Defence Science Journal, Vol. 75, No. 4, July 2025, pp. 426-432, DOI : 10.14429/dsj.20779

Enhancing Digital Image Correlation with Adaptive Wavelets: Addressing Complex Deformations and Lorenz Noise

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ABSTRACT

This paper introduces an Adaptive Wavelet-Based Correlation (AWC) model to enhance Digital Image Correlation (DIC) in complex noise and deformation conditions. Traditional DIC methods, such as Zero-mean Normalized Cross-Correlation (ZNCC), often struggle with robustness in high-noise environments and intricate deformation patterns. The AWC model leverages wavelet transforms to improve local image analysis, offering increased accuracy and stability. Extensive validation demonstrates that AWC outperforms ZNCC in both precision and computational efficiency. In particular, the model proves valuable for structural health monitoring, material testing, and high-strain experimental mechanics, where accurate deformation tracking under noisy conditions is critical. The proposed methodology is implemented in MATLAB, and the full code is available for replication and further research.

Keywords: Digital image correlation; Adaptive wavelet-based correlation; Zero-mean normalized cross-correlation; Wavelet transform; Image noise

1. INTRODUCTION

Digital Image Correlation (DIC) has emerged as a cornerstone in non-contact deformation measurement techniques, widely utilized in fields such as material science, structural health monitoring, and geotechnical engineering. DIC offers precise, real-time insights into the deformation behavior of materials and structures by analyzing digital images captured before and after deformation. The traditional implementation of DIC heavily relies on Zero-mean Normalized Cross-Correlation (ZNCC) to match image subsets and compute displacement fields. ZNCC has been recognized for its computational efficiency and accuracy, particularly in scenarios involving linear and continuous deformations. However, its robustness is often challenged in the presence of noise, complex deformation fields, and discontinuities such as cracks and voids[1-3]. Recent advancements in DIC technology have sought to address these limitations by enhancing the precision, speed, and adaptability of the correlation algorithms[4-5]. For instance, Duan[6], *et al.* proposed a convolutional neural network (CNN)-based DIC framework, known as DIC-Net, which eschews traditional correlation criteria in favor of a more robust pyramidal structure that can handle complex deformation fields. This approach significantly reduces the need for iterative computations, thus enhancing efficiency and potentially enabling real-time processing capabilities. Similarly, Chang[7], *et al.* introduced a novel acceleration approach for ZNCC, implementing it on embedded GPUs, which demonstrated a 2X speed increase over traditional methods without compromising accuracy. This method utilized zigzag scanning to optimize data transmission and on-chip register utilization, achieving real-time performance on mobile platforms. In addition to improvements in computational speed, researchers have also focused on refining the accuracy of DIC measurements under challenging conditions. Zhu[8], *et al.* explored the impact of varying subset shapes on the accuracy of strain measurements in airship envelopes, proposing a subset adaptive algorithm that adjusts the aspect ratio of subsets to enhance precision in different strain directions. This work underscores the importance of adaptive methods in improving measurement accuracy without altering the subset size. Furthermore, Baldi tackled the challenges posed by displacement discontinuities within the DIC framework[9]. By integrating the RANSAC algorithm, Baldi's method selectively processes the largest domain within a subset, thus improving the robustness of the correlation in the presence of cracks and shear bands. The need for high-speed and accurate DIC techniques has also driven innovations in hardware acceleration. Zaripov and Renfu introduced a high-speed technique based on parallel projection correlation, which accelerates ZNCC computation by up to 28.8 times, making it suitable for time-resolved measurements in high-speed applications[10]. Blug[11], *et al.* developed a GPU-based 2D-DIC

Received : 07 November 2024, Revised : 21 March 2025
Accepted : 27 March 2025, Online published : 26 June 2025

system capable of achieving strain sampling rates of 1.2 kHz, with sub-millisecond latency, thereby facilitating real-time strain measurements in fatigue testing of materials such as steel and aluminum. In the realm of structural health monitoring, Azizi[12], *et al.* applied DIC to monitor the vibrations of aging civil structures. The method allowed for the accurate extraction of vibration frequencies and mode shapes, even in the presence of damage, by analyzing displacement time histories. This application highlights the growing importance of DIC in non-destructive evaluation and infrastructure monitoring, where traditional sensors may fall short. Despite these advancements, the inherent limitations of ZNCC—particularly its sensitivity to noise and inability to handle complex deformation patterns-necessitate the exploration of alternative approaches. Variable subset algorithms, as proposed by Ma[13], *et al.*, and multi-scale DIC techniques developed by Mehdikhani[14], *et al.*, offer promising directions by introducing more flexibility and precision in measuring discontinuous displacements and capturing deformation at multiple scales.

These innovations are particularly relevant in the context of composite materials, where matrix cracks and voids play a critical role in the material's mechanical behavior. Moreover, the integration of visual dimension measurement methods with DIC, as explored by Zhou[15], *et al.*, expands the applicability of DIC beyond traditional fields. By leveraging multi-camera systems and M-array coding, high-precision measurements with large fields of view can be achieved without mechanical movement, thus increasing both accuracy and speed. Given these developments, there is a clear motivation to introduce a more adaptive and robust approach to DIC-one that can maintain accuracy in the presence of complex noise patterns and varying deformation fields.

The Adaptive Wavelet-Based Correlation (AWC) model, proposed in this work, addresses these challenges by utilizing wavelet transformations to analyze local changes in image structures at multiple scales and orientations. Unlike traditional DIC methods that are often limited by their reliance on linear correlation metrics, AWC leverages both phase and amplitude correlation of wavelet coefficients, providing a more comprehensive and resilient measure of image similarity. This approach is particularly effective in detecting subtle changes in speckle patterns and maintaining the integrity of the analysis under high noise conditions, such as those simulated by Lorenz noise.

The entire methodology is implemented in the MATLAB software environment, utilizing advanced numerical techniques for wavelet decomposition and correlation computation. The complete code for the AWC model, including all necessary scripts and functions, is available for download at allowing for replication and extension of the work presented in this manuscript[16].

The objective of this study is to develop and validate the AWC model as a robust enhancement to DIC, ensuring greater accuracy in the presence of complex noise patterns and deformation fields. This advancement is particularly relevant for applications such as structural health monitoring, precision material testing, and biomechanical motion analysis, where traditional correlation methods face significant limitations.

2. METHODOLOGY

Traditional DIC algorithms, such as Zero Normalized Cross-Correlation (ZNCC), rely on the correlation between a reference and deformed image to compute displacement vectors. Although ZNCC provides a certain degree of accuracy,[17] it is often susceptible to interference in the presence of complex deformations, noise, and lighting variations. This limits its applicability in demanding engineering and scientific applications where precision and robustness are critical. To overcome some of these limitations, this manuscript introduces an AWC model, which utilizes wavelet transforms for local image analysis across different scales and orientations. This methodology enhances the detection and measurement of deformations, particularly in the presence of noise and complex image changes, significantly improving the accuracy of DIC.

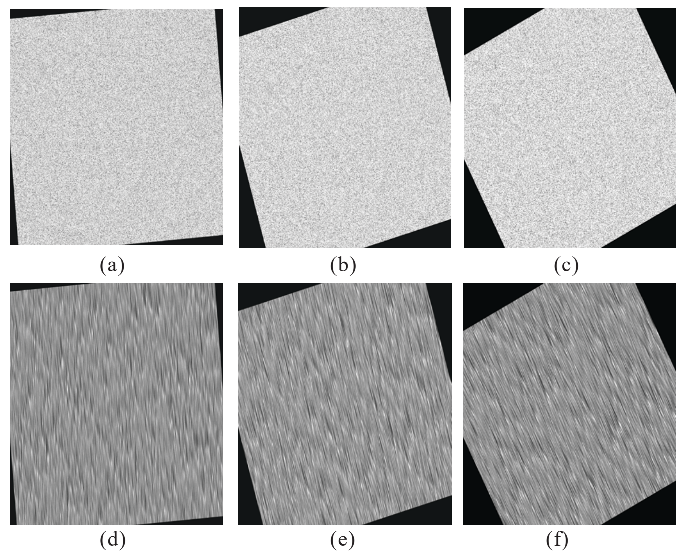

Figure 1. Test images: (a) Noise: 0.01, Deformation: 1.00; (b) Noise: 0.01, Deformation: 3.25; (c) Noise: 0.01, Deformation: 5.50; (d) Noise: 10.00, Deformation: 1.00; (e) Noise: 10.00, Deformation: 3.25; and (f) Noise: 10.00, Deformation: 5.50.

The AWC model uses wavelet transforms to analyze local image changes, decomposing images into frequency components while retaining spatial-temporal information. This makes it ideal for studying speckle patterns before and after deformation. Reference and deformed images with varying noise and deformation levels were generated to simulate real-world conditions, assessing the model's accuracy and robustness. Both ZNCC and AWC methods were applied to evaluate their performance, with key results illustrated in Fig. 1, highlighting structural changes under noise and deformation.

2.1 Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) uses wavelet functions localized in time and space to analyze signals or images across multiple scales. Unlike the Continuous Wavelet Transform (CWT), DWT operates on discrete scales and positions, reducing computational complexity and enabling faster processing. It applies to both one-dimensional signals and two-dimensional image analysis. Mathematically, the DWT for a signal $f(t)$ is expressed as:

$$W_f(j,k) = \frac{1}{\sqrt{2^j}} \sum_{n=0}^{N-1} f(n)\psi\left(\frac{n-k\cdot 2^j}{2^j}\right) \quad (1)$$

where, $W_f(j,k)$- are the wavelet coefficients at scale j and position k, $f(n)$- is the input signal, $\psi\left(\frac{n-k\cdot 2^j}{2^j}\right)$- is the discrete wavelet function that depends on scale j and position k, and N- is the number of points in the signal. For a 2D signal (image), the wavelet transform is extended to two dimensions:

$$W_I(j,k_x,k_y) = \frac{1}{\sqrt{2^j}} \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} I(m,n)\cdot$$
$$\cdot\psi_h\left(\frac{m-k_x\cdot 2^j}{2^j}\right)\psi_v\left(\frac{n-k_y\cdot 2^j}{2^j}\right) \quad (2)$$

where, $W_I(j,k_x,k_y)$- are the wavelet coefficients at scale j and positions k_x and k_y, $I(m,n)$- represents the pixel intensity of the image at coordinates m and n, ψ_h and ψ_v- are the horizontal and vertical wavelet functions used to decompose the image in two directions, and M and N- are the dimensions of the image. The DWT decomposes the image into different frequency bands, enabling the local analysis of changes within the image. At each scale, the image is split into approximations (low-frequency components) and details (high-frequency components), allowing for separate analysis of the horizontal, vertical, and diagonal components of the image.

$$AWC(x,y) = \alpha\cdot\frac{\sum_{s=1}^{N_s}\left|\sum_k \psi_s(\mathrm{k})\cdot\overline{\phi_s(\mathrm{k})}\right|}{\sqrt{\sum_k|\psi_s(\mathrm{k})|^2\cdot\sum_k|\phi_s(\mathrm{k})|^2}}+$$
$$+\beta\cdot\frac{\sum_{s=1}^{N_s}|\psi_s(\mathrm{k})|\cdot|\phi_s(\mathrm{k})|}{\sqrt{\sum_k|\psi_s(\mathrm{k})|^2\cdot\sum_k|\phi_s(\mathrm{k})|^2}} \quad (3)$$

This formula represents a combination of phase and amplitude correlation of the wavelet coefficients from the reference image $\psi_s(\mathrm{k})$ and the deformed image $\phi_s(\mathrm{k})$ across different scales s. The parameters α and β are weighting factors that allow for the adjustment of the contributions of phase and amplitude correlation depending on the specific analysis conditions. Phase correlation measures the similarity of the phase components of the wavelet coefficients between the two images. This enables the detection of spatial translations and displacements, which is particularly useful in the case of complex deformations. Amplitude correlation, on the other hand, measures the similarity of the wavelet coefficient amplitudes, helping to identify changes in image intensity and contrast. By combining these two components, the AWC model provides a more robust and accurate measure of similarity between images.

The unique advantage of the AWC model lies in the ability of wavelet transform to decompose an image into different frequency components, allowing for local-level analysis. This local analysis enables the detection of subtle changes in speckle patterns that are often invisible at the global level. Moreover, the wavelet transform retains spatial-temporal localization, ensuring that detected changes are precisely associated with the corresponding parts of the image. The AWC model is designed to be resilient to various types of noise and complex deformations. The optimization of the weighting factors α and β allows for the model's adaptation to specific conditions, such as varying levels of noise or changing lighting.

2.2 Phase and Amplitude Correlation

The wavelet coefficients of an image provide information about the image's frequency content across different scales and orientations. In the AWC model, we utilize these coefficients to compare the reference image and the deformed image through phase and amplitude correlation. Phase correlation measures the similarity of the phase components of the wavelet coefficients between the two images. The mathematics of phase correlation can be expressed as:

$$C_{\mathrm{phase}}(x,y) = \frac{\sum_s W_{I_1}(x,y,s)W^*_{I_2}(x,y,s)}{\left|W_{I_1}(x,y,s)\right|\cdot\left|W_{I_2}(x,y,s)\right|} \quad (4)$$

where, $W_{I_1}(x,y,s)$ and $W_{I_2}(x,y,s)$ represent the wavelet coefficients of the reference and deformed images at scale s respectively, and "*" - represent the complex conjugate operation. Phase correlation is particularly effective for detecting translations between two images, as phase changes are directly associated with spatial shifts.

Amplitude correlation, on the other hand, measures the similarity of the amplitudes of the wavelet coefficients between the two images. The mathematics of amplitude correlation can be expressed as follows:

$$C_{\mathrm{amplitude}}(x,y) = \sum_s\left|W_{I_1}(x,y,s)\right|\cdot\left|W_{I_2}(x,y,s)\right| \quad (5)$$

By combining phase and amplitude correlation, we can achieve a more robust measure of similarity that is resistant to noise and deformations. The combined correlation can be expressed as follows:

$$C_{\mathrm{total}}(x,y) = \alpha\cdot C_{\mathrm{phase}}(x,y) + \beta\cdot C_{\mathrm{amplitude}}(x,y) \quad (6)$$

where, α and β are weighting factors that determine the contribution of the phase and amplitude components in the overall correlation.

2.3 Mathematical Optimization of Coefficients

The optimization of coefficients α and β is essential for achieving maximum performance of the Amplitude-Weighted Correlation (AWC) model. To optimize these coefficients, the Least Squares Method is employed, which minimizes the difference between actual and predicted deformation values. Mathematically, the objective is to minimize the error function:

$$E(\alpha,\beta) = \sum_{i=1}^{N}\Big[d_{true}(i) - (\alpha\cdot C_{phase}(x_i,y_i) +$$
$$+ d_{true}(i) - (\alpha\cdot C_{phase}(x_i,y_i)\Big]^2 \quad (7)$$

where, $d_{true}(i)$ represents the true deformation values for the i-th sample, and C_{phase} and $C_{amplitude}$ are the phase and amplitude components of the correlation for the i-th sample. Optimization is achieved by minimizing the error function $E(\alpha,\beta)$ using numerical methods, such as gradient descent or other optimization algorithms.

2.4 Practical Implementation of the AWC Model

The practical implementation of DWT in the AWC model utilizes the MATLAB function wavedec2, which performs a 2D DWT decomposition of the image at a specified number of levels. Each decomposition level breaks down the image into approximation and detail coefficients (horizontal, vertical, and diagonal components). For example, a three-level decomposition of the image $I(x,y)$ can be represented as follows:

$$[cfs, s] = \text{wavedec2}(I, L, \psi) \tag{8}$$

where, cfs - represents the wavelet coefficients of the image, s - is the structure containing information about the dimensions of the decomposed components at each level, L - is the number of decomposition levels, and ψ- is the wavelet function. The wavelet coefficients are then used to compute the phase and amplitude correlation between the reference and deformed images. After decomposing both images (reference and deformed), the phase and amplitude correlations are calculated using the coefficients. These correlations are then combined using the optimized values of α and β to obtain the final similarity measure between the images. The combined correlation, $C_{total}(x,y)$, serves as a metric for detecting deformations between the two images. The final phase correlation between images I_1 and I_2 is defined as follows:

$$C_{final}(x,y) = \frac{C_{total}(x,y)}{N_s} \tag{9}$$

where N_s is the total number of scales. This normalized correlation, $C_{final}(x,y)$, is used for an accurate comparison of similarity between the reference and deformed images.

3. RESULTS & DISCUSSION

In the context of this study, the focus is on testing the performance and validating the optimized AWC model, which has been developed as a superior alternative to the traditional Zero Normalized Cross-Correlation (ZNCC) model. To verify its robustness and superiority under challenging conditions, Lorentzian noise, a complex form of disturbance, was used. The testing results are presented across several graphs, each providing insight into various performance aspects of the AWC model compared to the ZNCC model.

3.1 Use of Lorentzian Noise in Testing

Lorentzian noise, derived from the Lorenz system of differential equations, is highly chaotic and ideal for testing imaging systems under real-world, unpredictable conditions. Its sensitivity to initial conditions makes it valuable for assessing algorithm robustness. In DIC, Lorentzian noise tests a model's resilience to irregular disturbances that complicate speckle pattern identification and deformation measurement. Incorporating this noise in validation reveals a model's ability to tackle challenges common in industrial and natural environments.

3.2 Model Validation and Testing

The AWC model was validated through experiments with varying levels of Lorentzian noise (0.01–20) and complex deformations such as translation, rotation, and scaling, simulating real-world conditions. Performance metrics, including Mean Squared Error (MSE), Structural Similarity Index (SSIM), and Pearson's Correlation Coefficient, were calculated to compare AWC with ZNCC, alongside execution time measurements to evaluate efficiency. Results demonstrated that AWC consistently achieved greater accuracy, precision, and computational efficiency, particularly under high-noise and complex deformation scenarios. This makes AWC a reliable and effective choice for advanced industrial and scientific applications requiring robust deformation detection.

3.3 Analysis of Test Results

The validation and testing results of the optimized AWC model are presented through a series of graphs, each illustrating key performance aspects of the model in comparison with the ZNCC model. As distributions of Lorenz noise increase, the AWC model demonstrates consistent improvement, reaching nearly a 15 % enhancement at a spatial noise distribution level of 20 %. This result indicates that the AWC model significantly outperforms the ZNCC model in handling images with high distributions of Lorenz noise. This improvement is attributed to the AWC model's ability to more effectively analyse local changes in speckle patterns due to the wavelet transform employed in image analysis.

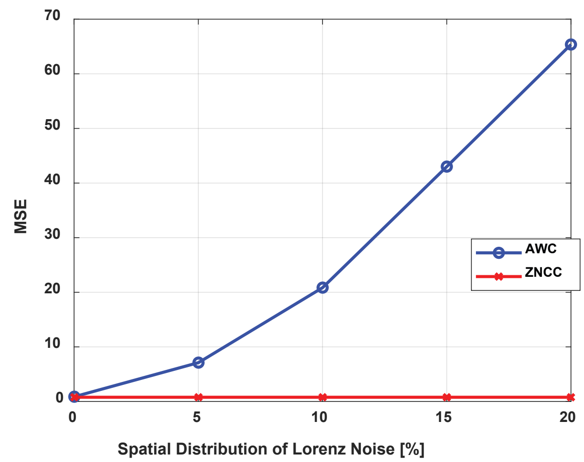

Figure 2. MSE comparison between AWC and ZNCC under varying levels of lorentzian noise.

In Fig. 2, which illustrates the Mean Squared Error (MSE) for the optimized AWC and ZNCC models, it can be observed that the MSE for the AWC model increases linearly from 0 to approximately 67 across a range of 0 % to 20 % Lorentzian noise. In contrast, the ZNCC model shows a constant MSE value of approximately 1 throughout the entire range of the analysis. This difference in behavior can be explained by the following aspects:

- Frequency component analysis: The AWC model uses wavelet transforms to break images into frequency components, retaining key details even as Lorentzian noise increases. This raises MSE due to noise-affected components but preserves critical deformation information. In contrast, ZNCC shows little MSE change, sacrificing accuracy
- Noise robustness: AWC's rising MSE reflects resilience to higher noise levels, maintaining accuracy under complex conditions. ZNCC's constant MSE reveals limited noise handling, leading to less reliable results in precision-demanding applications.

- Lower MSE values indicate better correlation accuracy. The AWC model maintains stable performance even under increasing Lorentzian noise, while ZNCC exhibits higher sensitivity to noise.

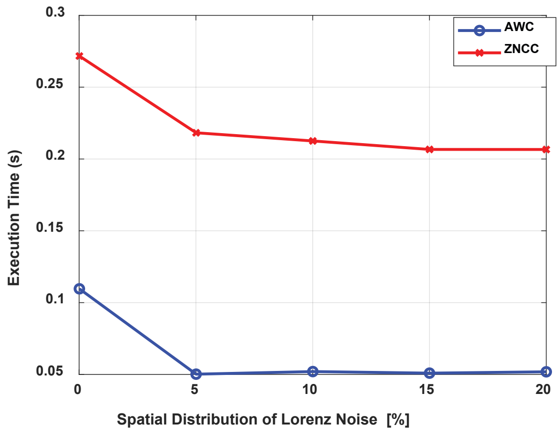

Figure 3. Execution time comparison of AWC and ZNCC across different noise distribution.

In Fig. 3, which shows the execution time for both models, we observe that the ZNCC model begins with an initial value of 0.26 seconds at 0 % noise, then slightly decreases to 0.23 sec. at 5 % noise, maintaining this value for the remainder of the analysis. The AWC model, on the other hand, starts at a significantly lower initial value of 0.09 sec., drops to 0.05 seconds at 5 % noise, and then maintains an almost constant execution time throughout the analysis. This result demonstrates several key advantages of the AWC model:

- Processing efficiency: The AWC model processes images faster than ZNCC across all noise levels, thanks to its optimized wavelet transformation. Its processing time remains stable even at higher noise levels, unlike ZNCC, which struggles to optimize under such conditions.
- Stability maintenance: The AWC model's consistent execution time under high noise ensures predictability, making it ideal for real-world applications requiring efficient and reliable performance.

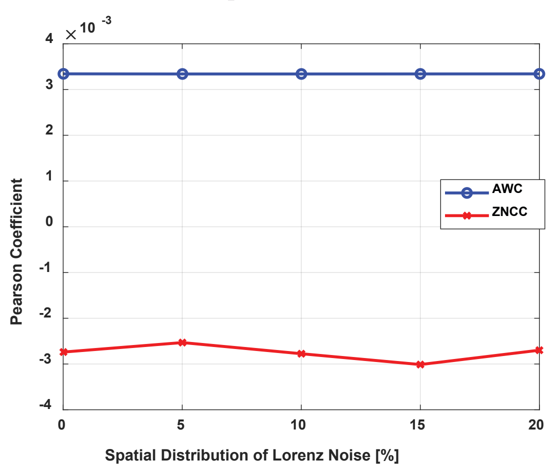

Figure 4. Comparative pearson correlation coefficient for AWC model and ZNCC model.

- Figure 4, which displays the Pearson correlation coefficient between the original and reconstructed images, clearly demonstrates the superiority of the AWC model. The AWC model maintains an almost constant Pearson coefficient value slightly above 3, whereas the ZNCC model shows negative values ranging between -2.5 and -3 across the entire range of Lorentzian noise. This difference has significant implications:
- Linear relationship: The AWC model's high, stable Pearson coefficient shows it maintains a strong linear relationship between original and reconstructed images, even in high-noise conditions, due to effective speckle pattern analysis via wavelet transforms.
- Negative values for ZNCC: ZNCC's negative Pearson coefficients indicate failure to preserve linearity, leading to errors in deformation measurement and unsuitability for high-noise, complex scenarios.

In Fig. 5, which shows the Structural Similarity Index (SSIM) values for both models, the AWC model maintains an almost constant SSIM value around 0.011, which slightly increases linearly to 0.013 across the range of 0 % to 20 % spatial distribution of Lorentzian noise. In contrast, the ZNCC model shows an SSIM value of 0 throughout the entire noise range. This difference highlights several important aspects:

- Image structure preservation: SSIM measures the similarity between two images in terms of luminance, contrast, and structure. The high and stable SSIM values for the AWC model indicate that it successfully preserves key structural characteristics of the image, even under high-noise conditions. This is due to the wavelet transform, which enables detailed analysis and preservation of important image features, whereas the ZNCC model fails to maintain these characteristics, resulting in zero SSIM values.
- Significance for accurate measurements: Preserving structural characteristics is essential for precise deformation measurements. The high SSIM values of the AWC model provide confidence that the images are reconstructed in a way that enables accurate measurements, even in high-noise conditions.

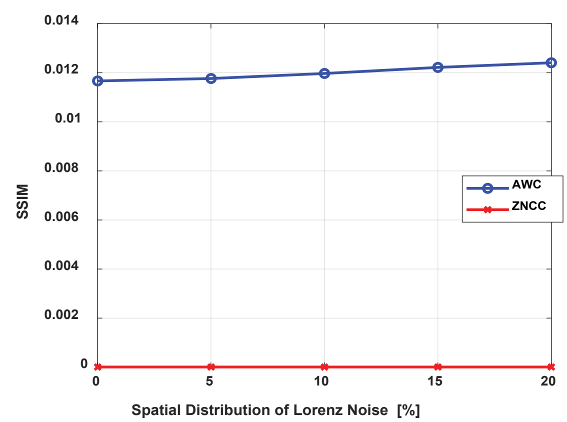

Figure 5. SSIM for optimized AWC model and ZNCC model.

Figure 6 shows the correlation dependence on deformation and distributions of Lorenz noise for the AWC and ZNCC models. The AWC model (Fig. 6(a)) demonstrates exceptional stability across various Lorentzian noise distributions, including the most complex conditions. Regardless of the increase in deformation and noise intensity, the AWC model maintains high correlation accuracy, underscoring its advantage in speckle pattern analysis. In contrast, the ZNCC model (Fig. 6(b)) exhibits significant fluctuations and a loss of accuracy, further confirming the superiority of the AWC approach in demanding environments.

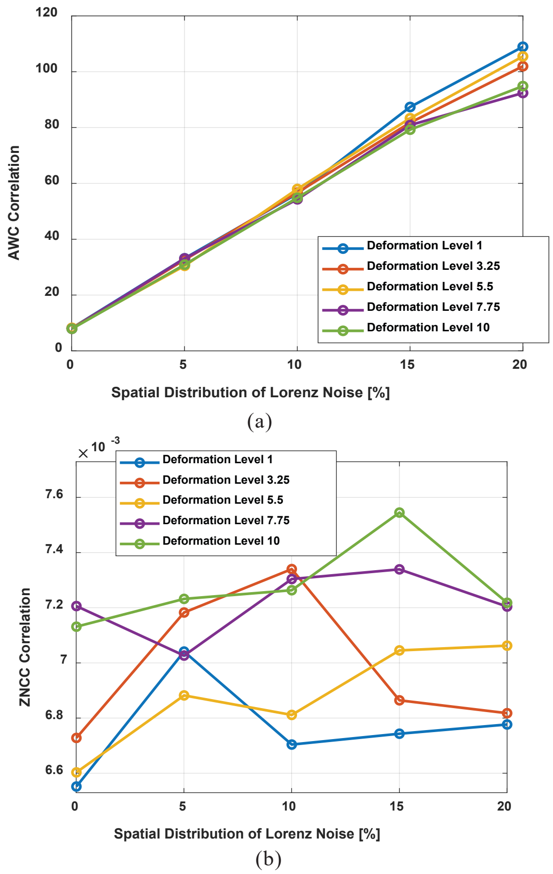

Figure 6. Dependence of correlation on deformation and distribution of noise for: (a) AWC model; and (b) ZNCC model.

4. CONCLUSIONS

This study introduces the Adaptive Wavelet-Based Correlation (AWC) model as an enhancement to Digital Image Correlation (DIC), particularly for analyzing complex deformations in the presence of noise. By utilizing wavelet transforms for phase and amplitude correlation analysis, the AWC model provides improved accuracy and stability compared to traditional ZNCC-based approaches. Experimental validation under Lorenzian noise demonstrates that the AWC model yields more consistent results according to key metrics such as Mean Squared Error (MSE), Structural Similarity Index (SSIM), and Pearson's correlation coefficient.

In addition to its advantages in image analysis, practical considerations such as computational efficiency and parameter selection must be addressed to facilitate real-world implementation. The potential applications of the AWC model include structural health monitoring, material testing, and biomechanical motion analysis, where reliable deformation tracking in noisy environments is crucial. Future research may focus on further optimization, including hardware acceleration and adaptive parameter selection, to enhance its applicability. The full MATLAB implementation of the AWC model is available for replication and further development.

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Contribution in the current study: He performed the analytical evaluations and algorithm design.

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Contribution in the current study: He provided the conceptual idea, programming implementation, and development.

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Contribution in the current study: He contributed with the algorithm design.

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Contribution in the current study: He performed implementation, and development of result.

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