# Assessing Noise Impact on DeepOrientation - A Convolutional Neural Network for Local Fringe Orientation Map Estimation

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**Abstract**—This paper discusses the noise robustness of DeepOrientation, a convolutional neural network developed for fast and accurate local fringe orientation map estimation, enhancing full-field optical measurement techniques such as interferometry and holographic microscopy. Using neural networks to determine the final result of the optical measurement may raise legitimate metrological concerns, and therefore, we still recommend using fully mathematically sound solutions for both fringe pattern prefiltration and phase retrieval. DeepOrientation does not replace mathematically rigorous algorithms but supports them by providing a fringe orientation map vital for 2D Hilbert transform phase demodulation, requiring prefiltered fringe data for optimal performance. Using simulated data, we analyze DeepOrientation sensitivity to prefiltration noise-related accuracy and validate results with experimentally recorded fringe patterns.

Optical testing techniques such as interferometry, holographic microscopy, fringe projection, and moiré techniques are among the most precise methods, offering rapid, non-invasive full-field measurement [1]. A feature that the aforementioned methods have in common is that they give the results in the form of a fringe pattern (interferogram/hologram/moiregram), where the phase function (optical path difference, measurand) is encoded in the intensity distribution (shape of fringes). Therefore, the information retrieval process consists of two steps: an opto-electronic measurement based on interferometry, holography and microscopy, followed by numerical processing to compute the intensity-encoded phase map. Two categories of numerical algorithms can be utilized for phase map demodulation: multi-frame [2] and single-frame [3-6] methods. While multi-frame methods are known for their highest accuracy, they are challenging to implement for transient events or unstable environments, highlighting the necessity and significance of developing single-frame algorithms. Improving the accuracy of single-frame methods is an important issue affecting the overall accuracy of the measurement. It is to be highlighted that the fringe orientation map is essential in various fringe processing and analysis tasks, where it enables or greatly enhances the calculations [7]. The examples are fringe filtering (denoising) [8], fringe pattern boundary padding [9], fringe skeletoning (contouring/following/tracking) [10], local fringe spatial frequency (fringe period) estimation [11] and fringe pattern phase demodulation [12].

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The quantity called local fringe orientation (FO) stores the information about the azimuth of the vector locally normal to fringes [7]. It can be calculated directly from the fringe pattern, and it is a modulo $\pi$ indicator. From the definition, FO can be estimated as an arctangent of the orthogonal spatial derivatives of phase function $\varphi(x,y)$:

$$FO(x,y) = \arctan\left(\frac{\partial\varphi(x,y)}{\partial x} / \frac{\partial\varphi(x,y)}{\partial y}\right), 0 \le FO(x,y) < \pi. \quad (1)$$

Estimating the local fringe orientation map is inherently challenging because the phase function required for accurate orientation determination is embedded in the argument of a cosine function within the fringe pattern, making it inaccessible in direct experimental scenarios. Our proposed approach, called DeepOrientation [13], addresses this problem using a convolutional neural network (CNN). The network takes a prefiltered grayscale fringe pattern (e.g., interferogram, hologram, moirégram) as input, and its output is defined using a known simulated phase function.

The important aspect to mention at this point is the fact that in some applications, the local fringe orientation map in the form of modulo $\pi$ needs to be further unwrapped to its modulo $2\pi$ form – local fringe direction map. For accurate unwrapping, discontinuities in the orientation map at steps of $\pi$ must be preserved. However, due to the nature of convolution operations in CNN, these critical discontinuity lines tend to blur, which cannot be entirely avoided despite mitigation efforts. Consequently, directly using the local fringe orientation map derived from Eq. (1) as the network output would make unwrapping to the fringe direction map impossible. To address this issue, we encode the fringe orientation map using a vectorial representation—two 2D matrices containing the cosine and sine of the orientation angle. Since the local FO map is defined as modulo $\pi$, we exploit the full periodicity of sine and cosine functions by encoding the doubled fringe orientation map in their arguments. These two encoded functions form the output of DeepOrientation, with FO easily accessible upon trigonometric decoding (arctangent).

Using neural networks to determine the result of the optical measurement may raise legitimate metrological concerns. Therefore, for the sake of versatility and independence from measurement techniques, we still recommend using fully mathematically sound solutions for both fringe pattern prefiltration and phase retrieval. It is worth acknowledging that the proposed DeepOrientation network does not supersede mathematically rigorous phase extraction algorithmic solutions but only supports them. Because we aim to process prefiltered fringe patterns [14], our simulated training dataset is free of varying backgrounds, amplitude modulation, and noise. This assumption was the main reason that we achieved a successful and universal learning outcome on a relatively small training dataset, including 2400 fringe patterns [13]. Consequently, the DeepOrientation input data must be prefiltered to get satisfactory results. In this work, we discuss the influence of noise on the resultant FO map estimated via the DeepOrientation network.

Although we assumed that the data input to the neural network would be prefiltered to minimize noise effectively, it remains valuable to examine the sensitivity of the proposed DeepOrientation method to noise. It is particularly interesting to explore whether low noise levels have a negligible impact on the accuracy of the estimated FO map, potentially reducing the strictness of prefiltration requirements. Since the local orientation maps consist of the angle information, to preserve its periodic nature, we introduced the orientation error (OE) [13], which may be considered as modified RMSE, where the straightforward difference between the retrieved map and its ground truth was replaced by the sine of that difference. Figure 1 presents an analysis of the proposed method's performance under noisy conditions, compared to a classical FO estimation algorithm, the combined plane fitting/gradient method (CPFG) [15]. Gaussian noise was simulated, with its intensity quantified by the standard deviation.

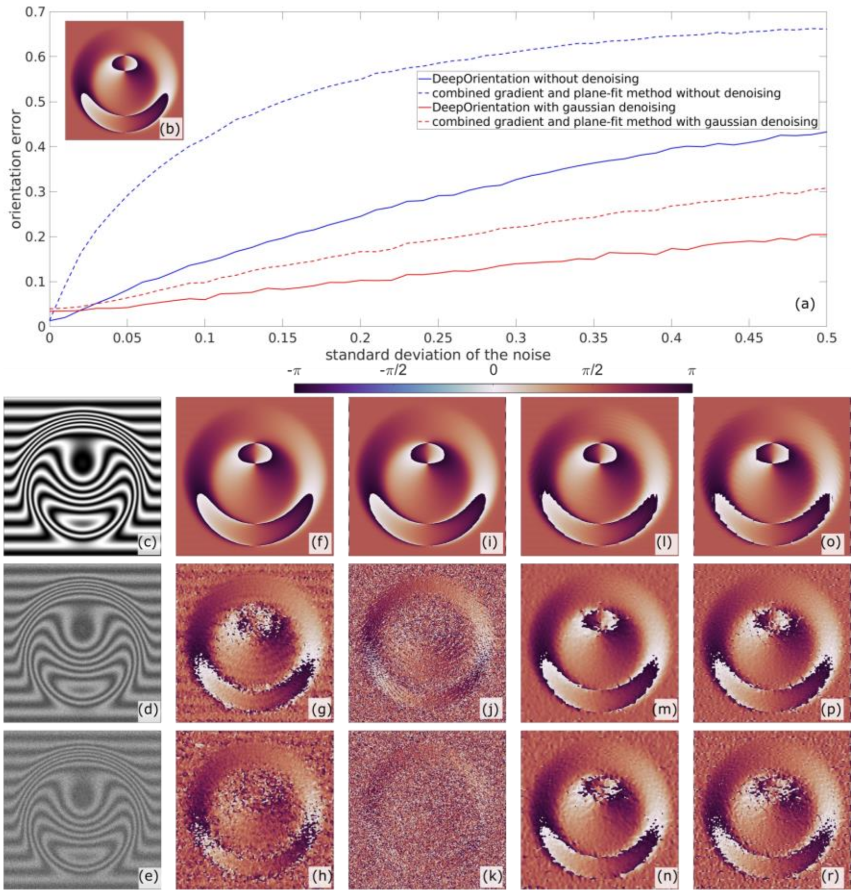


Fig. 1. Comparison of the performance of the DeepOrientation approach and classical one (CPFG [5]) in the presence of noise using simulated fringe patterns. (a) The orientation errors of both methods calculated for different levels of noise, (b) simulated FO map, (c), (d), (e) exemplary fringe patterns with no noise (std=0), medium (std=0.25) and high (std=0.5) level of noise, respectively, FO maps estimated by (f), (g), (h) DeepOrientation and (i), (j), (k) classical CPFG approach without any denoising and FO maps estimated by (l), (m), (n) DeepOrientation and (o), (p), (r) classical CPFG approach with gaussian denoising.

 

The results clearly show that unfiltered fringe pattern intensity noise propagates into the estimated FO map. The FO map becomes increasingly obscured as noise levels increase, eventually completely blending with the noise. However, at moderate noise levels (e.g., std = 0.25) or with simple Gaussian filtering, it is still possible to achieve a high-quality FO map suitable for fringe pattern analysis applications. Importantly, in noisy environments, DeepOrientation significantly outperforms the classical approach, demonstrating greater robustness to noise. This extends the potential applications of DeepOrientation and allows for a relaxation of stringent data prefiltration requirements. The conclusions drawn from numerical analysis are further validated by results obtained using an experimentally recorded interferogram, shown in Fig. 2. In the case of experimental data, the reference orientation map was calculated from Eq. (1) using a highly accurate multi-frame estimated phase map. The orientation error for DeepOrientation was equal to 0.01 for the fringe pattern without the noise and 0.07 for the noisy fringe pattern. In the case of the classical CPFG approach, the orientation error was 0.01 and 0.31, respectively.

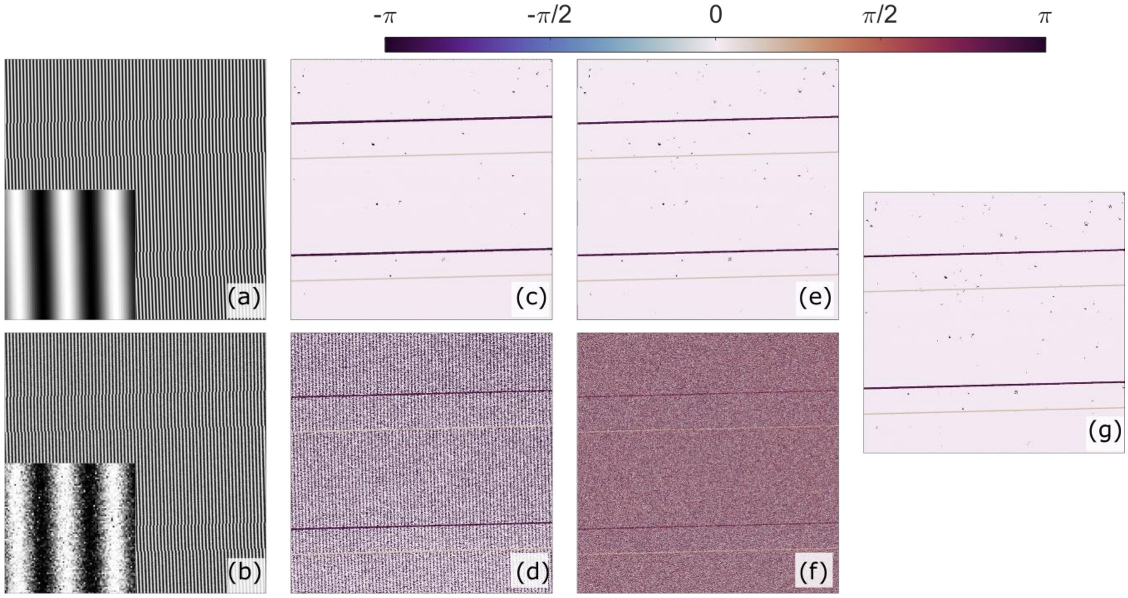


Fig. 2. Comparison of the performance of the DeepOrientation approach and classical one (CPFG [10]) in the presence of noise using experimental data.

The analysis highlights the superior robustness of the DeepOrientation method to noise, outperforming the classical CPFG approach, particularly under moderate to high noise levels. These findings suggest that DeepOrientation not only enhances the quality of FO maps but also reduces the necessity for stringent prefiltration, broadening its applicability to diverse fringe pattern analysis scenarios.

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