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Learning−Based DIC with Pixel−Wise Uncertainty for Robust Deformation Measurement

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Abstract

Digital Image Correlation (DIC) is a widely used non−contact method for full field displacement and strain measurement in experimental mechanics. However, both conventional and learning based DIC approaches often fall short on reliability assessment and remain sensitive to image noise, speckle degradation, and large deformation, limiting their applicability in real world conditions. In this work we address the issue of reliability in existing DIC methods using learning−based framework with pixel−wise uncertainty quantification, enabling accurate deformation measurement under challenging conditions. A probabilistic loss formulation is proposed to model predictive uncertainty and improve robustness under noisy conditions. A physics−informed consistency constraint is employed to enforce the relationship between displacement and strain fields, enhancing the physical credibility of predictions. The experiments are conducted on both synthetic and actual datasets and compared with conventional Deep DIC. Results show that the proposed framework achieves improved performance, particularly under high noise and large deformation scenarios, while providing meaningful uncertainty estimates that correlate with prediction errors.

Keywords: DIC | Uncertainty Quantification | Speckle Degradation | Deformation | Physics−informed Consistency

I. INTRODUCTION

Digital Image Correlation (DIC) has become a widely non−contact optical technique for full−field displacement measurement in experimental mechanics [1]. It's exceptional in various fields, which include material characterization, structural health monitoring, and tensile testing, due to its adaptability, high spatial resolution and simplicity of use [2−3]. By tracking the deformation of stochastic speckle patterns between reference and deformed images, DIC enables estimation of displacement fields, from which full−field strains are directly computed [4].

While the accuracy of displacement estimation is inherently limited by sub−pixel interpolation and subset correlation strategies, the reliability of strain computation is extremely sensitive to noise amplification [5]. However, in practical scenarios, experimental noise arising from illumination variations, sensor defects, and environmental disturbances

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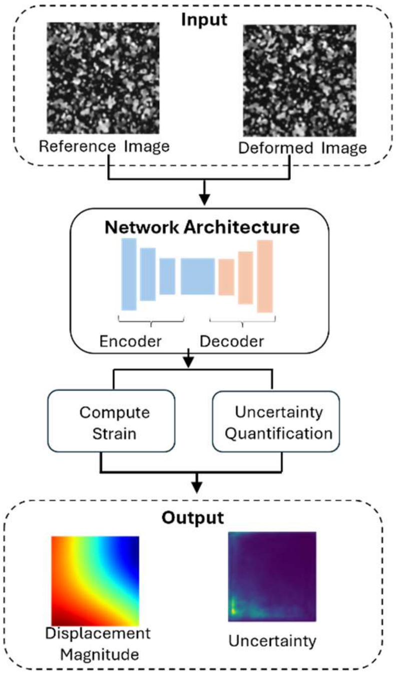

Fig. 1. The overview of learning based digital image correlation with Pixel-Wise Uncertainty Quantification for Robust Deformation Measurement

can significantly degrade the correlation quality. Under large deformation, traditional subset-based matching approaches may fail, leading to unstable measurement. To address these existing challenges, recent advances have explored the use of deep learning to improve DIC performance. Learning-based approaches uses Convolutional Neural Networks (CNNs) to directly estimate displacement and strain fields from image pairs, enabling end-to-end prediction and improved computational efficiency [6-7]. These approaches have proven effective in handling complex patterns [20-21]. Given that measurement confidence is critical in engineering applications, incorporating uncertainty quantification is essential to ease the widespread of these methods. Furthermore, ensuring the physical consistency between predicted displacement and strain fields is critical essential for reliable modeling [8].

In this work, we propose a learning-based DIC framework that incorporates pixel-wise uncertainty quantification to improve the robustness and reliability of deformation measurement. An overview of the proposed method is illustrated in Fig. 1.

The main contribution of this work is summarized as: First, we introduce a deep learning-based DIC framework featuring pixel-wise uncertainty quantification for reliable deformation measurement. Second, we propose a probabilistic loss formulation that significantly enhances model robustness against image noise and challenging imaging conditions.

II. RELATED WORK

A Digital Image Correlation (DIC) has a long history in experimental mechanics, with early methods relying on subset-based correlation techniques for displacement and strain measurement. Sub-pixel interpolation methods, such as bilinear, bicubic, and spline-based schemes, improved measurement precision, while noise-robust correlation criteria and adaptive windowing introduced to mitigate the effects of image noise and speckle degradation [9-11]. However, these classical methods are still sensitive to large deformation, speckle degradation, and low signal-to-noise conditions, and often require considerable computational resources.

To address these limitations, recent studies leverage deep learning architectures to achieve dense, pixel-wise deformation fields. This method uses Convolutional neural networks (CNNs) to directly predict displacement and strain fields from image pairs, enabling end-to-end learning and faster inference. Deep DIC uses dual networks (DisplacementNet and StrainNet) to predict displacement and strain simultaneously, showing impressive performance on deformations [4]. Other methods built upon U-Net architectures learn hierarchical deformation features and reconstruct high-resolution displacement fields [12, 22]. While standard Deep DIC architectures are highly prone to error propagation under poor speckle patterns or sudden lighting shifts. Our probabilistic loss formulation allows the network to learn a heteroscedastic noise model by treating displacement mapping as a distribution function rather than a point regression, hence down-weights corrupted regions during backpropagation.

Solving Digital Image Correlation with Neural Networks Constrained by Strain-Displacement Relations presents a neural-network-based framework for solving the DIC problem while enforcing strain-displacement compatibility. The approach uses neural networks to estimate displacement fields while incorporating mechanical constraints into the optimization process [8]. These methods show improved computational efficiency and handling of complex deformation patterns compared to classical approaches.

Despite these advances, critical limitations persist. Current deep learning-based methods produce deterministic point estimates without assessing prediction reliability, thereby hindering their deployment in noisy and ambiguous regions. Furthermore these approaches are trained predominantly on synthetic datasets, limiting their generalization to real-world imaging conditions with varying noise, speckle patterns, and illumination[13-14].

Beyond the DIC domain, uncertainty-aware architectures and physics-informed neural network (PINNs)ensure reliability and physical consistency in related vision tasks, such as optic flow and depth estimation. PINNs integrate physical laws such as partial differential equations (PDEs), directly into the neural network training pipeline. Rather than relying exclusively on data-driven inputs, the framework incorporates these physical principles as soft constraints within the loss function. This regularized optimization paradigm is particularly advantageous for inverse problems, computational mechanics, and data-sparse regimes [7]. While PNNS optimize spatial constraints without data-driven error margins, our method incorporates dual-constrained paradigm which balances optimization targets. This ensures stable network training and delivers reliable, self-supervised confidence metrics that map precisely to empirical errors under severe speckle and noise degradation.

Displacement-estimation for microscopy addresses a number of inherent imaging challenges, including weak signals, poor contrast and multitude of noise processes normally encountered during microscale image acquisition [2]. Measuring Microscale In-plane Indentation Displacement field for material characterization leverage optic flow algorithm (OF) for displacement estimation and Finite element for validation to accurately measure

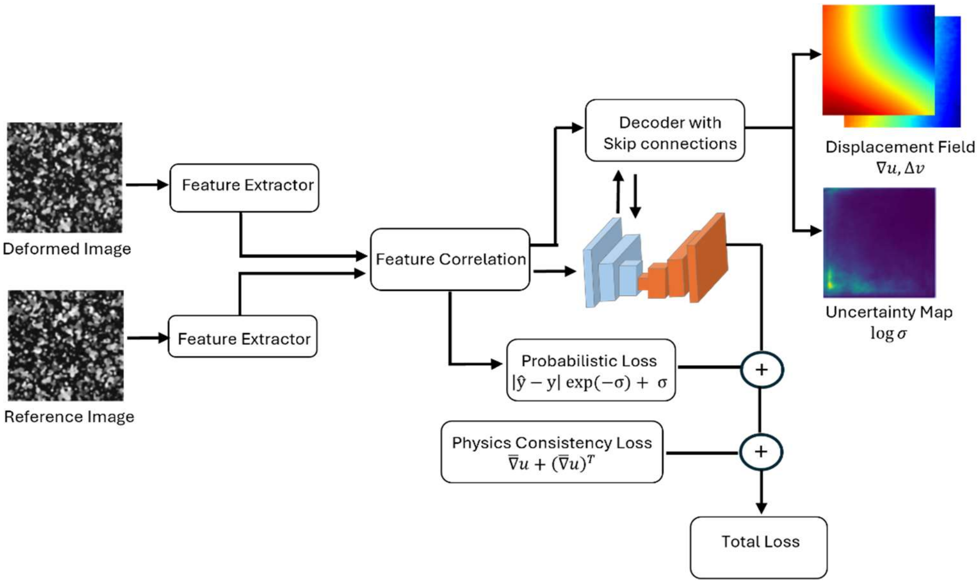

Fig. 2. Deep Learning–based Digital Image correlation framework that jointly estimates full field displacement and pixel wise uncertainty.

tiny(microscale) surface deformations caused by an indentation test [15–16].

III. PROPOSED METHOD

1. Overview

To achieve full–field displacement estimation and quantify localized errors, we developed a custom learning–based Digital Image Correlation (DIC) framework. The underlying architecture relies on an encoder–decoder paradigm that accepts paired image sequences as inputs. This network architecture processes spatial data to output both dense displacement fields and pixel–wise uncertainty maps as illustrated in Fig. 2. Additionally, probabilistic loss and physics–informed regularization is formulation to incorporate and enhance robustness and physical consistency.

2. Network Architecture

The underlying model utilizes deep Convolutional Neural Network (CNN)backbone. A modified Resnet backbone, configured for two–channels inputs, serves as the encoder [17]. To enable joint feature extraction, we concatenated two sequential grayscale images along the channel dimension then fed into the network. The resulting output is a hierarchical feature representation that captures both fine–grained texture details and global deformation patterns across multiple spatial resolutions.

Conversely a symmetric decoder is employed to progressively reconstruct the spatial resolution of the feature maps through a combination of bilinear up sampling with convolutional refinement layers. The resulting output is dual heads prediction. One displacement head that outputs a two–dimensional(2D) vector field and another tasked with predicting pixel–wise log–variance to correspond to system uncertainty.

3. Dataset

We trained the proposed model using synthetically generated dataset and later evaluated on actual experimental data to assess generalization performance under practical conditions. For each sample in the dataset consists a pair of grayscale images (reference image and corresponding deformed image) together with the ground-truth displacement field. Our synthetic data pipeline creates reference images by distributing random speckles across a digital canvas. To generate the deformed frames reference images are warped via predefined transformation models including affine and elastic. Fig. 3 illustrates a representative sample of these image pairs from the synthetic dataset.

We introduce various perturbations during data generation phase including additive noise, intensity variations, and contrast changes to enhance model robustness and accurately simulate real-world experimental environment. In total, the synthesized dataset is 4,786 image-pair samples alongside their respective ground truths. We used 3,396 samples of data for network training, 696 samples for validation and 696 samples for testing.

4. Probabilistic loss function

In conjunction with the displacement field, the network estimates associated uncertainty at each pixel location. This enables the model to explicitly be confidence in its predictions and effectively manage noisy regions. To achieve this, we formulated the prediction within a probabilistic framework by assuming a Gaussian distribution over the displacement field:

$$\boldsymbol{p(u|x) = N(u; \hat{u}, \sigma^2)} \qquad (1)$$

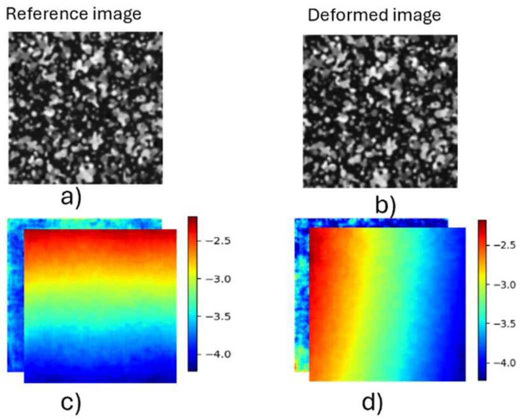

Fig. 3. A paired image sampled from the synthetic dataset figure (a) Reference Image, (b) Deformed image, (c) Horizontal displacement $\boldsymbol{U}$ and d) Vertical displacement $\boldsymbol{V}$ together with.

Where $\hat{u}$ denotes the predicted displacement and σ^2 stands for the corresponding pixel-wise predictive variance. This formulation introduces an adaptive weighting mechanism through the negative log-likelihood loss:

$$\boldsymbol{L_{prob} = \frac{1}{N}\sum_{i=1}^{N}\left[\left|\left|u_i - \hat{u}_i\right|\right|^2/\left(2\sigma_i^2\right) + (1/2)log\left(\sigma_i^2\right)\right]} \quad (2)$$

where N is the number of pixels. In this formulation, the residual error is modulated by the predicted uncertainty, allowing the model to dynamically adjust the influence of each pixel to the overall loss. Regions with higher predicted uncertainty impact less to the loss, effectively down weighting unreliable or noise corrupted predictions. Equally, in regions where the model exhibits high confidence (low uncertainty), errors are strongly penalized, thereby encouraging precise and physically consistent displacement estimation.

5. Training details

We implemented the network architecture using PyTorch library [18]. We optimize the parameter through Adam Optimizer. To ensure rapid convergence, the adaptive momentum parameters were set to $\beta 1 = 0.9$ and $\beta 2 = 0.999$ as recommended by [19]. Training was executed with a learning rate of 0.001 and batch size of 12 across 100 epochs.

Ⅳ. Experimental Results

1. Displacement Field

Fig. 4. illustrates the estimated deformation field by presenting the horizontal $\boldsymbol{u}$ and vertical $\boldsymbol{v}$ displacement components derived from the speckle pattern. These maps provide a dense, pixel-wise representation of the motion between the reference and deformed images, capturing both the magnitude and direction of displacement across the specimen. The smooth variation in the displacement fields indicates coherent deformation, while localized gradients correspond to regions of higher strain. Strain loss is derived as the mean of the squared gradients of the predicted displacement field. It encourages smoothness and physical plausibility in predictions by penalizing large gradients that can show unrealistic deformation. High strain (large gradient) shows unrealistic deformations while low strain shows overly smooth predictions that may miss key details.

$$\begin{aligned} \varepsilon_x x = \partial u/\partial x, \varepsilon_y y \\ = \boldsymbol{\partial v/\partial y}, \boldsymbol{\varepsilon_x} \\ = (1/2)(\partial u/\partial y + \partial v/\partial x) \end{aligned} \qquad (3)$$

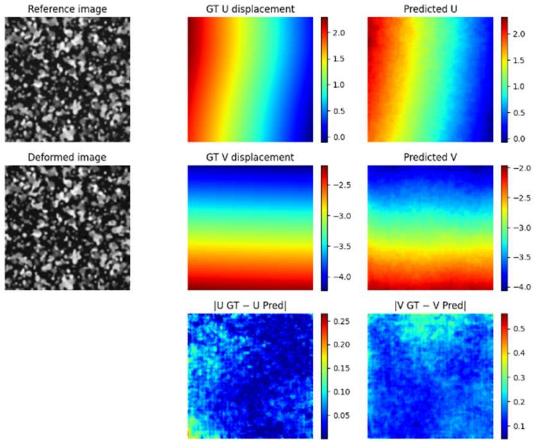

Fig. 4. The accompanying plot maps the deformation field, displaying the $\boldsymbol{u}$ (horizontal) and $\boldsymbol{v}$ (vertical) displacements derived from the speckle pattern.

2. Uncertainty Quantification

Uncertainty-awareness enforces the model to learn both accurate displacement predictions and their associated confidence. High confidence (s) predictions indicate low uncertainty (more penalty) While low confidence (s) predictions indicate high uncertainty The error penalized depending on the level of confidence, high confidence more penalized, subsequently low confidence less penalized. Uncertainty is derived from the log variance predicted by the model, which allows for better training stability and ensures that the uncertainty values are positive, as variance cannot be negative as illustrated in equation 4.

$$\boldsymbol{s = log(\sigma^2)} \quad (4)$$

Fig. 5. shows an example from the dataset along with the model's predictions and their quality. The input image (top left) is a speckle pattern used for tracking deformation. The displacement maps illustrate how the material has moved, with

colors standing for the magnitude and direction of displacement across the image. The uncertainty map shows the model's confidence in its predictions, where darker or cooler regions correspond to higher confidence and brighter regions indicate areas of greater uncertainty. The error map highlights the difference between the predicted displacement and the ground truth, showing where the model performs well and where inaccuracies occur.

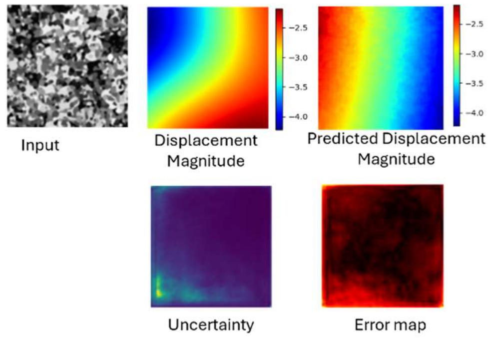

Fig. 5. Plot of an input sample from the dataset with its displacement map, uncertainty, and error map

3. Error Distribution and Threshold Based accuracy

We analyze the spatial distribution of pixel-wise errors via Endpoint Error (EPE) across median and 90th percentile benchmarks. Our proposed method attained a median EPE of 0.162 pixels, representing excellent sub-pixel tracking accuracy. The 90th percentile EPE is restricted to 0.401 pixels, which reveals consistent error bounds across the dense displacement field. Additionally, threshold-based accuracy metrics show that 98.80% of pixels maintain an EPE under 1.0 pixel, while 99.91% remain below 3.0 pixels.

Table 1: Displacement Accuracy Comparison performance

Model	↓Median error	↓90th Percentile	↑% < 1 px	↑%< 3px
Deep DIC	0.25	0.65	94.5%	98.2%
Our Model	0.1624	0.4007	98.80%	99.91%

V. Conclusion

This work presents a robust and reliable learning-based framework for DIC by explicitly addressing the limitations of existing methods under challenging real-world conditions. By embedding pixel-wise uncertainty quantification via a probabilistic noise formulation, the proposed approach enhances displacement tracking accuracy on noise and speckle degradation while delivering well-calibrated confidence metrics. Additionally, the incorporation of a physic-informed consistency constraint enforces the predicted displacement and strain fields to remain physically plausible even under large deformation scenarios. This framework advances the reliability of optical measurements and proves the necessity of integrating uncertainty-aware and physics-guided modeling for practical experimental mechanics applications.

A key limitation of the current framework is its heavy reliance on synthetic datasets for network training, which introduces a potential simulation-to-reality domain gap and limits validation in real-world scenarios. Future Work we plan to combine a rigorous introductory benchmark comparing our single-pass probabilistic model to traditional sampling-based Monte Carlo Simulations. We also intend to expand the validation matrix using real-world experimental benchmarks.

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