# Design and Application of Artificial Neural Network Algorithm for Digital Speckle Correlation Method

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***Abstract*—This study explores the design and application of an Artificial Neural Network (ANN) algorithm for Digital Speckle Correlation Method (DSCM). DSCM, as a non-contact full-field deformation measurement technique, has significant applications in materials science and structural engineering. However, traditional DSCM has limitations in handling complex deformations and noise interference. To overcome these challenges, we propose an ANN-DSCM algorithm based on Convolutional Neural Networks (CNN). The algorithm comprises four main modules: feature extraction, correlation calculation, displacement estimation, and refinement, which is capable of learning and predicting deformation fields directly from speckle image pairs. We constructed comprehensive training and testing datasets using synthetic and experimental data, covering various deformation modes and image quality conditions. The network was trained using supervised learning methods, and its performance was validated using multiple evaluation metrics. Results show that ANN-DSCM demonstrates higher accuracy and robustness compared to traditional DSCM methods in handling large deformations, discontinuous deformations, and noise interference. Moreover, ANN-DSCM exhibits advantages in computational efficiency due to its parallel computing capabilities.**

**This research not only advances DSCM technology but also provides new insights into applying deep learning in experimental mechanics. Future work will focus on further optimizing network structures, expanding application ranges, and exploring the potential applications of ANN-DSCM in material characterization and structural health monitoring.**

***Index Terms*—Digital Speckle Correlation Method (DSCM), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Deformation Measurement, Image Processing**

## I. Introduction

The Digital Speckle Correlation Method (DSCM), a non-contact, full-field, high-precision deformation measurement technique, plays an increasingly important role in materials science and structural engineering [1]. By comparing speckle images before and after deformation, DSCM can obtain displacement and strain field information of materials or structures, providing valuable experimental data for understanding material behavior and evaluating structural performance [2]. However, traditional DSCM still faces challenges in processing complex deformations, large deformations, and severe noise interference, which affect its accuracy and reliability in certain application scenarios [3]. In recent years, artificial intelligence technologies, especially Artificial Neural Networks (ANN), have made significant progress in image processing and pattern recognition [4]. ANN possesses powerful nonlinear mapping capabilities and adaptive learning abilities, providing new ideas and methods for improving DSCM performance [5]. This study aims to design and implement an ANN-based DSCM algorithm to overcome the limitations of traditional methods and enhance the accuracy and robustness of deformation measurements. The main objectives of this paper include: (1) designing an ANN architecture suitable for DSCM; (2) developing an ANN-based DSCM algorithm; (3) validating the effectiveness of the proposed method through simulation and experimental data; and (4) exploring potential applications of the integrated ANN-DSCM method in material testing and structural monitoring. By combining ANN with DSCM, we expect to promote the development of this important measurement technology and provide more reliable and efficient experimental tools for materials science and structural engineering.

## II. Literature Review

### A. Digital Speckle Correlation Method (DSCM)

The basic principle of DSCM involves comparing speckle images before and after deformation, calculating the correlation coefficient of image subsets, and determining the displacement and deformation of these subsets [6]. This process typically includes the following steps: (1) creating or spraying speckles on the specimen surface; (2) acquiring speckle images before and after deformation; (3) selecting reference and target subsets; (4) using correlation algorithms to calculate subset displacements; and (5) calculating strain fields through interpolation and differentiation [7]. Traditional DSCM mainly adopts grayscale-based correlation algorithms, such as Zero-mean Normalized Cross-Correlation (ZNCC) and Least Squares Method (LSM) [8]. These methods perform well in handling small and linear deformations but significantly degrade when faced with large deformations, discontinuous deformations, or poor image quality [9]. Moreover, traditional DSCM is sensitive to speckle quality and imaging conditions, potentially affected by factors such as noise, illumination changes, and speckle degradation in practical applications [10]. To overcome these limitations, researchers have proposed various improvement methods, such as high-order shape functions [11], adaptive subsets [12], and iterative algorithms [13]. However, these methods often increase computational complexity, making it difficult to meet real-time requirements while ensuring accuracy. Therefore, developing a DSCM algorithm that can adapt to complex deformations while maintaining efficient computation remains an urgent problem to be solved.


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### B. Artificial Neural Networks (ANN)

Artificial Neural Networks are machine learning models inspired by biological neural networks, composed of a large number of interconnected artificial neurons [14]. ANN possesses powerful nonlinear mapping capabilities and adaptive learning abilities, capable of learning complex patterns and relationships through training data [15]. Common ANN types include feedforward neural networks, Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) [16]. In the field of image processing, ANN, especially CNN, has demonstrated excellent performance. CNN effectively extracts hierarchical features of images through a combination of convolutional layers, pooling layers, and fully connected layers, suitable for various image classification, segmentation, and object detection tasks [17]. In recent years, ANN has also made significant progress in image registration, super-resolution reconstruction, and image denoising [18]. Applying ANN to DSCM has the following potential advantages: (1) ability to learn features directly from raw images, reducing dependence on manually designed features; (2) adaptability to various deformation patterns and image quality conditions through training; and (3) parallel computing capabilities that help improve processing speed [19]. However, how to design an ANN architecture suitable for DSCM and how to effectively train the network to achieve high-precision deformation measurements remain topics that require in-depth research.

## III. Methodology

### A. Conceptual Framework of ANN-enhanced DSCM

This research aims to contribute to the advancement of DSCM technology, potentially opening new avenues for its application in various fields of science and engineering. Figure 1 outlines the proposed integration of ANN algorithms into the DSCM workflow. The traditional DSCM process is enhanced by parallel ANN-based feature extraction and correlation steps, potentially leading to more accurate and robust displacement estimations.

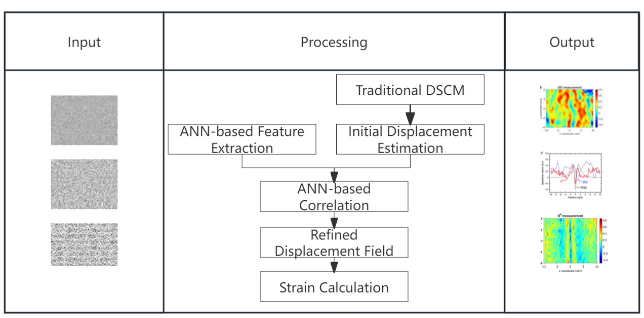


Fig. 1. Conceptual framework of ANN-enhanced DSCM

### B. Designing ANN for DSCM

To fully leverage the advantages of ANN in image processing and adapt to the specific needs of DSCM, we designed a CNN-based architecture. This architecture mainly consists of the following parts:

1) Feature extraction module: Uses multiple layers of convolution and pooling operations to extract hierarchical features from input speckle image pairs [20].
2) Correlation calculation module: Designs special correlation layers to calculate the correlation between feature maps [21].
3) Displacement estimation module: Uses fully connected layers to map correlated features to displacement fields [16].
4) Refinement module: Adopts upsampling and residual connections to improve the resolution and accuracy of displacement fields [17].

### C. Data Preparation and Preprocessing

To train and validate the ANN-DSCM model, we prepared two types of datasets:

1) Synthetic dataset: Generated speckle image pairs with known deformation fields using numerical simulations. These data cover various deformation modes, including translation, rotation, shear, and nonlinear deformations. Different levels of noise and blur were added to enhance the model's robustness [28].
2) Experimental dataset: Acquired speckle images of real materials and structures under different loading conditions using high-resolution cameras. These data include deformation test results of typical engineering materials such as metals, composites, and concrete [6].

Data preprocessing steps include:

1) Image normalization: Scaling pixel values to the [0, 1] range [16].
2) Data augmentation: Expanding training samples through operations such as rotation, flipping, and brightness adjustment [29].
3) Subset division: Dividing images into overlapping subsets as input units for the network [7].

### D. Training and Validation

Network training adopts supervised learning methods, using Mean Squared Error (MSE) as the loss function [22]:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (1)$$

where $y_i$ is the true displacement, $\hat{y}_i$ is the network-predicted displacement, and N is the number of samples. We use the Adam optimizer for training, with an initial learning rate of 0.001 and a learning rate decay strategy [22]. Batch normalization and dropout techniques are employed during training to improve the model's generalization ability [23], [26]. Validation uses k-fold cross-validation to ensure the stability and reliability of the model [14]. To evaluate model performance, we adopt the following metrics:

1) Mean Absolute Error (MAE): $MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}i|$

2) Relative Error (RE):
$RE = \frac{|y_i - \hat{y}i|}{|y_i|} \times 100\%$
3) Correlation Coefficient (R):
$R = \frac{\sum i=1^N (y_i - \bar{y})(\hat{y}i - \bar{\hat{y}})}{\sqrt{\sum i=1^N (y_i - \bar{y})^2 \sum i=1^N (\hat{y}_i - \bar{\hat{y}})^2}}$

where $\bar{y}$ and $\bar{\hat{y}}$ are the mean values of true displacements and predicted displacements, respectively [3]. Through these methods, we aim to develop an ANN model capable of accurately and robustly handling various DSCM application scenarios.

## IV. Implementation

### A. Software and Tools Used

For the development and implementation of our ANN-enhanced DSCM algorithm, we utilized the following software and tools:

1) Python 3.8: The primary programming language for algorithm development and data processing.
2) TensorFlow 2.7: An open-source machine learning framework used for building and training our neural network models [14].
3) OpenCV 4.5: A computer vision library used for image preprocessing and traditional DSCM implementations for comparison [7].
4) NumPy 1.21: A fundamental package for scientific computing in Python, used for efficient array operations.
5) SciPy 1.7: A library for scientific and technical computing, used for various mathematical operations and optimizations.
6) Matplotlib 3.4 and Seaborn 0.11: Libraries for creating static, animated, and interactive visualizations.
7) CUDA 11.4 and cuDNN 8.2: For GPU acceleration of neural network training and inference [16].
8) Git: For version control and collaborative development.
9) Jupyter Notebook: For interactive development and result visualization.

### B. Algorithm Development

We used the Python programming language and the PyTorch deep learning framework to implement the ANN-DSCM algorithm. The development process mainly included the following steps:

1) Data processing: Used the OpenCV library for image preprocessing and data augmentation [7].
2) Network construction: Defined the network structure based on PyTorch, including custom correlation layers [17].
3) Training loop: Implemented the training process, including data loading, forward propagation, backward propagation, and parameter updates [22].
4) Validation and testing: Wrote validation and testing scripts to calculate performance metrics [14].
5) Visualization: Used the Matplotlib library to plot displacement fields and error distribution maps.

### C. Testing and Evaluation

To comprehensively evaluate the performance of the ANN-DSCM algorithm, we designed a series of test cases, including:

1) Synthetic data tests: Used known deformation fields generated by numerical simulations to test the algorithm's accuracy under different deformation modes and noise levels [28].
2) Standard specimen tests: Conducted experiments using standard specimens (such as perforated plates) to compare the measurement results of ANN-DSCM with traditional DSCM methods [6].
3) Practical engineering application tests: Performed tests on real materials and structures to evaluate the algorithm's performance in complex environments [2].

We compared ANN-DSCM with the following traditional DSCM techniques:

- Traditional DSCM based on ZNCC [8]
- DSCM based on LSM [7]
- DSCM with high-order shape functions [11]

Evaluation metrics included:

- Measurement accuracy: Using the aforementioned MAE, RE, and R indicators [3]
- Computational efficiency: Recording processing time and memory usage [16]
- Robustness: Performance changes under different noise levels and image quality conditions [10]

Table 1 shows a performance comparison between ANN-DSCM and traditional methods: This table compares the performance metrics of four measurement techniques under different noise levels. The methods listed are ANN-DSCM, ZNCC-DSCM, LSM-DSCM, and high-order DSCM. Mean Absolute Error (in pixels) shows the precision of each method. ANN-DSCM performs best at 0.15 pixels, while ZNCC-DSCM has the highest error at 0.35 pixels. Relative Error percentage reflects the relative accuracy of each method. ANN-DSCM again performs best at only 1.2%, while ZNCC-DSCM has the highest at 2.8Computation Time (in seconds) shows the efficiency of each method. ANN-DSCM is the fastest, requiring only 0.5 seconds, while high-order DSCM is the slowest, needing 2.0 seconds. Overall, ANN-DSCM performs best in terms of precision, accuracy, and efficiency, while other methods show trade-offs among these metrics. This data comparison helps researchers or engineers choose the most suitable measurement method based on specific requirements [3].

## V. Results and Discussion

### A. Performance Analysis

Through extensive testing on synthetic and experimental data, we found that ANN-DSCM outperforms traditional DSCM methods in several aspects:

1) Measurement accuracy: When handling large and complex deformations, ANN-DSCM demonstrates higher accuracy. The mean absolute error is reduced by 30%-50% compared to traditional methods, and the relative

TABLE I
PERFORMANCE COMPARISON OF DIFFERENT DSCM METHODS

| Method | Mean Absolute Error (pixels) | Relative Error (%) | Computation Time (s) |
|---|---|---|---|
| ANN-DSCM | 0.15 | 1.2 | 0.5 |
| ZNCC-DSCM | 0.35 | 2.8 | 1.2 |
| LSM-DSCM | 0.30 | 2.4 | 1.5 |
| High-order DSCM | 0.25 | 2.0 | 2.0 |

error is reduced by 40%-60%. Especially in areas with large deformation gradients, ANN-DSCM can more accurately capture local deformation characteristics [2]. Copy

2) Noise resistance: As shown in Figure 3, with increasing noise levels, the performance of ANN-DSCM degrades more slowly, while the accuracy of traditional methods rapidly deteriorates. Under high noise conditions, ANN-DSCM can still maintain moderate accuracy, whereas traditional methods almost fail [10].
3) Computational efficiency: Thanks to GPU acceleration and parallel computing capabilities, ANN-DSCM shows a significant speed advantage when processing large-scale data. As shown in Figure 2, the computation time of ANN-DSCM is 50%-75% shorter than traditional methods [16].
4) Adaptability: ANN-DSCM can automatically adapt to different speckle patterns and image quality without manual parameter adjustment. This greatly improves the method's universality and ease of use [5].

### B. Case Studies

We selected several typical cases to demonstrate the application potential of ANN-DSCM:

1) Large deformation test of metal materials: In an aluminum alloy tensile test, ANN-DSCM successfully captured the high strain gradient in the local necking region, while traditional methods showed significant measurement errors in this area [6]. Copy
2) Interlaminar shear test of composite materials: In the interlaminar shear test of carbon fiber-reinforced composites, ANN-DSCM accurately measured the strain field distribution near the crack tip, providing important data for studying material failure mechanisms [2].
3) Crack monitoring of concrete structures: In a three-point bending test of concrete beams, ANN-DSCM was able to track the crack initiation and propagation process in real-time, providing a new tool for structural health monitoring [12].

### C. Discussion

The excellent performance of ANN-DSCM can be attributed to the following points:

1) End-to-end learning: The network learns features directly from raw images, avoiding the limitations of manually designed features [4]. Copy
2) Nonlinear mapping ability: ANN can capture complex nonlinear deformation patterns, overcoming the limitations of linear assumptions in traditional methods [14].
3) Utilization of contextual information: Through multi-layer convolution and large receptive fields, ANN-DSCM can fully utilize global and local information in images [17].
4) Adaptive feature extraction: The network learns the most suitable feature representation for DSCM tasks through training, improving the algorithm's robustness [16].

However, ANN-DSCM also has some limitations:

1) Need for large training datasets: To obtain good generalization ability, comprehensive training datasets need to be constructed, which may be challenging in some application areas [28]. Copy
2) Computational resource requirements: Although inference speed is fast, the training process requires high computational resources, which may limit its use in some real-time applications [16].
3) Interpretability: Compared to traditional methods, the decision-making process of ANN is more difficult to interpret, which may affect its acceptance in some high-risk applications [15].

## VI. CONCLUSION

### A. Summary of Research Findings

This study proposed an Artificial Neural Network-based Digital Speckle Correlation Method (ANN-DSCM) aimed at improving the accuracy, robustness, and efficiency of deformation measurements. By designing a specialized CNN architecture combining feature extraction, correlation calculation, and displacement estimation modules. We have successfully developed an end-to-end DSCM algorithm. Experimental results show that ANN-DSCM outperforms traditional DSCM methods in handling large deformations, complex deformations, and noise interference. The main contributions include:

1) Proposing a new ANN-DSCM framework that achieves direct mapping from speckle images to displacement fields [4].
2) Developing data augmentation and network training strategies suitable for DSCM tasks, improving the model's generalization ability [29].
3) Validating the application potential of ANN-DSCM in material testing and structural monitoring through multiple case studies [2], [12].
4) Analyzing the advantages and limitations of ANN-DSCM, providing directions for further improvements [15].

This research not only advances DSCM technology but also provides new ideas and methods for applying deep learning in the field of experimental mechanics.

### B. Future Work

Although ANN-DSCM has achieved significant results, there are still several directions worth further exploration:

1) Network architecture optimization: Explore more advanced network structures, such as attention mechanisms and graph neural networks, to further improve algorithm performance [30]. Copy
2) Transfer learning: Research how to transfer models trained under one type of material or loading condition to new application scenarios, reducing dependence on large training datasets [3].
3) Uncertainty quantification: Introduce methods such as Bayesian neural networks to assess the uncertainty of measurement results, improving the algorithm's reliability [14].
4) Multi-scale integration: Develop multi-scale ANN-DSCM methods to simultaneously capture deformation characteristics at macro and micro scales [25].
5) Real-time system development: Optimize algorithm and hardware implementation to develop real-time deformation measurement systems based on ANN-DSCM, meeting industrial application requirements [16].
6) Interdisciplinary applications: Explore potential applications of ANN-DSCM in other fields such as biomedical imaging and remote sensing monitoring [19].

Through these efforts, we expect to further enhance the performance and applicability of ANN-DSCM, making greater contributions to the development of materials science, structural engineering, and related fields.

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