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Denoising of Wrapped Phase in Digital Speckle Shearography Based on Convolutional Neural Network

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Abstract: Speckle-shearing technology is widely used in defect detection due to its high precision and non-contact characteristics. However, the wrapped-phase recording defect information is often accompanied by a lot of speckle noise, which affects the evaluation of defect information. To solve the problems of traditional denoising algorithms in suppressing speckle noise and preserving the texture features of wrapped phases, this study proposes a speckle denoising algorithm called a speckle denoising convolutional neural network (SDCNN). The proposed method reduces the loss of texture information and the blurring of details in the denoising process by optimizing the loss function. Different from the previous simple assumption that the speckle noise is multiplicative, this study proposes a more realistic wrapped image-simulation method, which has better training results. Compared with representative algorithms such as BM3D, SDCNN can handle a wider range of speckle noise and has a better denoising effect. Simulated and real speckle-noise images are used to evaluate the denoising effect of SDCNN. The results show that SDCNN can effectively reduce the speckle noise of the speckle-shear wrapping phase and retain better texture details.

Keywords: material safety; digital shearing speckle pattern interferometry; wrapped phase; speckle denoising; convolutional neural network



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1. Introduction

Material safety stands as a crucial factor for ensuring aircraft structural integrity. Therefore, the detection and assessment of material defects to ensure they remain within critical limits are of paramount importance. This underscores the significance of employing a highly precise and versatile inspection method. To ensure the dependable performance of structures, non-destructive testing (NDT) is increasingly being employed. Among the various NDT techniques, digital speckle interferometry has emerged as an indispensable approach due to its universal applicability, ease of implementation, and exceptional accuracy. Speckle interference techniques encompass digital speckle-pattern interferometry (DSPI) [1–4] and digital speckle-shearing pattern interferometry (DSSPI) [5–9]. DSPI excels in accurate displacement measurement but necessitates a more controlled environment and may result in fuzzier detection of defect edges. In contrast, DSSPI is less sensitive to displacement and requires lower levels of vibration isolation. However, shear misalignment may introduce fuzziness or loss of information around certain defect edges. Consequently, a denoising process becomes essential to obtain clear defect edges.

Numerous related algorithms have been proposed for speckle-noise reduction [10–17]. While non-local mean filtering algorithms, such as NLN [10] and OBNLM [11], effectively reduce noise, they exhibit high computational complexity and tend to compromise texture detail preservation. Three-dimensional block-matching algorithms like BM3D [12] excel at denoising, with good detail preservation, but face challenges with complex structures. The wavelet thresholding method [13] introduces boundary blurring during denoising, accompanied by the challenges of threshold adjustment and increased computational

complexity. The windowed Fourier transform (WTF) [14] has demonstrated efficacy in denoising wrapped phases, albeit requiring substantial adjustments and processing time. The sine/cosine average filter (SCAF) [15] is introduced to address speckle noise by separate denoising of the numerator and denominator of the arctangent, effectively resolving the phase 2π discontinuity and noise issues.

As neural networks progress, more study is focused on speckle-noise reduction. In Reference [16], CNNs are used to denoise DSPI fringe maps in batches, effectively reducing medium-level noise in fringes but potentially causing slight edge blurring. Reference [17], based on DnCNN [18], proposed a method for the speckle suppression of digital holography, which is effective for noise reduction of stripes with different noise levels, but it is not good for edge recovery of stripes. Reference [19] proposed a DBDNet based on dilated blocks, which effectively recovers DSPI-striped images with high noise levels. In Reference [20], a lightweight residual dense neural network, LRDUNet, is proposed for ESPI stripe noise reduction based on U-Net. While effective in noise reduction, a single model is tasked with handling stripe maps of varying noise levels.

To denoise the wrapped phase, this study introduces a processing approach for denoising interferograms acquired through DSSPI. To address the issues of noise and boundary blurring within the wrapped phase, we propose a deep-learning technique for denoising the sine and cosine fringes. Subsequently, the denoised sine and cosine fringes are processed using the arctangent function to obtain an improved wrapped phase. Simulation and experimental results demonstrate the effectiveness of this method in successfully suppressing speckle noise and eliminating the boundary blurring associated with defects.

2. Theoretical Analysis and Proposed CNN Denoiser

2.1. Related Theoretical Model of DSSPI

In this study, the Wollaston shearing system is used as an example to introduce DSSPI. As shown in Figure 1, a helium–neon laser is irradiated on the object surface after beam expansion, and the scattered field emitted from the diffuse reflective object surface is imaged by the Wollaston shearing system (object surface-shearing imaging). The intensity of the sheared scattered field is recorded by the CCD and stored in the computer.

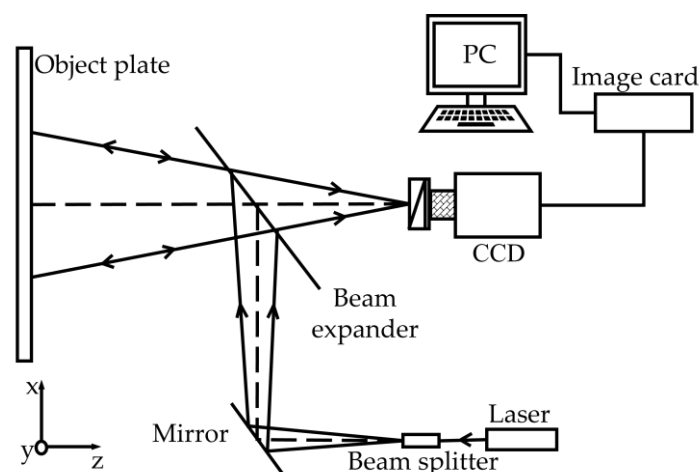


Figure 1. Digital speckle-shearing interferometry system.

For single-beam laser irradiation, assume that I_{o1} and I_{o2} are the intensity of the speckle fields corresponding to the two points $O_1(x_0, y_0)$ and $O_2(x_0 + \Delta x, y_0 + \Delta y)$ on the object surface recorded at one point on the CCD, which can be expressed as

$$I_{o1}(x, y) = A_1 \exp[i\varphi_1(x, y)], \quad (1)$$

$$I_{o2}(x, y) = A_2 \exp[i\varphi_2(x, y)], \quad (2)$$

where A_1 and A_2 are the beam amplitudes corresponding to $I_{o1}(x, y)$, $I_{o2}(x, y)$ respectively, and $\varphi_1(x, y)$ and $\varphi_2(x, y)$ are the initial phases of the two speckle fields. Before the deformation of the object, the intensity recorded on the CCD can be written as

$$I_1(x, y) = |I_{o1}(x, y) + I_{o2}(x, y)|^2 = I_{o1}(x, y) + I_{o2}(x, y) + 2\sqrt{I_{o1}(x, y)I_{o2}(x, y)}\cos[\Delta\varphi(x, y)], \quad (3)$$

where $\Delta\varphi(x, y) = \varphi_2(x, y) - \varphi_1(x, y)$, denotes the initial phase difference. The intensity distribution of the speckle field after the object is deformed by the load can be expressed as

$$I_2(x, y) = I_{o1}(x, y) + I_{o2}(x, y) + 2\sqrt{I_{o1}(x, y)I_{o2}(x, y)}\cos[\Delta\varphi(x, y) + \Delta\delta(x, y)], \quad (4)$$

where $\Delta\delta(x, y) = \delta_2(x, y) - \delta_1(x, y)$. $\delta_1(x, y)$ and $\delta_2(x, y)$ are the deformation phases of the two speckle fields, and $\Delta\delta(x, y)$ denotes the deformation phase difference. The intensity distributions before and after the deformation are subtracted and squared to obtain the speckle fringe pattern, which can be expressed as

$$E(x, y) = [I_2(x, y) - I_1(x, y)]^2 = 8I_{o1}(x, y)I_{o2}(x, y)\sin^2\left[\Delta\varphi(x, y) + \frac{\Delta\delta(x, y)}{2}\right][1 - \cos\Delta\delta(x, y)] \quad (5)$$

By Equations (3)–(5), the speckle fringe patterns are obtained by the four-step phase-shift method [1] with phase shifts of -3α , $-\alpha$, α , and 3α .

$$E_i(x, y) = A(x, y) + B(x, y)\cos[\Delta\delta(x, y) + (2i - 5)\alpha], \quad i = 1, 2, 3, 4 \quad (6)$$

The phase distribution of the object deformation is obtained by Equations (7) and (8).

$$\Delta\delta(x, y) = \arctan\left\{\tan\beta(x, y)\frac{[I_2(x, y) - I_3(x, y)] + [I_1(x, y) - I_4(x, y)]}{[I_2(x, y) + I_3(x, y)] - [I_1(x, y) + I_4(x, y)]}\right\}, \quad (7)$$

$$\beta(x, y) = \arctan\sqrt{\frac{3[I_2(x, y) - I_3(x, y)] - [I_1(x, y) - I_4(x, y)]}{[I_2(x, y) - I_3(x, y)] + [I_1(x, y) - I_4(x, y)]}}, \quad (8)$$

The phase distribution can be further derived so that

$$\Delta\delta(x, y) = \arctan\frac{S_0(x, y)}{C_0(x, y)}, \quad (9)$$

where $S_0(x, y)$ is sine fringe patterns, $C_0(x, y)$ is cosine fringe patterns. $\Delta\delta(x, y)$ is the wrapped phase containing speckle noise, which is distributed in $(-\pi/2, \pi/2]$.

2.2. Proposed CNN Denoiser

2.2.1. Network Architecture

CNN has been successful in processing various visual tasks and has demonstrated effective performance in handling Gaussian denoising. In this work, SDCNN for denoising the wrapped phase is based on FFDNet [21]. The deeper neural network architecture is illustrated in Figure 2. SDCNN consists of a series of 3×3 convolution layers. Each layer is composed of three types of operations: convolution (Conv), batch normalization (BN), and rectified linear units (ReLU). More specifically, “Conv + ReLU” is adopted for the first convolution layer, “Conv + BN + ReLU” for the middle layers, and “Conv” for the last convolution layer. The noisy S_{N0} and C_{N0} fringe patterns are, respectively, reshaped into four sub-images, which are then input into the 32-layer CNN together with the noise-level map. The final output is reconstructed by the four denoised sub-images.

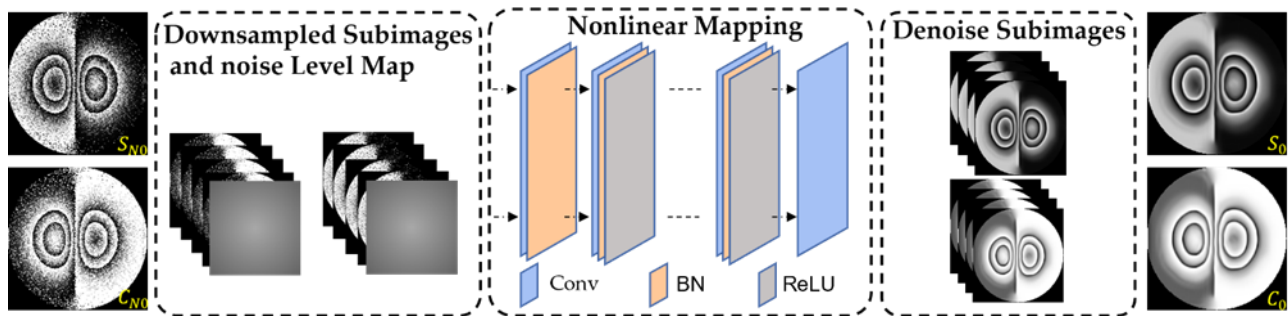


Figure 2. The architecture of the proposed network for image denoising.

2.2.2. Loss Function

To better deal with the case of wrapped-phase boundary blurring, this work uses smooth_{L_1} to replace the L_2 loss function. The L_2 loss function typically results in a significant loss of texture details when dealing with speckle maps. On the contrary, the denoising model based on the L_1 loss function can obtain an image with relatively clearer edges. The L_1 loss function calculates the average distance between the denoised image $f(x)$ and its corresponding noise-free image y . The definition and gradient calculation equations are as follows

$$L_1 = \sum_{i=1}^N |f(x_i) - y_i| / N, \quad (10)$$

$$\frac{\partial L_1}{\partial d} = \begin{cases} 1, & d > 0 \\ -1, & d < 0 \end{cases} \quad (11)$$

where x_i is the block of the input, x , y_i is the block of the corresponding position of the real value y , and $d = f(x_i) - y_i$. From Equations (10) and (11), for any input other than $d = 0$, the absolute value of the gradient is the same. The increased stability of the gradient suggests its resilience to outliers and reduced likelihood of gradient explosions. However, when the d value is very small, the absolute value of the gradient is still one, and the model convergence is difficult. In addition, the non-differentiability of L_1 at $d = 0$ is also a shortcoming that cannot be ignored. Therefore, this paper uses the smooth_{L_1} [22] loss function. The definition of the loss function and its gradient calculation equations are as follows

$$\text{smooth}_{L_1}(d) = \begin{cases} 0.5e^2, & \text{if } |e| < 1 \\ |e - 0.5|, & \text{otherwise} \end{cases} \quad (12)$$

$$\frac{\partial \text{smooth}_{L_1}(d)}{\partial d} = \begin{cases} d, & \text{if } |d| < 1 \\ \pm 1, & \text{otherwise} \end{cases} \quad (13)$$

In Equations (12) and (13), the smooth_{L_1} loss function retains the advantage that L_1 is not easy to gradient explosions and can be derived at any point. Meanwhile, when the d value is small, the corresponding gradient value is also small enough. Therefore, without increasing the complexity of the model and affecting the real-time performance, a low-cost solution is proposed; smooth_{L_1} is used to replace the traditional L_1 and L_2 as the loss function. Based on this, the trained denoising model can better preserve the image details while denoising and reduce the loss of edge information.

2.2.3. Dataset Generation and Network Training

The establishment of the database is necessary to train the model. Combining Equations (1)–(6) for data simulation, the undeformed intensity I_1 can be generated by Equation (3). The amplitude A is set as a random variable distributed within $(0, 1]$, and the initial phase difference $\Delta\varphi$ is set as a random variable uniformly distributed within $(-\pi, \pi]$. Similarly, after the object deformation, the deformed intensity I_2 can also be simulated by Equation (4), where the phase φ of the object beam is changed into $\Delta\varphi + \Delta\delta$.

The deformation of I_2 is controlled by expanding Equation (2) and varying it according to Equation (14).

$$\begin{aligned}\varphi_2(x, y) &= \varphi_1(x, y) + \lambda \times (1 + \cos(Q)) \times Z, \\ Z &= 3 * (1 - x)^2 \times \exp(-x^2 \times (y + 1)^2) - \\ &10 \times \left(\frac{x}{5} - x^3 - y^5\right) \times \exp(-x^2 - y^2) - \frac{1}{3} \times \exp(-(x + 1)^2 - y^2)\end{aligned}\quad (14)$$

where the laser wavelength $\lambda = 632.8$ nm, Q denotes the angle of light incidence relative to the object surface, and Z symbolizes a three-dimensional surface subject to deformation through adjustments in its value, thereby altering the object surface. By manipulating the value of Z , such adjustments involve adding or removing various terms and modifying coefficients. Figure 3 illustrates the wrapped phase resulting from distinct deformations.

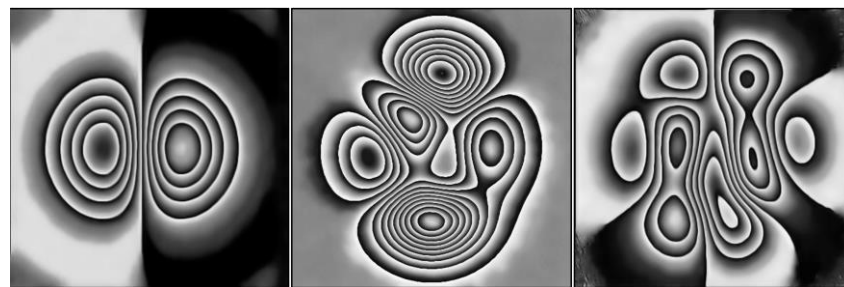


Figure 3. The wrapped phase produced by different deformations.

In addition, assume that the incident laser is perpendicular to the object surface and the surface is sheared along the x direction. The relationship between the deformation phase, the derivative of the out-of-plane displacement along the x direction, and the phase-shift shear is shown in Equation (15).

$$\Delta\delta = \frac{4\pi}{\lambda} \times \frac{\partial G(x, y)}{\partial x} \times \Delta S \quad (15)$$

$$G(x, y) = 600 \times \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x - \varepsilon)^2 + (y - \varepsilon)^2}{2\sigma^2}\right) \quad (16)$$

where $\partial G(x, y)/\partial x$ is the derivative of the out-of-plane displacement in the x direction by adjusting the Gaussian function with the different mean values (from 1 to 80) and standard deviations (from 1 to 80) shown in Equation (15) to simulate the pixel displacement. The wrapped phase produced by different shears ΔS (from 20 to 60) is shown in Figure 4.

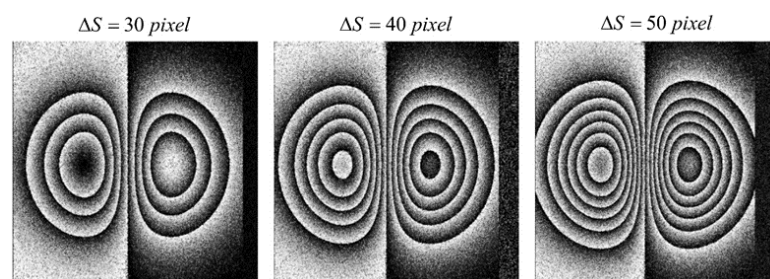


Figure 4. The wrapped phase produced by different shear amounts.

FFDNET introduces different noise-level maps to make the denoising model adapt to different noise levels. In order to make the model adapt to different levels of speckle noise, this paper proposes a new wrapped-phase map generation method based on the character-

istics of speckle noise. A clean wrapped-phase diagram is obtained from Equations (1)–(9), and wrapped-phase maps with different noise levels are obtained from Equations (17)–(19).

$$\Delta\delta(x, y)_N = \Delta\delta(x, y) \times I_G + I_N \quad (17)$$

$$I_G(x; k, \theta) = \frac{x^{k-1} e^{-\frac{x}{\theta}}}{\Gamma(k) \theta^k} \quad (18)$$

$$I_N(x; \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \quad (19)$$

where I_G is a random variable whose value conforms to gamma distribution. k denotes the shape parameter, with the default value of 1. θ is the inverse scale parameter of the distribution. The larger the value, the lower the visibility of the wrapped-phase fringe. In this paper, θ is used to adjust the noise level of the training image, $\theta = 0.5$ to 4. I_N is a random variable whose value obeys the Gaussian distribution and σ is the variance. The greater the value, the greater the noise, $\sigma = 25$ to 100.

3. Experiments

In this study, we conducted simulation experiments using an NVIDIA RTX 1080 Ti GPU (NVIDIA, Santa Clara, CA, USA) with 11 GB of memory and implemented the Python 3.6 programming language. The neural network was trained and tested using PyTorch 0.4.1. Our training dataset consists of 21,847 speckle-wrapped phase images with different shear amounts and different 3D deformations, each with a size of 480×480 pixels. During SDCNN training, we employ a chunking strategy to divide the images into 32×32 pixels. Finally, the training effect is verified using 100 random images generated in the same way. Furthermore, we utilize both PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural SIMilarity) and RMSE (Root Mean Square Error), to holistically evaluate the denoising effectiveness.

3.1. Influence of the Input Noise Level

In this section, we evaluate the sensitivity of SDCNN by varying the input noise levels while maintaining a constant simulated ground level of noise. In practical applications, accurately estimating the noise-level map from observed noise can be challenging, often resulting in a mismatch between the estimated input and the actual noise levels. When the input noise level is lower than the real noise level, complete noise removal becomes unfeasible. Consequently, users typically opt for higher noise levels to enhance noise reduction, although this may inadvertently lead to the removal of some image details along with the noise. In real-world scenarios, it is essential for denoising models to exhibit tolerance towards such mismatches in noise levels. To address this, we utilized Equation (16) to train the model by adjusting parameters θ and σ and enabling control over the input noise level. The testing results of this training are presented in Table 1, offering the following key observations.

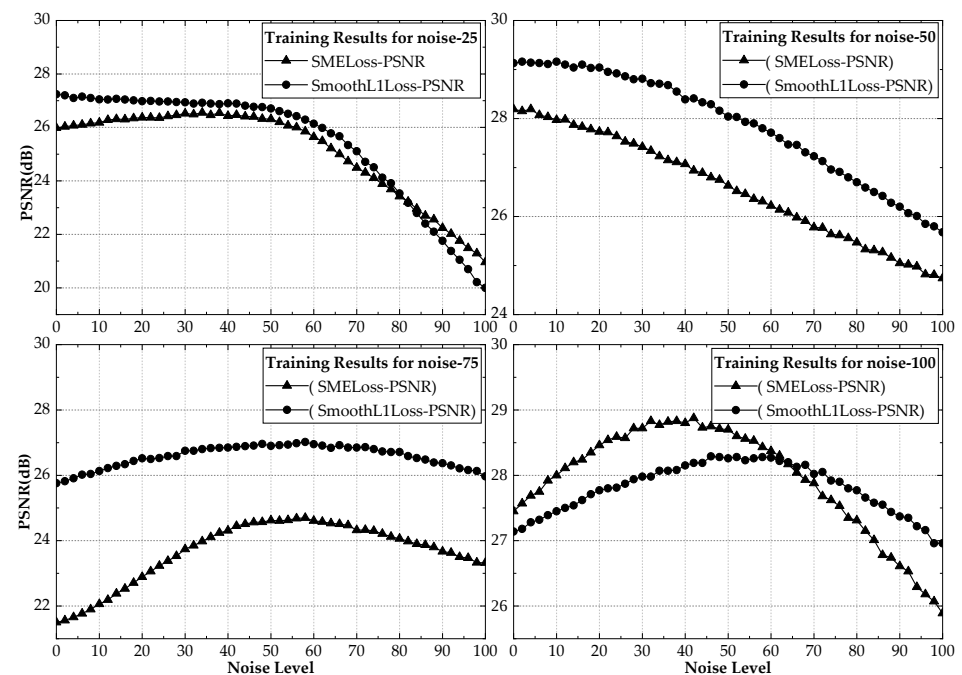
The testing results of this training are presented in Table 1. Various trained models, each with a distinct input noise level (e.g., ‘SDCNN-1-25’ signifying SDCNN with a fixed input noise level of 1–25), are assessed using simulated images characterized by noise levels ranging from 0.5–0 to 4–100. The multiplicative noise coefficient of the input noise image was determined, and different additive noise coefficients were applied during training. The sensitivity of the trained models to additive noise is evaluated using a variety of noise speckle images. The results reveal that SDCNN exhibits robust adaptability to denoise different additive noise speckle images. Similarly, when the multiplicative coefficient is set to one, SDCNN produces better results in reducing noise and maintaining structural similarity.

Table 1. The average PSNR(dB), SSIM, and RMSE results of SDCNN on simulated noise images with different noise level combinations $\theta = 0.5, 1, 2, 4$ and $\sigma = 10, 50, 90$.

Additive Coefficient	$\sigma=10$			$\sigma=50$			$\sigma=90$		
Multiplicative Noise coefficient $\theta = 0.5$									
Model- θ - σ	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE
SDCNN-0.5-25	22.73	0.916	0.073	20.96	0.85	0.089	11.99	0.282	0.251
SDCNN-0.5-50	23.87	0.892	0.064	22.3	0.868	0.077	17.42	0.658	0.135
SDCNN-0.5-75	20.96	0.847	0.089	22.4	0.899	0.076	18.48	0.724	0.119
SDCNN-0.5-100	16.71	0.788	0.146	22.06	0.864	0.079	18.79	0.766	0.115
Multiplicative Noise coefficient $\theta = 1$									
Model- θ - σ	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE
SDCNN-1-25	24.64	0.896	0.059	23.16	0.867	0.069	18.36	0.665	0.121
SDCNN-1-50	25.25	0.92	0.054	23.58	0.868	0.066	19.29	0.75	0.108
SDCNN-1-75	24.6	0.898	0.059	23.75	0.88	0.065	20.91	0.85	0.09
SDCNN-1-100	24.22	0.902	0.061	24.13	0.899	0.062	22.93	0.877	0.071
Multiplicative Noise coefficient $\theta = 2$									
Model- θ - σ	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE
SDCNN-2-25	25.01	0.918	0.056	20.34	0.851	0.096	16.37	0.61	0.152
SDCNN-2-50	22.04	0.865	0.079	23.17	0.881	0.069	17.14	0.643	0.139
SDCNN-2-75	20.88	0.887	0.09	23.4	0.894	0.068	20.74	0.809	0.092
SDCNN-2-100	19.35	0.831	0.108	23.08	0.846	0.07	20.54	0.818	0.094
Multiplicative Noise coefficient $\theta = 4$									
Model- θ - σ	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE	PSNR	SSIM	RMSE
SDCNN-4-25	24.3	0.907	0.061	17.02	0.686	0.141	12.94	0.372	0.226
SDCNN-4-50	21.43	0.891	0.085	20.87	0.807	0.09	14.37	0.415	0.191
SDCNN-4-75	22.74	0.848	0.073	17.43	0.707	0.134	13.68	0.371	0.207
SDCNN-4-100	21.16	0.795	0.087	19.19	0.732	0.11	16.58	0.583	0.148

3.2. Influence of the Loss Function

Furthermore, in order to evaluate the effectiveness of the SmoothL1 loss function in denoising and detail preservation, a comparative analysis of the model performance based on the two loss functions, SMeLoss and SmoothL1Loss, is presented in Figures 5 and 6.

**Figure 5.** PSNR comparison between two loss functions on different input noise levels.

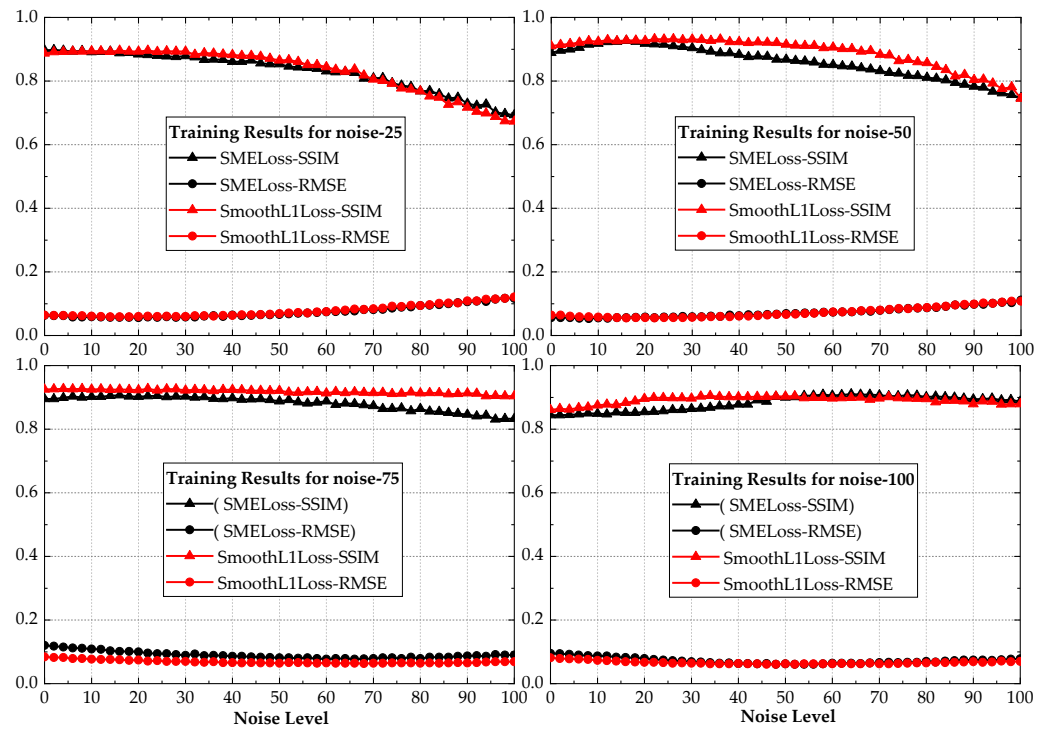


Figure 6. SSIM and RMSE comparison between two loss functions on different input noise levels.

The comparative results indicate that the SMELoss model, overall, exhibits slightly lower denoising effectiveness than the SmoothL1Loss model. However, as the input noise level increases, the difference between the two becomes negligible, particularly when the noise level reaches 60. Furthermore, the SMELoss model notably lags behind the SmoothL1Loss model in preserving image details, a trend that persists even at higher input noise levels.

3.3. The Denoising Effect on Simulated Images

In order to test the training effect of the model more fully, this paper proposes a method to generate wrapped phases with different noise intensities. This work first performs low-pass filtering on the two speckle fields of Equations (1) and (2) by adjusting the aperture size in the 4f system [2], and the filtered speckle field intensity can be expressed as

$$I_{1,2} = F^{-1}\{f(d) \times F[A \exp(i\phi_{1,2})]\} \quad (20)$$

where F represents the Fourier transform, F^{-1} represents the inverse Fourier transform, $f(k_1, k_2)$ represents a low-pass filter. The speckle fringes (480×480 pixels) with the different aperture sizes generate different speckle sizes, where the smaller selected aperture produces a larger speckle size.

In addition, to evaluate the denoising performance of SDCNN on wrapped phases generated by apertures of different sizes, we conducted tests on 100 images and compared the results with the algorithms OBNLM, BM3D, and DNCNN. The test comparison results are illustrated in Figure 6; the test data is presented in Table 2.

Figure 7 and Table 2 reveal that SDCNN significantly outperforms OBNLM, BM3D, and DNCNN in terms of denoising efficacy and the preservation of intricate details in speckle-corrupted maps. This phenomenon clearly demonstrates the strong generalization ability of SDCNN for effectively balancing noise reduction and detail preservation.

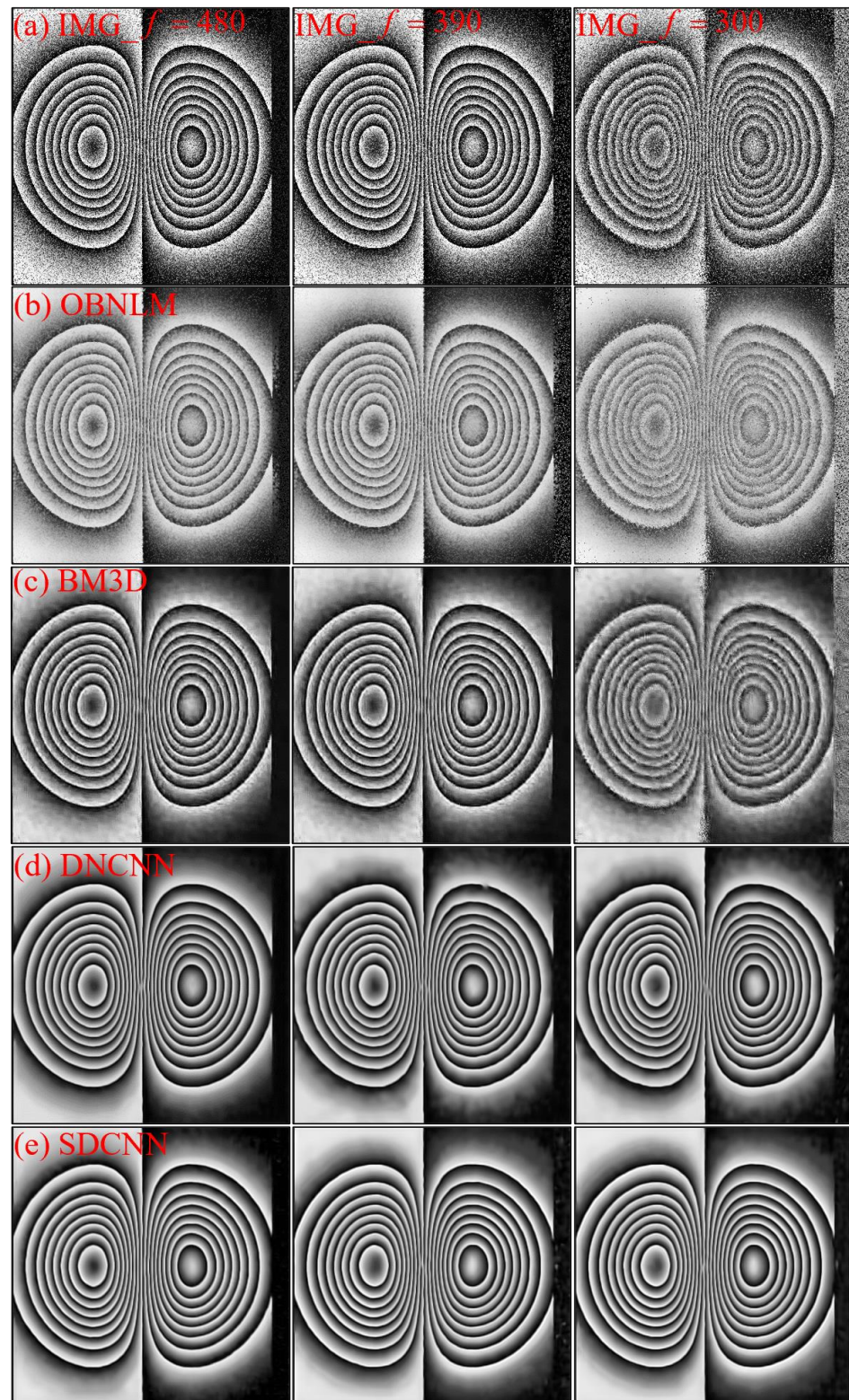
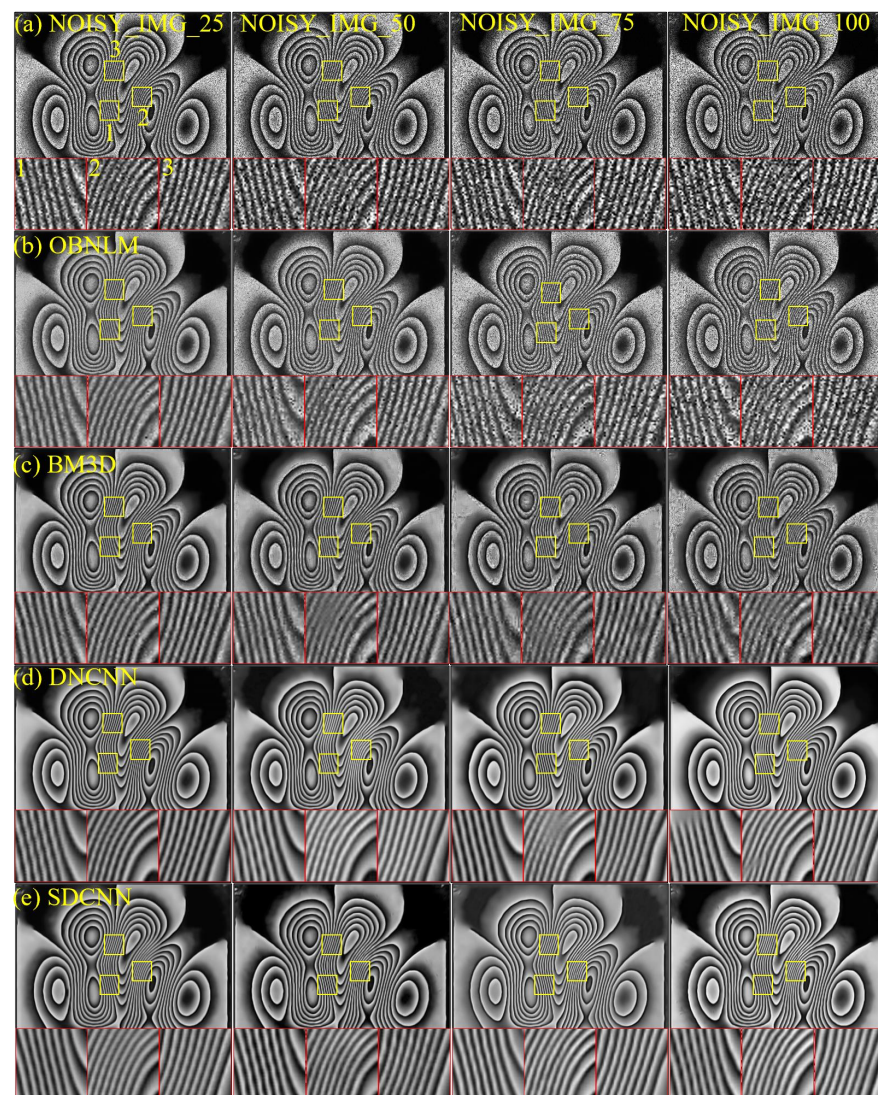


Figure 7. Denoising results on the wrapped phase of different aperture simulations: (a) noise image; (b) denoising result of OBNLM; (c) denoising result of BM3D; (d) denoising result of DNCNN; and (e) denoising result of SDCNN.

An illustrative example, depicting the test results presented in Figure 8, reveals that SDCNN significantly outperforms OBNLM, BM3D, and DNCNN in terms of denoising efficacy and the preservation of intricate details in speckle-corrupted images.

Table 2. The average PSNR(dB), SSIM, and results RMSE of different methods on simulated noise images with different noise level combinations $\theta = 1$ and $\sigma = 0, 25, 50, 75, 100$.

Methods	Noise Level	PSNR (dB)	SSIM	RMSE	Time (s)
OBNLM	25	20	0.76	0.1	85
	50	18.84	0.65	0.11	80.6
	75	17.63	0.56	0.13	79.63
	100	16.68	0.49	0.15	75.6
BM3D	25	25	0.97	0.13	289
	50	23.07	0.95	0.30	290
	75	21.8	0.94	0.26	287
	100	21.46	0.93	0.18	292
DNCNN	25	24.41	0.895	0.06	0.01
	50	23.50	0.864	0.07	0.01
	75	22.53	0.87	0.07	0.01
	100	21.84	0.866	0.08	0.01
SDCNN	25	25.88	0.89	0.05	0.01
	50	24.78	0.92	0.06	0.01
	75	23.64	0.88	0.06	0.01
	100	22.16	0.89	0.07	0.01

**Figure 8.** Denoising results on images from the test dataset with different noise levels by different methods: (a) noise maps with different noise levels; (b) denoising results of OBNLM; (c) denoising results of BM3D; (d) denoising results of DNCNN; and (e) denoising results of SDCNN.

The enlarged details, highlighted by the red border in the image, provide compelling evidence of this superiority. In Figure 8b, OBNLM performs well in denoising at lower noise levels, but its effectiveness diminishes significantly when the noise intensity is higher. In Figure 8c, BM3D demonstrates relative effectiveness in speckle-noise reduction while excelling at preserving fine details. However, the BM3D algorithm performs filtering in the transform domain, resulting in the appearance of pseudo-texture artifacts in the denoised images, which can affect the accuracy of phase unwrapping in the denoised images. Conversely, in Figure 8d, DNCNN achieves remarkable denoising effects but introduces noticeable boundary blurring, impacting visual quality. As evident from Figure 8e, images processed by SDCNN not only attain outstanding denoising results but also exhibit clearer edges and textures, preserving a greater amount of image detail.

3.4. The Denoising Effect on Experimental Data

To demonstrate the denoising effect of the model in structural damage detection, data were obtained using the digital speckle-shear interferometry system shown in Figure 1 to validate the performance. The experimental setup depicted in Figure 9 utilizes a 120 mm diameter circular plate made of 6061 aluminum alloy, with a thickness measuring 4 mm. Furthermore, coherent light from a helium–neon laser, characterized by a wavelength of 632.8 nm, is employed.

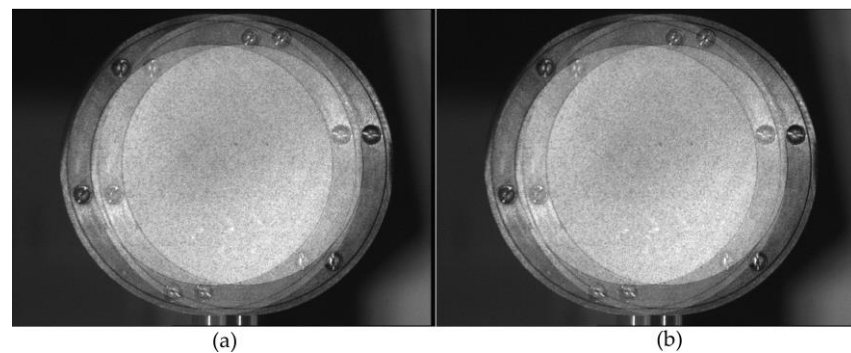


Figure 9. Digital speckle-shear interferogram: (a) speckle-pattern image before deformation; (b) speckle-pattern image after deformation.

In Figure 10, the contour pattern obtained by the four-step phase-shifting method is shown. In addition, since there is no ground-truth image for a real noisy image, visual comparison is employed to evaluate the performance of SDCNN. We choose the BM3D and DNCNN method for comparison because it is widely accepted as a benchmark for denoising applications.

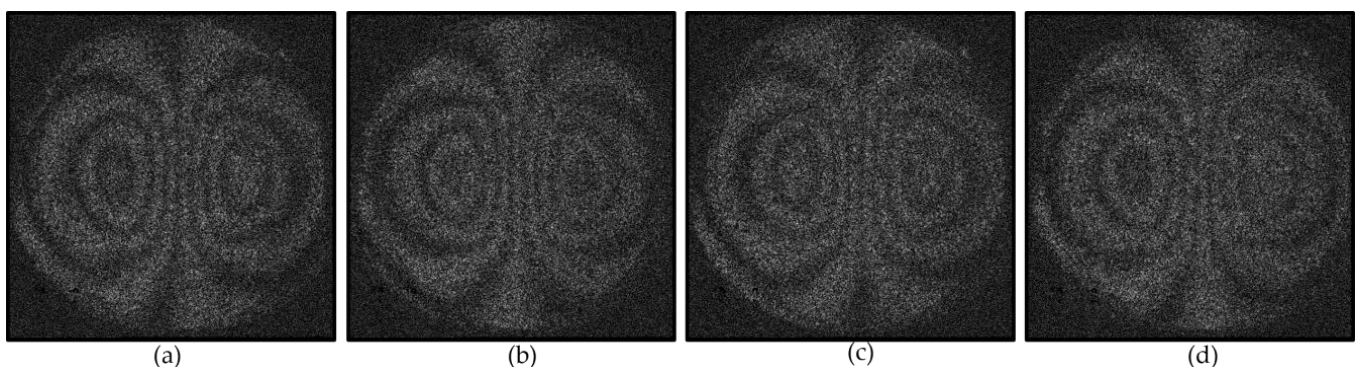


Figure 10. Experimental speckle-pattern image: (a) fringe pattern with phase shift -3α ; (b) fringe pattern with phase shift $-\alpha$; (c) fringe pattern with phase shift α ; and (d) fringe pattern with phase shift 3α .

Figure 11 compares the denoising results of BM3D, DNCNN, and SDCNN on wrapped-phase maps. Visually, all three methods, BM3D, DNCNN, and SDCNN, effectively remove a significant amount of speckle noise. BM3D and DNCNN show comparable denoising results, but they are slightly outperformed by SDCNN. Regarding detail preservation, the red border in the lower right corner of the image demonstrates the effects on details. BM3D and DNCNN reduce noise but may introduce blurring in details, potentially impacting subsequent phase unwrapping. Figure 12a,b demonstrates the phase unwrapping effect of BM3D and DNCNN, from which the boundary blurring caused by poor noise reduction can be clearly seen. In contrast, SDCNN not only removes noise but also keeps important details intact, avoids interference between fringes, and shows better generalization abilities. Figure 12c shows the effect of phase unwrapping after noise reduction, and the unwrapping is significantly smoother and clearer.

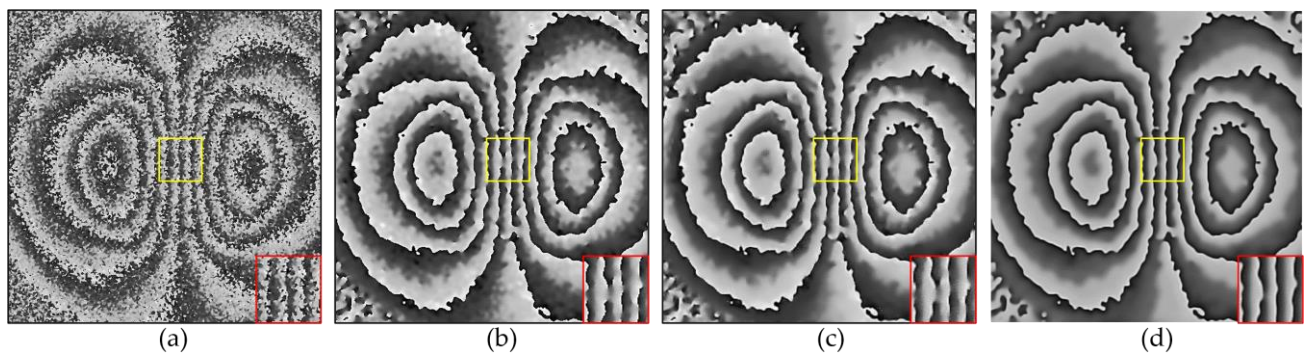


Figure 11. Denoising results on experimental speckle-pattern map: (a) noise map; (b) denoising result of BM3D; (c) denoising result of DNCNN; and (d) denoising result of SDCNN.

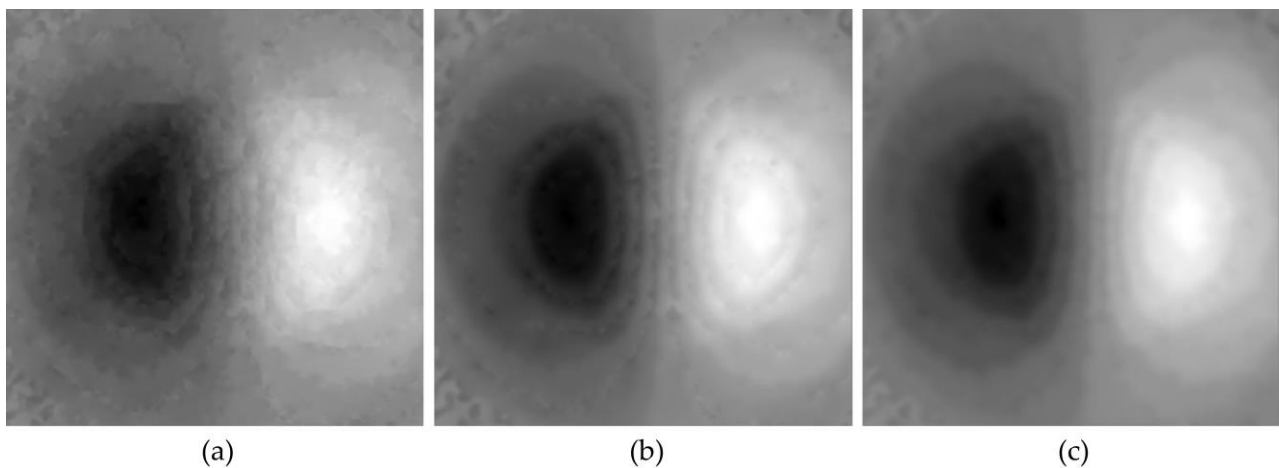


Figure 12. The unwrapped phase of Figure 11: (a) the unwrapped phase of BM3D; (b) the unwrapped phase of DNCNN; and (c) the unwrapped phase of SDCNN.

Figure 13 provides additional insight into the denoising capabilities of SDCNN on a series of authentic experimental maps. The visual results are notably effective. From Figure 13b, it is obvious that the SDCNN presents good results in both stripe preservation and noise-reduction effects, while Figure 13c unpacks the phase of the parcels after noise reduction. The unpacked phase information can be more intuitively seen in Figure 13d.

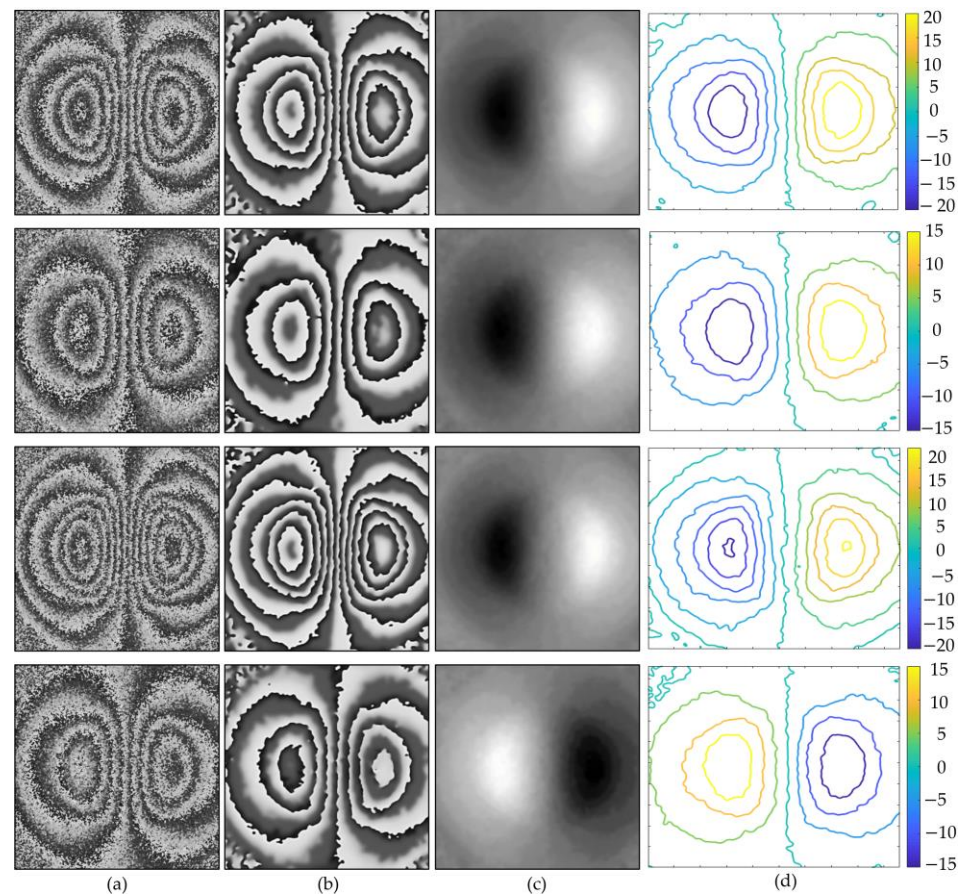


Figure 13. Experiment results: (a) experimental wrapped-phase noise maps; (b) denoising result of (a) by SDCNN; (c) the unwrapped phase of (b); and (d) contour map of (c).

4. Conclusions

In this study, we introduce a CNN model, called SDCNN, with the aim of achieving a balance between speckle-noise reduction and boundary preservation in the context of defect detection using speckle-shear interferometry. To realize this objective, we incorporate various techniques during the network's design and training phase, including cosine regularization, a more realistic speckle-noise simulation approach, and the application of a specific loss function. Based on the results obtained from four-step phase-shifting simulated images, SDCNN demonstrates outstanding performance not only when the input noise levels match the actual speckle noise but also in effectively harmonizing denoising and detail preservation in the wrapped phase. Furthermore, through a comprehensive analysis of experimental results pertaining to the wrapped phase, we observe that SDCNN also performs favorably in handling real-world speckle-noise scenarios. Consequently, SDCNN provides valuable insights and a practical tool for future research in wrapped-phase denoising.

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