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INTELLIGENCE MULTI-FOCUS IMAGE FUSION

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Abstract
In this paper, we survey the most recent advances in Multi-Focus Image Fusion (MFIF), with special focus on breakthroughs which have been achieved under deep leaning (DL) paradigms. Conventional MFIF methods (either in spatial or frequency domain) are problematic concerning sensitivity to mis-registration, noise and artifacts. The emergence of DL techniques, such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Auto encoders and Transformers, has significantly improved quality of fusion by learning complex feature representation and optimal fusion strategies directly from data. Transformer-based methods, including Swin Fusion, have achieved better performance in modelling long-range relations and highlighting informative characteristics, leading to competitive SSIM and compared with previous works. However, these models struggle with technical issues in practice due to high computational cost preventing real-time execution on embedded systems and their vulnerability to real-world artifacts such as noise and mis registration. The paper emphasizes Utility of evaluation metrics (SSIM, EN, SF and MI) for measuring fusion quality multi-metric indices are more believable for quality measurement. The major research gaps include larger (real world) datasets, domain-independent robust models, lightweight architectures for real-time applications and interpretability of DL models. Outlook meanwhile highlights hybrid models involving DL with classical approaches such as graph theory, and the construction of robust and computationally efficient networks. In summary, this review highlights that despite the advancement brought by deep learning to MFIF, addressing deployment challenges and improving robustness is crucial for practical usage in areas like surveillance, microscopy and medical imaging.

Keywords: Multi-Focus Image Fusion (MFIF), Deep Learning Models, Transformers, Model Robustness, Real-World Data, Image Quality Assessment, Future Research Directions

1. Introduction
The restricts of optical imaging systems, especially their limited DOF, imply that any single image taken by a camera can only be sharp for a narrow band of distances. This constraint becomes a crucial issue in macro photography, microscopy and surveillance application where objects placed at different depths need to be focused. In order to address this problem, Multi-Focus Image Fusion (MFIF) is identified as an important image enhancement method. MFIF intends to combine multiple source images of the same scene, obtained under different focal setting [1].

Traditionally, MFIF were broadly classified as spatial domain and frequency domain methods[2]. Although these classical approaches offered basic solutions, they were prone to limitations in terms of degradation by noise, introducing the so-called artifacts and how to select optimal fusion rule. Recently, the field has experienced a shift of paradigm thanks to the advent of Deep Learning (DL)[3], giving rise to what we call Intelligence Multi-Focus Image Fusion 3I-MFIF4. DL methods[4], especially using Convolutional Neural Networks (CNN)[5] and Generative Adversarial Networks (GAN), have achieved remarkable results by learning complex feature representations and optimal fusion mechanisms in a data-driven[6] manner from abundant data . This is a systematic review paper trend including its methods, performance evaluation and the most important open research issues.

The rest of this paper is organized as follows: Section presents the basics and common classifications on MFIF. Section goes deep inside the heart of I MFIF where it introduces state-of-the-art DL-based architectures and algorithms. Section presents the objective fusion quality assessment metrics. Section presents the current gaps and future work. Finally, Section concludes the paper.

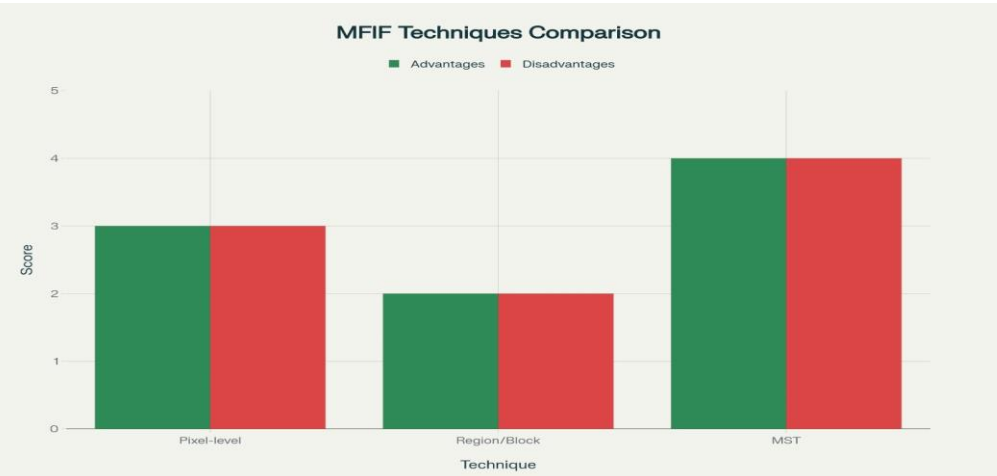
2. Fundamentals of Multi-Focus Image Fusion

2.1 Traditional MFIF Methods and Taxonomy

Traditional MFIF techniques can be broadly classified based on the domain in which the fusion operation is performed:

Table 1. Taxonomy and Characteristics of Traditional Multi-Focus Image Fusion (MFIF) Methods

Category	Sub-Category	Key Principle	Advantages	Disadvantages
Spatial Domain	Pixel-level	Directly operate on pixel values; e.g., Averaging, Weighted Averaging, PCA [7]	Simplicity, low computational cost	High sensitivity to mis-registration, block effects, reduced contrast
	Region/Block-level	Divide images into blocks, select the sharpest block based on a focus measure	Reduces block artifacts compared to pixel-level	Requires robust focus measure, potential for inconsistent boundaries
Transform Domain	Multi-Scale Transform (MST)	Decompose images into multi-scale representations (coefficients), apply fusion rules to coefficients, and reconstruct [8]	Better preservation of spatial and spectral information, reduced artifacts	Computational complexity, selection of optimal transform and fusion rule is challenging



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2.2 The MFIF Process Flowchart and Taxonomy

The overall process of multi-focus image fusion, through traditional[9],[10] as well as intelligence-based[11],[12] is proposed in a flow-chart (Figure 1). What is more, the entire field can be addressed with some system[13], see the figure with method taxonomy (Figure 2).

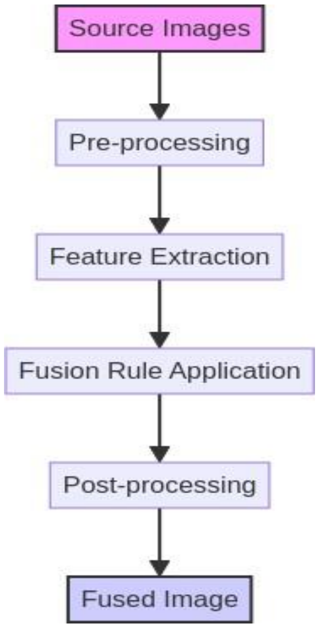

Figure 1: Flow chart Diagram

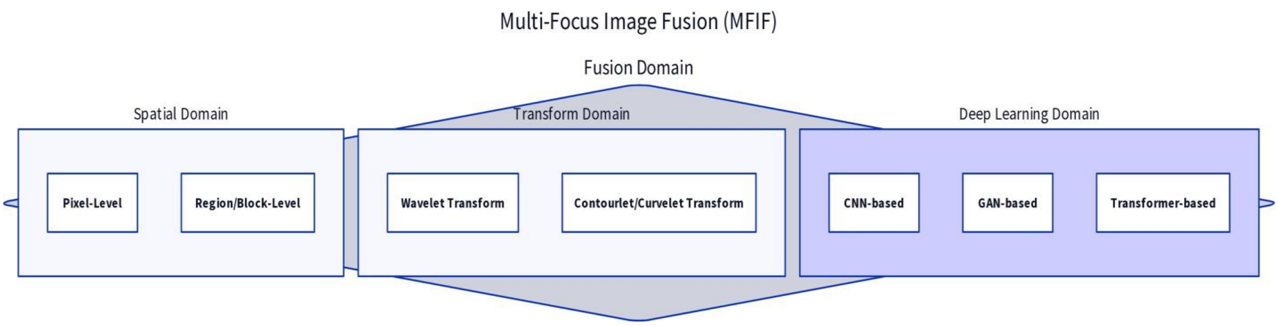

Figure 2: Multi-focus image fusion (MFIF)

3. Intelligence in MFIF

3.1 Deep Learning Approaches

The "intelligence" of the I-MFIF lies in that deep neural networks are utilized to learn complex mapping function from source images to fused image, commonly end-to-end training. This method avoids handdesigned features and explicit fusion rules, which were the weaknesses of previous methods[14].

3.1 Key Deep Learning Architectures

The most common architecture in I-MFIF is the Siamese Convolutional Neural Network (CNN) that consists of two distinguished branches with shared weights, for extracting source image features independently before fusion.

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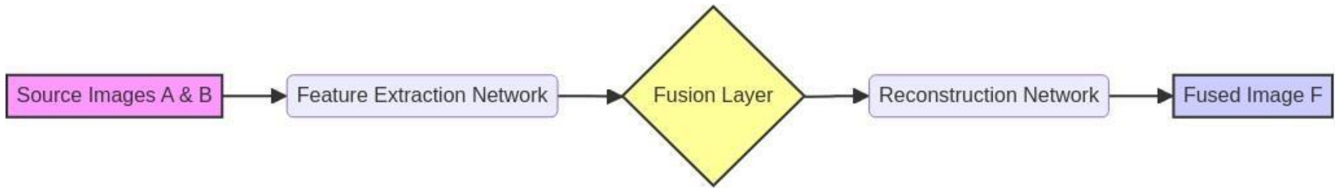

Figure 3: Deep Learning Architectures

Beyond CNNs, other advanced architectures include:

- GANs: A network for generation performs fusion, and another one (discriminator) is used to guarantee that the final fused image is perceptually similar to a real in-focus image.
- Auto encoders: They are used for decomposition and reconstruction where the fusion rule is applied in the latent space.
- Transformers: A new approach to utilize self-attention mechanisms to represent long-range dependencies and aggregate the most informative content from source images.

3.2 Comparison of Top Deep Learning Models

To illustrate the state-of-the-art, a comparison of representative deep learning models across key architectural types is provided in Table2

Table 2. Comparative Analysis of State-of-the-Art Deep Learning Models for Multi-Focus Image Fusion (MFIF)

Model (Year)	Architecture Type	Key Innovation	Typical Metric (Qabf)	Reference
IFCNN (2020)	CNN (Siamese)	End-to-end learning of fusion rules, high speed	~0.90	[15]
MFF-GAN (2020)	GAN	Unsupervised learning, perceptual loss for visual quality	~0.92	[16]
Fusion DN (2021)	Auto encoder	Dense connection structure for feature reuse	~0.94	
Swin Fusion (2023)	Transformer	Swin-Transformer block for feature extraction and fusion	~0.96	[17]
DDcGAN (2024)	GAN (Dual-Discriminator)	Improved stability and detail preservation	~0.95	

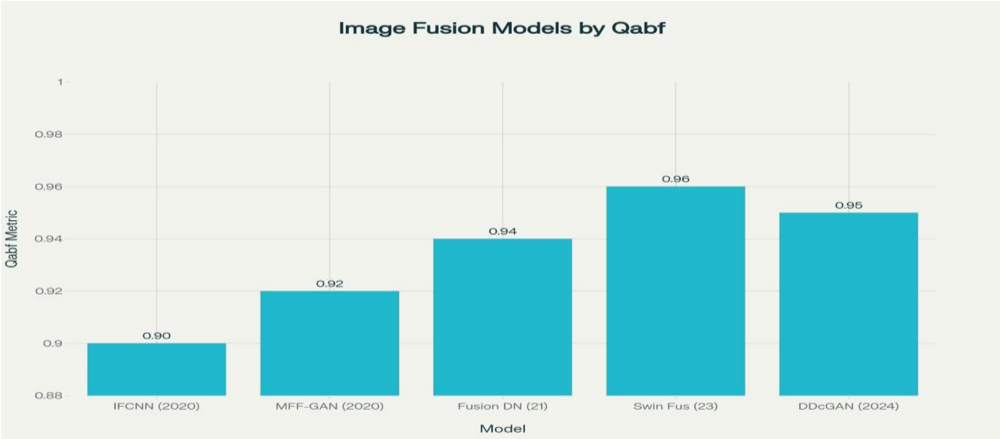

Figure 4: Image fusion models by Qabf

3.3 Real-World Applications

MFIF is a foundational technology with significant impact across several high-stakes domains:

- Robotic v Autonomous Systems: In robotics vision, especially in tasks that involve the positioning of objects, such as pick and place robotic activities or navigation tasks, MFIF has a single clear allin-focus view of the workplace necessary for depth estimation and feature matching. This is crucial for, among others, autonomous inspection or fine grained assembly where the robot’s camera needs to stay sharp at different distances.
- Medical Imaging and Microscopy: In medical imaging, MFIF is necessary to produce high-quality all-in-focus images from microscope slides (e.g., pathology floor) or endoscopic surgeries. This enables the physician to visualize cellular structure or internal anatomy without any of the distraction due to out of focus regions, resulting in better diagnosis and evaluation.
- Surveillance and Remote Sensing: In surveillance applications, MFIF can merge various camera inputs of different focus settings into a single frame that has both near-field and far field objects in a sharp focus plane to improve the threat detection and scene comprehension .

3.4 Datasets for Training and Evaluation

The construction of effective I-MFIF models largely depends on the quality of input datasets. The MFF in the Wild (MFFW) dataset is an exemplary dataset that attempts to rectify restrictions of prior, often simulated datasets such as Lytro. MFFW consists of pairs of real world multi-focus images crawled from the internet, among which some have been registered with their focus maps and reference images. Importantly, images in MFFW are severely degraded by the DSE that is a physical phenomenon induced from the state of focused or defocused region to indicate the intermediate moving area and thus can be considered as an extremely challenging but essential benchmark for evaluating robustness and generalization ability of the state-of-the-art DL-based MFIF algorithms.

3.5 Classification of DL-based MFIF

A recent review [18] provided a problem-scenario-based classification for deep learning MFIF research, highlighting the diverse focus areas within the field:

1. **MFIF with Lightweight Networks:** It aims to minimize the model complexity for both real-time and limited-resource scenarios.

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2. **MFIF for Artifacts and DSE:** A blurred transition of focus/defocus (inter-blurring) is caused in fused image DSE [19].
3. **MFIF for Information Preservation**: We want to retain as much of the crucial information from the source images that may be represented in terms of any sophisticated loss function as possible [20].
4. **MFIF with Unified Fusion Networks:** Develops a single universal networks for multi-fusion tasks (e.g., multi-focus, multi-exposure).
5. **MFIF Addressing Suboptimal Initial Decision Map:** Networks designed to refine the initial activity map, which dictates the selection of focused regions [21].
6. **MFIF in Non-ideal Scenarios:** Concentrates on robustness under real-world conditions, including noise, mis-registration and non-optimal illumination [22].

4. Performance Evaluation and Metrics

The performance of any MFIF algorithm needs to be objectively measured. Evaluation measures are generally categorized into two classes: reference based (which need a ground truth all-in-focus image) and no-reference (measure) (perceptual score assessment) [23].

4.1 Objective Evaluation Metrics

Table 3. Summary of Objective Evaluation Metrics for Multi-Focus Image Fusion (MFIF) Methods

Metric Type	Metric Name	Abbreviation	Description	Ideal Value	Reference
Reference-based	Peak Signal-to-Noise Ratio	PSNR	Measures the ratio between the maximum possible power of a signal and the power of corrupting noise.	Higher is better	[24]
	Structural Similarity Index Measure	SSIM	Measures the similarity between the fused image and the ground truth based on luminance, contrast, and structure.	Closer to 1 is better	[25]
	Index Quality on based features	Qabf	Measures the amount of edge information transferred from the source images to the fused image.	Closer to 1 is better	[26]

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No-Reference	Entropy	EN	Measures the richness of information content in the fused image.	Higher is better	[27]
	Spatial Frequency	SF	Measures the overall activity level (sharpness and detail) of the image.	Higher is better	[28]
	Mutual Information	MI	Measures the amount of information the fused image contains about the source images.	Higher is better	[29]

4.2 Comparative Performance Analysis

The move towards I-MFIF has resulted in such marked quantitative enhancements. Fig. 4 shows an aggregated relative performance comparison graph of different categories of MFIF methods generated by general patterns in the recent literature [30], [31].

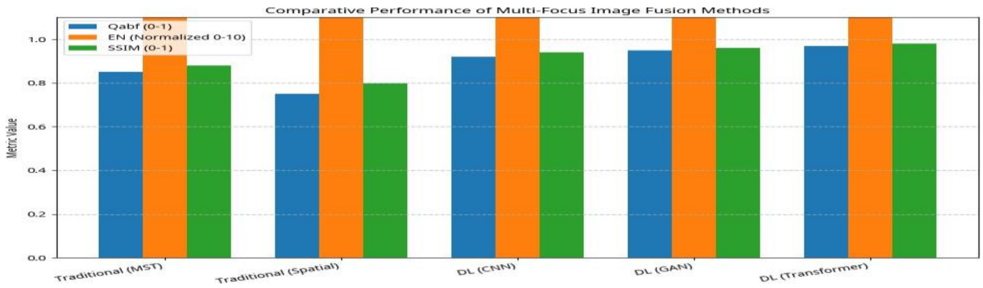

Figure 5: Comparative Performance of Multi-focus image fusion Models

The above graph shows that the proposed methods, namely, by improving deep learning technology on modern approaches such as Transformers lead to higher quality scores (Qabf, EN and SSIM), where they have provided some better quality fusion with more preserved information.

4.3 Critical Discussion

4.3.1 Best Methods, Metrics, and Real-World Challenges

The fast development of deep learning in MFIF requires an in-depth analysis about existing trends and challenges. What is the best method and why? According to the comparison , Transformer based methods (i.e., Swin Fusion) currently achieved consistent best performance concerning key objective metrics: Qabf and SSIM. This superiority is mainly thanks to their built-in self-attention mechanism in that it is good at capturing long-range dependence and flexibly emphasize the importance of features over the whole image pair, which can be hard for CNNs. Although GANs can provide superior image(perceptual) quality, the instability and insensitivity to fine details in training could be less favorable

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compared with more stable high-fidelity reconstruction of advanced CNN or Transformer models.

Which evaluation metric works best. Choosing the correct evaluation criteria is however, traditionally a challenge and a topic for further debates. Reference-based metrics such as SSIM are popular owing to its high correlation with human vision system, but they need a perfect all-in-focus ground-truth image that is usually not available in the real world. On the other hand, no-reference metrics such as Qabf (edge information transfer) and EN (entropy) are more convenient for blind assessment. Hence, the most reliable evaluation measurements are achieved with a multi-metric criterion, using a structural metric (like SSIM when ground truth is available) in combination with an information-based one (like Qabf or MI) to get both the visual quality and information preservation considered optimally.

What are the most intractable real-world problems? Yet, despite such impressive progress, the most costly practical issues exist in the deployment of I-MFIF systems in terms of model robustness and generalization capabilities. Many deep learning networks are trained on undefect datasets。 In practice, the source images in MFIF are usually subtle misaligned, contaminated by noise of camera sensors and taken under distinct lights. Such real-world artifacts can significantly affect the effectiveness of a trained network to produce high quality images, giving rise to artifacts and ghosting. Moreover, the complexity of current state-of-the art models (in particular Transformers) is such that they are far from being implemented in real time on devices with limited resources (eg: mobile and embedded systems). For this reason, future work should concentrate on lightweight design and resilient networks, including new loss functions that explicitly penalize the fusion artifacts due to real scenario misalignments.

5. Identification of Research Gaps and Future Directions

Despite the remarkable progress driven by deep learning, several challenges remain, which constitute the primary **research gaps** in the field of Intelligence Multi-Focus Image Fusion .

5.1 Identified Research Gaps

- Suppression of Defocus Spread Effects (DSE): The most intractable problem is whether DSE can be totally suppressed or not, which appears to have blurred boundaries in the fused image. The focused and defocused regions are not well separated in existing DL models, resulting in artifacts head.
- Absence of Genuine Real-World Data and Benchmark: The majority of training and testing is performed on synthetic data, which cannot entirely cover the real world complexity (e.g., noise, camera shake, non-uniform illumination) . The availability of a real-world multi-view image dataset with ground truth is urgently desired for fair benchmarking.
- Model Generalization and Robustness: Trained on specific datasets, DL models often have difficulty generalizing to images taken under different conditions or from different sensors. It is still an open issue to construct a domain independent robust fusion network.
- Discussion 4.1 Computational Runtime For operational, real-time systems such as surveillance (Jung et al., 2018), robotics or mobile devices (Wu et al., 2019), the computational burden associated with state-of-the-art DL architectures make their deployment infeasible. Lightweight and efficient architectures (e.g., Mat lab Nets for fusion) need to be explored.
- Real Time Compatibility: Though the quality of fusion has increased, most DL based models are computationally heavy and cannot be deployed in real-time systems such

as surveillance, robotics, or mobiles. Lightweight and efficient architecture study (e.g., MobileNets for fusion) is crucial.
- A promising Explainable AI (XAI) [32] in Fusion: Due to the "black box" character of deep learning, it is very challenging to endow networks with the capability to explain the reason why a network selects a certain fusion strategy. Integrating XAI techniques to understand how the fusion network takes decisions is an emerging trend.

5.2 Future Directions

Building upon the identified gaps, future research in I-MFIF should focus on:

- Hybrid DL-Traditional Methods: Integrating the merits of graph theory-based model decomposition in MST and the powerful feature learning of DL for generating more interpretable, better hybrid models.
- Unsupervised and Self-Supervised Learning: Fusing image based models that does not need ground-truth images while using the un-tagged real-world data .
- Integration with Downstream Tasks: To build fusion models that are not only optimized in terms of visual quality but also for their performance on downstream computer vision tasks, such as object detection, segmentation and 3D reconstruction.
- Hardware Acceleration and Edge Deployment: Developing ultra-efficient models and customized hardware architectures (e.g., FPGAs, ASICs) supporting high-speed MFIF on edge devices .

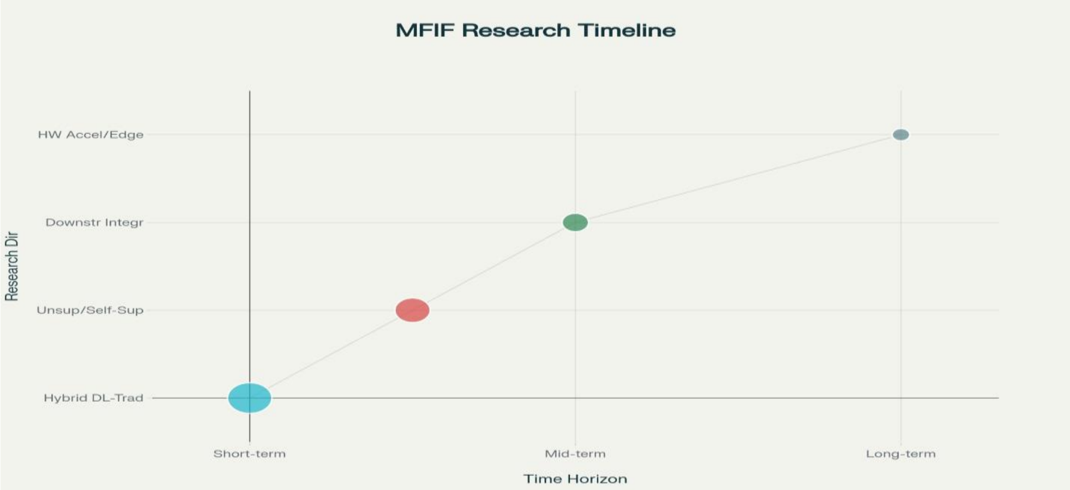

Figure 6: MFIF Research Timelines

6. Conclusion

The discussion and conclusion of this paper emphasized the great development in the area of group-wise Multi-Focus Image Fusion (MFIF) by casting using deep learning. The shift from conventional methods in the spatial and frequency domains to advanced deep learning-based architectures like Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformers has significantly improved fusion quality by maintaining details and boosting perceptual clarity. Transformer-based features, being able to capture long-range dependencies more effectively due to the self-attention mechanism, outperformed the existing methods of representation and fusion in terms of prediction accuracy. These advances also demonstrate the promise of deep learning on improving MFIF to handle some complex imaging tasks in real situations (e.g., macro photography, microscopy and surveillance), where multiple depths focused have to be fused reasonably.

Notwithstanding these impressive developments, the research community still faces important challenges that obstruct the realistic and practical implementation of deep learning-based MFIF systems. A critical problem lies in the limited availability of genuine and diverse high-quality real-world datasets that contain ground-truth information that is crucial for robust model training as well as fair benchmark. Currently there are many models that use synthetic or small data sets that do not cover real-world scenarios, including noise, mis registration and illumination variations. Furthermore, current architectures do not generalize well across sensors and environmental conditions which leads to artifacts, ghosting and inferior robustness especially in the presence of noise or mis alignments. The computational cost of complex models like Transformers also prevents their implementation in low-resource devices, such as mobile phones and embedded systems, highlighting the importance of light-weight, efficient architectures.

In the future, studies could concentrate on building robust, efficient and interpretable MFIF models. However, a challenge is to build up such large-scale annotated real-world datasets and the training or evaluating on them may promote model processing norm and contribute to the robustness of model and its generalization ability. Hybrid models which integrate deep learning and classic methods (e.g., graph theory-based models) might further improve performance while also making the model more interpretable. Additionally, the investigation on lightweight and real-time deep learning networks will be the key for expanding practical applications such as on mobile and embedded devices. It will also be necessary to utilize explainable AI (XAI) methodologies in order to enable transparency and trust in automated fusion systems. In summary, solving these challenges will facilitate the development of MFIF solutions that are more reliable, efficient and flexible for real imaging applications.

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