used to obtain the target reconstructions for the training dataset of the neural network. Then the trained network was used to make reconstructions of new photoelastic samples.

A. Fresnel Method

The holographic reconstruction with the Fresnel method was accomplished by a discretization of the diffraction integral of Huygens-Fresnel with a one-order Taylor expansion [9,10].

For this, the hologram and the reference images are used as input. After an initial data treatment, the logarithm of the absolute value of the hologram transform is calculated. A manual selection of the region of interest in the Fourier space is made, and then a construction of the image plane matrix is obtained from a propagation matrix of the hologram plane.

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Finally, calculations of the Chirp function, by a first-order approximation of the Taylor series, and the reconstruction matrices are made and the final images are saved [9,10].

B. Neural Network - UNet

The neural network architecture was that of a U-Net. As shown in Fig. 2, the structure starts with the input hologram, with dimensions of 256x320x1 pixels, passing through two convolutional layers (Conv), each one with 3x3 kernels and a ReLu activation function, then a Max Pooling layer (M/P). This structure has been applied a total of three times in the decoder part of the network, with 32 filters in the first block, 64 in the second, and 128 in the third, for the convolutional layers. This structure is then followed by two additional convolutional layers, with 256 filters.

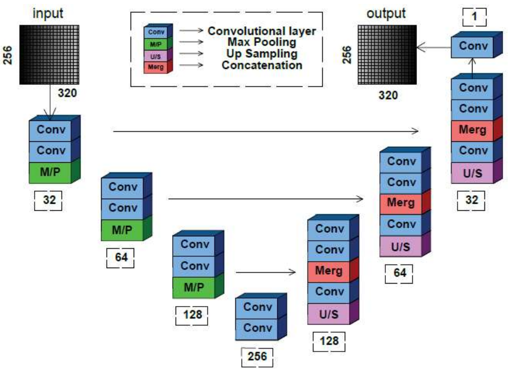

Fig. 2. Unet neural network archtecture.

The decoder blocks of the neural network consist of an Up Sampling layer (U/P), a convolutional layer, followed by a Concatenation layer (Merg), and two more convolutional layers. To return the output image to the same dimensions as the original hologram, this structure is also applied three times with a final convolutional layer, with only one filter. Additional dropout layers were included in the encoder part of the network to prevent overfitting to the training data.

The neural network presented a total of 1,925,281 trainable parameters and utilized an Adam optimizer, with a learning rate of 2E-4. For the network training, the hologram image is used as an input and the corresponding reconstruction is used as a target image. The difference between the output and the target was calculated via Mean Squared Error (MSE) and Mean Absolute Error (MAE) loss functions. While both functions presented an overall good performance, the MSE function presented slightly better results. The neural network was trained with a dataset that was divided into 80% for a training set a 20% for a validation set. The training was made with a batch size of 32 and 100 epochs.

IV. Results

When compared with the reconstructed hologram in the Fresnel method, the neural network was not able to provide visually identical images as the target reconstruction. However, the network presented a low validation MSE value of ~0.006. In comparison, the MSE of ten reconstructed images from the Fresnel method, when the manually selected region of interest is slightly different, is ~0.009. This error was sufficient to provide the dispersion coefficient with the same order of magnitude as the one obtained from the reconstructions by the Fresnel method, as shown in Table 1.

A data collection with a new sample, that was not used for the network training, was made. This sample generated a total of 12 holograms images, were each one was reconstructed by the trained neural network.

The dispersion coefficient in holography ($\mathcal{H}$) was calculated using equation (1) [5,9,10]:

$$\langle \Delta\sigma_{external} \rangle = \frac{\lambda}{2\pi e \mathcal{H}} \langle \Delta\phi \rangle \quad (1)$$

where $\langle \Delta\sigma_{external} \rangle$ is the mean differences of stresses, $\langle \Delta\phi \rangle$ is the mean differences of phase maps, and e is the sample thickness. The differences in stresses are obtained via the known mass and the area over which the force is applied. The mean phases were obtained by the average of the pixel values of the reconstructed, demodulated, phase maps.

Table 1 presents the calculated dispersion coefficient of the sample used in the neural network, as well as the coefficient of another sample, with similar mechanical properties, obtained by the Fresnel method [3].

TABLE I. Dispersion coefficients by the two methods

	Dispersion coefficient
Fresnel Method	**3.44 10^{-12} m^2/N**
Neural Network	**7.84 10^{-12} m^2/N**

V. Conclusion

The dispersion coefficient, obtained through the evaluation of mean stress differences and phase map differences, demonstrated comparable results between the neural network and the well-established Fresnel method. The neural network approach exhibited distinct advantages, including reduced computational power and the elimination of manual region selection for reconstruction. This shows the potential of the neural network approach as an efficient and automated alternative for holographic reconstruction.

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