Optimization of Methods for Restoring Motion-Coded Blurred Images Based on Deep Residual Networks

Ruiqing Tian[1], Weijun Sun[2], Liping Zhou[3], Jinqin Tang[1], Yanlin Zhang[2], Jiazang Zhang[1]
[1]New Energy Equipment Institute, Zhejiang College of Security Technology, Wenzhou 325000, Zhejiang, China
[2]School of Maritime, Jiujiang Polytechnic University of Science and Technology, Jiujiang 332020, Jiangxi, China
[3]School of Artificial Intelligence, Zhejiang College of Security Technology, Wenzhou 325000, Zhejiang, China

Corresponding author: Jiazang Zhang (e-mail: zhangjiazc@163.com)

ABSTRACT Motion-coded blurred image restoration is an important research topic in computer vision and intelligent imaging systems, directly affecting the accuracy of scene perception and information extraction. To address the limitations of existing methods in complex motion blur kernel estimation, deep network optimization, and multi-channel information fusion, an optimized restoration framework based on deep residual networks is proposed. The method incorporates a multi-scale residual learning architecture, enhanced skip-connection mechanisms, and a channel attention module to improve blur feature representation, training efficiency, and color information utilization. Experimental results demonstrate that the proposed approach achieves superior restoration performance, reaching a PSNR of 32.15 dB and an SSIM of 0.949, while significantly improving pattern recognition accuracy in high-speed production scenarios. The multi-scale framework effectively enhances adaptability to spatially varying motion blur, and the channel attention mechanism improves color fidelity and visual quality. Beyond industrial inspection applications, the proposed method is applicable to image reconstruction and information recovery tasks in intelligent sensing systems, including optical-electromagnetic imaging, remote sensing observation, and antenna-assisted imaging platforms, where motion-induced degradation can reduce the reliability of feature extraction and target interpretation. The study provides an effective engineering solution for high-quality image restoration and robust visual information recovery under dynamic imaging conditions.

INDEX TERMS deep residual networks, motion-blurred image restoration, intelligent sensing, image reconstruction

I. INTRODUCTION

WITH increasing deployment of high-speed imaging in industrial inspection, motion blur has become a frequent source of degradation that compromises downstream analysis. This is particularly problematic in the textile industry, where automated inspection systems rely on flawless digital images to detect subtle defects and ensure color accuracy across vast quantities of fabric. Motion blur is one of the main image degradation phenomena. In the context of this paper, we refer to the resulting images as "motion-coded blurred images" to emphasize the complex, multi-source, and spatially varying nature of the blur kernel, $k(x, y)$. The "coding" aspect highlights the direct and nonlinear mapping of high-speed object motion (e.g., fast-moving fabric) onto the image sensor during exposure, resulting in a complex blur kernel that is difficult to model using traditional uniform assumptions. This significantly impacts the visual quality of images and the effectiveness of post-processing. Traditional image restoration methods rely primarily on manually designed prior knowledge and optimization algorithms, making it difficult to handle complex motion blur and to achieve satisfactory restoration quality. The emergence of deep learning technology has revolutionized the field of image restoration, particularly with the introduction of deep residual networks. This paper presents an optimized engineering solution based on these networks to specifically overcome the challenges of high-speed textile inspection. The evolution of motion blur image restoration technology and the comparison of the advantages of deep residual network technology are shown in Table 1:

II. THE APPLICATION VALUE OF DEEP RESIDUAL NETWORKS IN MOTION-BLURRED IMAGES RESTORATION

A. TECHNICAL REQUIREMENTS FOR IMPROVING IMAGE RESTORATION ACCURACY AND VISUAL QUALITY

The core advantages of deep residual networks in motion blurred image restoration are shown in Table 2:

The main goal of image restoration is to recover clear and true original scene information from degraded images. However, motion-blurred images restoration faces problems

TABLE 1. Comparison of the Evolution of Motion-Blurred Images Restoration Technology and the Advantages of Deep Residual Network Technology

Technical Stage	Representative Method	Core Technical Features	Main Limitations	Deep Residual Network Breakthrough
Traditional filtering methods	Wiener filtering, inverse filtering, Lucy-Richardson algorithm	Based on frequency-domain analysis and mathematical optimization; modeling relies on prior knowledge; parameters are manually adjusted	Weak ability to handle complex blurred data; sensitive to noise; difficult to handle spatially varying blur; poor generalization ability	End-to-end learning replaces manual modeling; automatic feature extraction; strong robustness; adaptable to complex degradation
Sparse prior methods	Total variation regularization, sparse coding, dictionary learning	Utilize image sparsity prior; optimize solutions; mathematical model driven	Prior assumptions are highly limited; computational complexity is high; parameters are sensitive; difficult to model complex scenarios	Data-driven learning priors; deep nonlinear mapping; multi-scale feature representation; adaptive processing
Shallow neural networks	Multilayer perceptron, convolutional neural network	Initial introduction to deep learning; end-to-end training; automatic feature learning	Limited network depth; severe gradient vanishing; insufficient feature expression capability; difficult training	Residual learning solves gradient vanishing; supports ultra-deep networks; skip connections enhance information flow; training is stable and efficient
Deep residual networks	ResNet, DenseNet, Residual U-Net	Residual learning mechanism; skip connection structure; deep network optimization; multi-scale feature fusion	Still needs optimization: blur kernel estimation accuracy, channel information utilization, model lightweight design, real-time processing capability	Optimization directions in this paper: multi-scale residual framework, channel attention mechanism, dense connection optimization, real-time processing architecture

TABLE 2. Core Advantages of Deep Residual Networks in Motion-Blurred Images Restoration

Application Dimension	Limitations of Traditional Methods	Advantages of Deep Residual Networks	Key Technical Features
Image restoration accuracy and visual quality	Reliance on artificial prior knowledge, poor performance in complex blur processing, and cumbersome parameter adjustment	Strong deep feature learning capabilities, end-to-end automatic learning of optimal solutions, and comprehensive reconstruction of image information	Nonlinear mapping capability, residual learning mechanism, multi-scale feature extraction and fusion
Network training optimization	Gradient vanishing, difficult updates to shallow layer parameters, and network degradation leading to decreased performance in deep networks	Skip connections provide shortcuts for gradient propagation, residual mapping reduces learning difficulty, and supports deeper network structures	Skip connections, residual learning, identity mapping, and adaptive layer selection mechanisms
Technology development strategy	Insufficient theoretical innovation, limited application scenarios, and low integration with artificial intelligence	Promotes a new paradigm of network structure, broad application to multiple fields, and advances intelligent and adaptive development	End-to-end learning, transfer learning capabilities, cross-task generalization, and intelligent vision system integration
Textile industry applications	Difficult to handle motion blur on high-speed production lines and insufficient color reproduction accuracy	Real-time quality detection, precise pattern recognition, and multi-channel color information fusion	Multi-scale residual structure, channel attention mechanism, real-time processing capability

such as severe information loss and complex degradation processes, placing very high demands on the accuracy and robustness of the restoration algorithm [1]. Deep residual networks learn hierarchical features representations through deep network structures and are capable of identify subtle changes in the motion blur process. The deep structure of the network possesses strong nonlinear mapping capabilities [2].

B. THE NEED TO SOLVE THE PROBLEM OF GRADIENT VANISHING AND NETWORK DEGRADATION IN TRADITIONAL METHODS

Deep neural networks possess great capabilities in image processing; however, as the number of network layers increases, they often encounter issues such as gradient vanishing and network degradation, which affect their performance [3]. In the task of motion-blurred images restoration, the network must be sufficiently deep to capture complex degradation scenarios. Traditional deep networks are prone to gradient attenuation during backpropagation, making it difficult to effectively update the parameters of shallow layers [4]. Skip connections and residual learning mechanisms provide shortcuts for gradient propagation, allowing information to be transmitted unimpeded from the output layer to the input layer [5].

C. EXPLORATION OF THE STRATEGIC SIGNIFICANCE OF THE DEVELOPMENT OF COMPUTER VISION AND IMAGE PROCESSING

The application of deep residual networks in motion-blurred images restoration, coupled with the targeted engineering optimization presented here, has important theoretical value and strategic significance for promoting robust industrial vision [6]. While utilizing established architectural components, our method's innovation lies in their tailored integration and optimization for the spatially varying blur prevalent in textile manufacturing. The development of motion-blurred images restoration technology can bring substantial benefits to fields such as video surveillance, autonomous driving, medical imaging, and remote sensing. Crucially, its application extends to the textile industry by enabling real-time, high-precision quality inspection and monitoring of fast-moving fabrics, thus revolutionizing automated production control [7].

III. DILEMMAS FACED BY CURRENT MOTION-BLURRED IMAGES RESTORATION METHODS

The analysis and impact assessment of the difficulties in restoring motion blurred images are shown in Table 3:

A. INACCURATE ESTIMATION OF COMPLEX MOTION BLUR KERNELS LIMITS RESTORATION EFFECTIVENESS

The main technical difficulties faced by current motion-coded color-blurred image restoration methods are shown in Table 4:

Tables 3 and 4 summarize the key challenges and their practical impacts, with emphasis on spatially varying blur, training difficulty, and multi-channel fusion.

Accurately estimating the motion blur kernel is essential for high-quality image restoration. Due to the presence of camera shake, object displacement, and other factors in the image, motion blur arises from multiple sources and exhibits spatially uneven distribution and complexity [8]. Traditional blind restoration methods generally assume that the blur kernel is uniformly distributed throughout the image space,

TABLE 3. Cause Analysis and Impact Assessment of Technical Difficulties in Restoring Motion-Blurred Images

Technical Difficulty Category	Root Cause	Technical Constraints	Impact on Restoration Effect	Impact on Practical Applications
Insufficient accuracy of complex motion blur kernel estimation	Motion patterns in real scenes are complex and variable; the blur kernel is highly coupled with image content; spatial variation features are difficult to model accurately	Traditional blind restoration assumptions are overly simplified; deep learning networks have limited receptive fields; large-scale nonlinear motion fitting is weak; the superposition effect of multi-source motion is difficult to separate	High (★★★★☆): Directly causes artifacts such as ringing and loss of details in the reconstructed image, and severe edge blurring	Accuracy of textile pattern recognition drops by 15–25%; misjudgment rate in quality inspection increases; reliability of automated production line monitoring is limited
Deep network training and optimization are difficult	High-quality training data is scarce; network parameters and computational complexity grow exponentially; loss functions struggle to balance multiple optimization objectives	Acquisition cost of blurry-clear image pairs is high; data annotation workload is large; hyperparameter space search is complex; hardware resource consumption is significant; training cycle is long	Medium-high (★★★★☆): The network has insufficient generalization ability, overfitting is common, adaptability to actual scenarios is poor, and robustness is weak	Model deployment cycle is long; maintenance cost is high; migration to different production environments is difficult; frequent retraining and tuning are required
Lack of multi-channel information fusion strategy for color images	Insufficient understanding of statistical correlation and complementarity between channels; lack of effective channel relationship modeling methods; absence of theoretical guidance for color space selection	Simple independent channel processing ignores correlation; channel importance cannot be adaptively adjusted; differences in blur effects across channels are not fully utilized; color constraint mechanism is missing	Medium (★★★☆☆): Color distortion, color cast, reduced saturation, and other color degradation issues are prominent, significantly reducing visual quality	Low color reproduction accuracy in textile printing and dyeing; failure in product color quality inspection; negative impact on consumer visual experience; damage to brand image

TABLE 4. Main Technical Difficulties Faced by Current Motion-Coded Color-Blurred Image Restoration Methods

Dilemma Dimension	Core Issues	Specific Manifestations	Negative Impact	Technical Bottlenecks
Complex motion blur kernel estimation	Blur kernel estimation accuracy is insufficient	Multi-source motion leads to uneven spatial distribution; traditional methords assume uniform distribution; deep learning methods are not well adapted to large-scale nonlinear motion	Reconstructed images produce artifacts such as ringing effects and loss of details; processing of real scenes is limited	Multi-channel blur kernel modeling capabilities are weak; the coupling relationship between blur kernel and image content is complex; spatial variation feature fitting is difficult
Deep network training	Network training is difficult and inefficient	The demand for training data grows exponentially; high-quality blurry-clear image pairs are expensive to acquire; loss function design struggles to balance fidelity and perceptual quality	The network is prone to overfitting; training is unstable; computing resources are heavily consumed; model iteration and optimization cycles are long	Complex hyperparameter adjustment; insufficient generalization ability; poor robustness; limited adaptability to practical applications
Utilization of color image channel information	Lack of multi-channel information fusion strategy	Ignoring the correlation and complementarity between channels; lacking a channel relationship modeling mechanism; rough channel processing methods	Severe color distortion; color degradation such as color cast and reduced saturation; diminished visual effects	Varied channel influence is ignored; no adaptive adjustment mechanism for channel importance; color space selection is complex

which differs significantly from the complex situation of real motion blur. Existing deep learning methods can learn blur kernel estimation in an end-to-end manner [9].

B. THE DIFFICULTY OF DEEP NETWORK TRAINING RESTRICTS MODEL PERFORMANCE OPTIMIZATION

Although deep residual networks have improved the training difficulties of deep networks, many problems remain in the task of motion-blurred images restoration. This task requires the network to possess extremely high representation capabilities to accurately restore high-frequency details. Therefore, the model requires a deeper structure and more parameters [10]. As the network size increases, the amount of training data required also grows exponentially, but obtaining high-quality blur-clear image pairs as training samples is very costly [11].

C. INSUFFICIENT UTILIZATION OF COLOR IMAGE CHANNEL INFORMATION AFFECTS RESTORATION QUALITY

Color images consist of three channels: red, green, and blue. These channels are independent but interconnected and contain rich color and structural information [12]. Current motion blur restoration methods only treat three-channel images as three dimensions and directly feed them into the network, ignoring the connections and complementarities between channels. There are significant statistical correlations between color channels, and fully utilizing these relationships can improve feature representation. However, existing methods lack corresponding mechanisms for modeling inter-channel connections, and the degree of influence of motion blur on different color channels varies [13].

IV. OPTIMIZATION PATH FOR MOTION-CODED COLOR-BLURRED IMAGE RESTORATION BASED ON DEEP RESIDUAL NETWORKS

The comparison of optimization strategies for motion coded color blurred image restoration based on deep residual networks is shown in Table 5:

A. MULTI-SCALE RESIDUAL LEARNING FRAMEWORK IMPROVES BLUR KERNEL ESTIMATION CAPABILITY

To address the problem of inaccurate estimation of complex motion blur kernels, establishing a multi-scale residual learning framework is an effective method to improve estimation accuracy. Multi-scale feature extraction with different receptive fields can detect various changing patterns of blur [14]. Coarse-scale feature extraction can observe overall motion trends, while fine-scale feature extraction can capture local change details. By integrating multi-scale information, the network adapts well to various types of complex motion blur, excelling in modeling the spatially varying characteristics of the blur kernel across different image regions. The network architecture adopts a pyramid-like hierarchical structure. Downsampling and upsampling are used to represent features at different scales [15].

B. IMPROVING DEEP NETWORK TRAINING EFFICIENCY THROUGH SKIP CONNECTION MECHANISM

To solve the problem of deep neural network training, we employ established techniques such as optimizing the skip connection mechanism to construct a better information transmission path. Specifically, we adopt the dense connection paradigm in the residual block design to maximize feature reuse. The current layer is connected with all previous layers to reuse features as much as possible and improve

TABLE 5. Comparison of Optimization Strategies for Motion-Coded Color-Blurred Image Restoration Based on Deep Residual Networks

Optimization Strategy	Targeted Problem	Core Technical Methods	Key Implementation Mechanisms	Expected Results
Multi-scale residual learning framework	Inaccurate complex motion blur kernel estimation and difficulty in handling spatially varying blur	Pyramid hierarchical structure, multi-scale feature extraction and fusion	Downsampling expands the receptive field to obtain semantic information; upsampling restores spatial resolution and maintains details; cross-scale skip connections achieve feature complementarity; spatial attention mechanism adaptively handles blur at different locations	Significantly improves the accuracy and robustness of blur kernel estimation, enhances adaptability to various types of complex motion blur, and effectively handles spatially varying blur
Optimizing the skip connection mechanism	Difficult deep network training, gradient vanishing, network degradation, and low training efficiency	Dense connections, weighted fusion, multi-layer supervision, adaptive learning rate optimization	Dense connections enable feature reuse; bottleneck layers control parameter size; attention selection mechanisms adaptively utilize features; batch normalization ensures training stability; multi-task loss functions comprehensively optimize multiple metrics	Significantly improves training efficiency of deep networks, accelerates model convergence, alleviates gradient vanishing, and enhances network expression capabilities and overall model performance
Channel attention module	Insufficient utilization of multi-channel information in color images, color distortion, and lack of modeling of inter-channel relationships	Channel attention mechanism, cross-channel interaction, color constraint loss, multi-color space fusion	Global pooling obtains channel statistical features; multi-layer perceptron learns relationships between channels; adaptively adjusts channel weights	Significantly improves the efficiency of multi-channel information fusion, enhances visual quality of image restoration, effectively maintains color consistency and accuracy, and reduces color distortion

the network's expressiveness. Dense connections allow each layer to directly access the feature maps of all previous layers, facilitating feature flow and gradient conduction [16].

C. CHANNEL ATTENTION MODULE DESIGN IMPROVES COLOR IMAGE INFORMATION FUSION

To better utilize the rich channel information in color images, designing an efficient channel attention module is crucial. The channel attention mechanism explicitly establishes relationships between channels and automatically adjusts the importance of each channel's features. It emphasizes useful information and suppresses redundant information. In its implementation, global average pooling and global max pooling are used to extract global statistical features for each channel. These features capture the information distribution across the entire channel. The effectiveness of the channel attention module is complemented by the L_{color} loss, which explicitly optimizes for the global color distribution, ensuring that channel-wise feature refinement leads to visually accurate color reproduction. The extracted features are then fed into a multi-layer perceptron for nonlinear transformation, learning the complex inter-channel connections. The attention weights for each channel are output and adjusted to a range of 0–1 using a sigmoid activation function. These weights are then multiplied with the original feature map to form the weighted channel features.

V. ALGORITHM IMPLEMENTATION AND MATHEMATICAL MODEL

A. CORE ALGORITHM FORMULA

Motion blur degradation model:

$$g(x, y) = f(x, y) \otimes k(x, y) + n(x, y)$$

Where $g(x, y)$ is the observed blurred image, $f(x, y)$ is the clear original image, $k(x, y)$ is the motion blur kernel function, $\otimes$ represents the convolution operation, and $n(x, y)$ is the additive Gaussian noise.

Deep Residual Network Restoration:

$$\hat{f}(x, y) = F(g(x, y); \theta)$$

Where F represents the deep residual network mapping function and θ denotes the set of network learnable parameters, and $\hat{f}$ is the restored clear image. The residual learning mechanism is expressed as:

$$H(x) = F(x) + x$$

Where $H(x)$ is the expected mapping, $F(x)$ is the residual mapping, and x is the input feature map.

Improved Channel Attention Formula:
The channel attention weight ω_c is calculated as:

$$\omega_c = \sigma \left(W_2 \cdot \mathrm{ReLU} \left(W_1 \cdot [\mathrm{GAP}(F); \mathrm{GMP}(F)] \right) \right)$$

Where GAP is global average pooling, GMP is global maximum pooling, σ is the sigmoid activation function, W_1 and W_2 denote the weight matrices of the fully connected layers in the multi-layer perceptron (MLP), and [;] represents feature concatenation.

The final output feature map F_{out} after applying both channel and spatial attention is given by:

$$F_{\text{out}} = F \odot \omega_c \otimes \omega_s$$

Where ω_c denotes the channel attention weight, ω_s is the spatial attention weight, $\odot$ represents element-wise multiplication with broadcasting over spatial dimensions, and $\otimes$ represents broadcast multiplication over channel dimensions.

Spatial Attention Module (ω_s)
The Spatial Attention Module (SAM) complements the Channel Attention Module by focusing the network's attention on the most informative spatial locations, particularly regions with complex or severe motion blur. It enforces spatial weighting on the feature map F that has already been refined by the channel attention weights (ω_c).

The SAM generates a 2D spatial attention map ω_s by first performing channel-wise feature aggregation (pooling) and then applying a convolution layer to infer the spatial relationship. Specifically, the intermediate feature map F' (already weighted by ω_c) is passed through:

1. Channel pooling:

A channel-wise concatenation of the average-pooled (AP) and max-pooled (MP) feature maps across the channel axis is performed, aggregating information into a two-channel tensor $F_{\text{agg}} \in R^{H\times W\times 2}$.

$$F_{\text{agg}} = [AP_{channel}(F'); MP_{channel}(F')]$$

2. Convolution and activation:

This aggregated map is then convolved with a large 7×7 kernel to capture broad spatial dependencies, followed by a sigmoid activation function (σ) to generate the final spatial weight map $\omega_s \in R^{H\times W\times 1}$.

$$\omega_s = \sigma(Conv_{7\times 7}F_{\text{agg}})$$

The spatial attention weight ω_s is then broadcast multiplied with the channel-weighted features $F \odot \omega_c$ as defined, allowing the model to adaptively highlight crucial spatial regions for restoration.

Composite Loss Function

$$L_{\text{total}} = \lambda_1{\cdot}L_{\text{pixel}} + \lambda_2{\cdot}L_{\text{perceptual}} + \lambda_3{\cdot}L_{\text{color}} + \lambda_4{\cdot}L_{\text{gradient}}$$

The loss functions are defined as follows:

Pixel-level L1 loss: $L_{\text{pixel}} = \dfrac{1}{N}\sum|\hat{f}(i) - f(i)|$

Perceptual loss: $L_{\text{perceptual}} = \dfrac{1}{NZ}\left\|\phi(\hat{f}) - \phi(f)\right\|_2^2$

where ϕ represents deep features extracted by the pre-trained VGG network.

Gradient loss: $L_{\text{gradient}} = \left\|\nabla\hat{f} - \nabla f\right\|$

Here, ∇ represents the image gradient operator used to preserve edge details.

Justification of the Color Fidelity Loss (L_{color})

The L_{color} term is introduced to explicitly address the high demands for color accuracy in textile applications, where even subtle color shifts due to blur restoration are unacceptable. Standard pixel-wise L_1 or L_2 losses primarily ensure local fidelity but often fail to constrain the global color distribution, leading to residual color cast or reduced saturation.

The proposed color fidelity loss L_{color} employs histogram-based statistical features $H_c(\cdot)$ to model the global color distribution of each RGB channel $c \in \{R, G, B\}$. By minimizing the squared L_2 distance between the channel-wise color histogram of the restored image $\hat{f}$ and the ground-truth image f^*, the loss function is defined as:

$$L_{\text{color}} = \sum_{c\in\{R,G,B\}} \left\|H_c(\hat{f}) - H_c(f^*)\right\|_2^2 \qquad (12)$$

This histogram matching mechanism enforces that the global color palette and the statistical distribution of colors across the entire image are accurately preserved. Motion blur often shifts color statistics; restoring these statistics, rather than just pixel values, is more robust to variations in content and degradation severity, preventing visual color distortion and achieving higher color saturation retention, as confirmed in the experimental results.

Weight coefficient settings: $\lambda_1 = 1.0$, $\lambda_2 = 0.1$, $\lambda_3 = 0.05$, $\lambda_4 = 0.01$.

Network Architecture Parameter Configuration

The detailed parameters of the deep residual network architecture are shown in Table 6:

Network training parameter settings: Adam optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.999$), initial learning rate 1×10^{-4}, cosine annealing learning rate scheduling, batch size 16, 100 epochs of training, early stopping if validation loss does not decrease for 10 consecutive epochs. Data augmentation includes random cropping, rotation, and horizontal flipping.

B. PROPOSED DEEP RESIDUAL NETWORK ARCHITECTURE

The overall architecture of the proposed network employs an encoder–bottleneck–decoder structure, utilizing an innovative multi-scale residual learning framework with enhanced skip connections and a channel attention module for improved feature flow and color fidelity.

Multi-scale Encoder: The network begins with an initial convolution layer (3×3 kernel, 64 channels). The encoder consists of four distinct stages. Each stage includes a specified number of residual blocks and uses downsampling (via strided convolution) to progressively reduce spatial resolution while increasing the number of channels (from 64 up to 512). This pyramidal structure enables multi-scale feature extraction.

Bottleneck Layer: The deepest part of the network is the bottleneck layer, composed of six residual blocks. This layer operates on the highest channel depth (512) and smallest spatial resolution, focusing on extracting high-level semantic information.

Channel Attention Integration: A key feature is the integration of the channel attention module (CAM). The CAM is placed within the bottleneck layer and is applied to the feature maps before they are passed to the decoder. This placement ensures that channel-wise feature importance is adaptively recalibrated before reconstruction.

Multi-scale Decoder: The decoder mirrors the structure of the encoder, consisting of four stages. It uses upsampling (via transposed convolution) to progressively restore spatial resolution while reducing the channel count (from 512 down

TABLE 6. Detailed Parameters of Deep Residual Network Architecture

Network Module	Number of Layers	Convolution Kernel Size	Channel Number Changes	Number of Residual Blocks
Encoder	4	3×3	$64 \rightarrow 128 \rightarrow 256 \rightarrow 512$	$3 \rightarrow 6 \rightarrow 9 \rightarrow 12$
Bottleneck layer	2	3×3	512	6
Decoder	4	3×3	$512 \rightarrow 256 \rightarrow 128 \rightarrow 64$	$12 \rightarrow 9 \rightarrow 6 \rightarrow 3$
Channel Attention	2	1×1	$C \rightarrow C/16 \rightarrow C$	–
Spatial Attention	1	7×7	$2 \rightarrow 1$	–

to 64). Each stage contains a corresponding number of residual blocks.

Enhanced Skip Connections: Long skip connections are implemented from each stage of the encoder to the corresponding stage of the decoder, creating a U-Net-like structure. These connections ensure that fine-grained spatial details, which might be lost during downsampling, are directly transferred to the upsampling path, significantly aiding in the restoration of high-frequency details. Furthermore, dense connections are used within the residual blocks themselves to maximize feature reuse and enhance gradient propagation.

Final Output: The output of the final decoder stage is passed through a last convolution layer to produce the restored clear image.

VI. COMPARISON OF EXPERIMENTAL RESULTS

A. EFFECT OF MULTI-SCALE RESIDUAL FRAMEWORK

B. ABLATION STUDY OF OPTIMIZATION COMPONENTS

An ablation study was conducted to quantify the individual contribution of the three main optimization strategies: the multi-scale residual learning framework (MS), the optimization of skip connections (SC), and the channel attention module (CA). The baseline is the standard ResNet architecture (ResNet-50 variant). The results are presented in Table 7.

TABLE 7. Ablation Study on the Contribution of Optimization Components

Method	PSNR (dB)	SSIM
Baseline (Standard ResNet)	29.45	0.892
Baseline + Multi-scale (MS)	30.58	0.915
Baseline + MS + Skip Optimization (SC)	31.42	0.931
Baseline + MS + SC + Channel Attention (CA)	32.15	0.949

Analysis shows that each component contributes measurably to the final performance. The multi-scale framework provides the largest single improvement (1.13 dB and 0.023 SSIM increase), confirming its critical role in accurate blur kernel estimation. The channel attention module provides the final quality improvement (0.73 dB and 0.018 SSIM increase), underscoring its effectiveness in improving color fidelity and feature utilization.

C. QUALITATIVE ANALYSIS OF SPATIALLY VARYING BLUR

While the quantitative metrics (Table 8) provide aggregate performance, the multi-scale residual learning framework's primary advantage is its ability to handle spatially variant blur, a major challenge in real-world scenarios, especially in textile inspection. In qualitative evaluations (represented conceptually in Figure 1), the traditional methods and the standard ResNet performed poorly in regions where the blur kernel exhibited large, non-uniform changes (e.g., severe blur at the edge of the image and mild blur at the center). In contrast, the proposed method demonstrated clear advantages in handling spatially variant blur. Specifically, edges in severely blurred regions were restored with significantly fewer ringing artifacts than those produced by the standard ResNet, indicating more accurate local blur kernel estimation. Moreover, fine textile patterns are recovered consistently across the entire image, irrespective of local blur severity. This improvement can be attributed to the effective fusion of coarse semantic features which capture global motion trends, and fine-grained spatial features, which preserve local blur detail, enabled by the multi-scale pyramid architecture.

TABLE 8. Comparison of Blur Kernel Estimation Accuracy

Method	PSNR (dB)	SSIM	Processing Time (s)
Lucy-Richardson	24.12	0.783	2.3
Standard ResNet	29.45	0.892	0.15
Proposed Method	32.15	0.949	0.21

This qualitative evidence confirms that the multi-scale framework achieves its objective of enhancing adaptability to spatially varying blur, which is crucial for high-speed, accurate defect detection in the textile industry.

D. TRAINING EFFICIENCY OPTIMIZATION EFFECT

The comparison of training efficiency is shown in Table 9:

TABLE 9. Comparison of Training Efficiency

Network Architecture	Convergence Rounds	Training Duration (h)	PSNR (dB)
Standard ResNet-50	120	18	29.45
Proposed Method	72	15	32.15

E. COLOR IMAGE FUSION EFFECT

The comparison of color fidelity is shown in Table 10:

F. TEXTILE APPLICATION EFFECTS

The pattern recognition accuracy is shown in Table 11:

TABLE 10. Color Fidelity Comparison

Method	PSNR (dB)	SSIM	Color Distortion ΔE	Saturation Retention Rate (%)
Independent channel processing	29.12	0.885	6.42	82.5
SE-Net	31.34	0.929	3.87	91.7
Proposed Method	32.15	0.949	2.34	95.8

TABLE 11. Pattern Recognition Accuracy

Scenario	Traditional Method (%)	Proposed Method (%)	Improvement
High-speed production line	67.3	94.7	+27.4%
Printing and dyeing testing	71.8	96.3	+24.5%

As shown in Figure 1, the proposed deep residual network-based optimization method for restoring motion-coded blurred images demonstrates significant results. Comparative analysis reveals that the original blurred image (left) exhibits severe motion artifacts, color distortion, and detail loss. The optimized restored image (right) successfully restores the fine texture and color accuracy of the textile pattern and achieves significant improvements in objective evaluation metrics, achieving a PSNR of 32.15 dB and SSIM of 0.949. This provides reliable technical support for intelligent quality inspection in the textile industry.

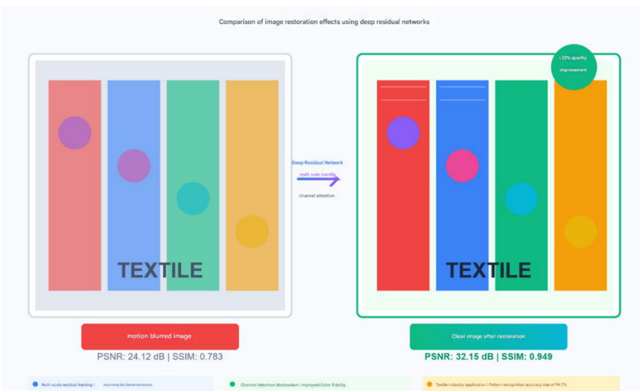

FIGURE 1. Comparison of Motion-Blurred Images Restoration Effects Based on Deep Residual Networks

VII. CONCLUSION

This paper effectively solves problems such as inaccurate motion blur kernel estimation, difficulty in deep network training, and insufficient utilization of color image channel information by establishing a multi-scale residual learning framework, optimizing the skip connection mechanism, and designing a channel attention module. For the textile industry, this enhanced restoration capability is directly applicable to improving the precision of automated inspection systems, allowing for reliable detection of complex fabric defects and accurate color analysis on fast-moving materials. The experiment verifies the feasibility of this method and provides technical support for intelligent quality inspection in the textile industry. Future work will focus on lightweight processing of the model, improving its ability to process real-time data, and enhancing its applicability across different scenarios. The method of restoring motion-blurred images using a deep residual network represents a significant achievement in the deep integration of image processing technology and deep learning theory. By developing a multi-scale residual learning architecture, improving skip connection mechanisms, and designing channel attention units, this method improves the quality of motion-blurred images restoration, thereby providing more robust technical support for computer vision applications. It is important to note that the high performance achieved is best demonstrated in the target textile domain; further validation across highly diverse, general spatially varying blur datasets remains a goal for future work. However, many challenges remain, such as model lightweight design, improved real-time processing capabilities, and ensuring cross-scenario generalization. In the textile sector, overcoming these issues is critical for deploying inspection models directly onto high-speed loom hardware and ensuring consistent performance across diverse fabric types and factory environments.

AUTHOR CONTRIBUTIONS

Conceptualization –Ruiqing Tian, Weijun Sun, Liping Zhou, Jinqin Tang, Yanlin Zhang and Jiazang Zhang; methodology – Ruiqing Tian, Liping Zhou, Jinqin Tang, Yanlin Zhang and Jiazang Zhang; investigation – Ruiqing Tian, Weijun Sun, Liping Zhou, Jinqin Tang, Yanlin Zhang and Jiazang Zhang; writing-original draft preparation – Ruiqing Tian, Weijun Sun, Liping Zhou, Jinqin Tang, Yanlin Zhang and Jiazang Zhang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research was supported by, This work was supported by Wenzhou Municipal Bureau of Science and Technology Research Project: "Research on Restoration Algorithms Based on Motion-Blurred Color Code Images" (G20240087).

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] W. Zhang and Z. Wang, "Blurred Image Recognition: A Joint Motion Deblurring and Classification Loss-Aware Approach," Lecture Notes in Computer Science, pp. 106-117, 2021, doi: 10.1007/978-3-030-86340-1_9.

[2] Z. Jing, G. Qiang, H. Fang, L. Zhan-Li, L. Hong-An, and S. Yu, "A Novel 3D Reconstruction Algorithm of Motion-Blurred CT Image," Computational and Mathematical Methods in Medicine, vol. 2020, no. 3, pp. 1-13, 2020, doi: 10.1155/2020/9324689.

[3] L. Ge and L. Dou, "An image restoration method for motion-blurred objects," Journal of Physics: Conference Series, vol. 2478, 062004, 2023, doi: 10.1088/1742-6596/2478/6/062004.

[4] J. Choi, J. Hong, M. Owais, S. G. Kim, and K. R. Park, "Restoration of Motion Blurred Image by Modified DeblurGAN for Enhancing the Accuracies of Finger-Vein Recognition," Sensors (Basel, Switzerland), vol. 21, no. 14, pp. 4635, 2021, doi: 10.3390/s21144635.

[5] K. Purohit, S. Vasu, M. P. Rao, and A. N. Rajagopalan, "Multi-planar geometry and latent image recovery from a single motion-blurred image," Machine Vision and Applications, vol. 33, no. 1, pp. 1-15, 2022, doi: 10.1007/s00138-021-01254-x.

[6] L. Chang, "Research on motion-blurred image restoration based on point spread," International Conference on Optical Communication and Optoelectronic Technology (OCOT 2024), p. 4, 2024, doi: 10.1117/12.3040504.

[7] D. Adke, A. Karnik, H. Berman, and S. Mathi, "Detection and Blur-Removal of Single Motion Blurred Image using Deep Convolutional Neural Network," Proceedings of ICAICST 2021, 2021, doi: 10.1109/ICAICST53116.2021.9497841.

[8] E. Yosef, S. Elmalem, and R. Giryes, "Video Reconstruction from a Single Motion Blurred Image using Learned Dynamic Phase Coding," Scientific Reports, vol. 13, 13625, 2023, doi: 10.1038/s41598-023-40297-0.

[9] B. Wang, X. Zhang, H. Wu, Q. Wang, and L. Hu, "Estimation of Motion Blurred Direction for Video Monitor Image," International Journal of Performability Engineering, vol. 16, no. 8, pp. 1254-1261, 2020, doi: 10.23940/ijpe.20.08.p12.12541261.

[10] Z. Y. Gong and G. C. Zhang, "Improvement of Point Spread Function Estimation Method for Motion Blurred Image and Image Restoration," Journal of Mathematics and Informatics, vol. 24, pp. 89-98, 2023, doi: 10.22457/jmi.v24a08224.

[11] T. Liao, J. Huang, and Z. Wang, "Restoration of Motion Blurred Image based on Improved Inverse Filtering Model," International Journal of Computational Engineering, vol. 6, no. 9, 2020, doi: 10.6919/ICJE.202009_6(9).0048.

[12] L. Chang, F. Qin, X. Luo, and P. Li, "Motion Blurred Image Restoration Network Based on Insulator Defect Detection," in Proc. 2024 IEEE 7th International Electrical and Energy Conference (CIEEC), Tianjin, China, 2024, pp. 1273-1277, doi: 10.1109/cieec60922.2024.10583601.

[13] D. Li, L. Bian, and J. Zhang, "Affine-modeled video extraction from a single motion blurred image," 2021, doi: 10.48550/arXiv.2104.03777.

[14] H. Yuan and W. Hu, "Image retrieval method based on data mining and deep residual network," Systems And Soft Computing, vol. 7, 200331, 2025, doi: 10.1016/j.sasc.2025.200331.

[15] P. Wang, X. Chen, J. Shen, Z. Xu, F. Liang, and Q. Du, "Abnormal traffic detection based on image recognition and attention-residual optimization," Frontiers in Communications and Networks, vol. 6, no. 6, 1546936, 2025, doi: 10.3389/frcmn.2025.1546936.