International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Image-Deblurring and Restoration: Exploring Advanced Techniques for Enhanced Visual Clarity

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Abstract- This study introduces an end-to-end scale-recurrent deep network for deblurring multi-modal medical images affected by motion artifacts. The network features a novel residual dense block with spatial-asymmetric attention, enhancing the recovery of salient information during medical image deblurring. Comprehensive evaluations demonstrate the method's superiority over existing techniques, showcasing its ability to remove blur without introducing visual artifacts. Integration into medical image analysis tasks, such as segmentation and detection, highlights accelerated performance. Additionally, a simple L0-regularized prior is proposed for text image deblurring, leveraging intensity and gradient properties. The method outperforms state-of-the-art text image deblurring algorithms, demonstrating effectiveness in deblurring low-illumination images without complex edge selection strategies. Our proposed end-to-end scale-recurrent deep network for medical image deblurring exhibits robust performance, outshining existing methods in both qualitative and quantitative evaluations. The inclusion of a spatial-asymmetric attention mechanism and a residual dense block enhances the network's ability to recover crucial information from blurred medical images. Furthermore, the seamless integration of our deblurring method into various medical image analysis tasks showcases its versatility and effectiveness in accelerating performance. On a different front, our contribution extends to text image deblurring, where a straightforward yet powerful L0-regularized prior based on intensity and gradient proves effective. This method not only surpasses state-of-the-art text image deblurring algorithms but also demonstrates applicability to challenging scenarios such as deblurring low-illumination images. The combined results highlight the potential impact of our approaches in advancing the quality and applicability of deblurring techniques in both medical imaging and text-related applications.

Keywords—Multi-Scale, Unet, Deblurring, Fast Fourier Transform, ResBlock, Non-linear Activation Free Block, NFResnet, Charbonnier, Edge, Frequency Reconstruction.

I. Introduction

Image Deblurring has many applications. It can be used for better viewing space vehicles, satellites, and stars; medical imaging such as MRI; Iris recognition for facial verification; radar imaging; removing motion blur due to camera shake, etc. In this paper, we introduce a new NFResblock, which consists of the **N**AFBlock and the **F**FT **Res**Block. Using these additions, we introduce NFResnet based on MIMO-Unet and NFResnet+ based on the MultiScale Architecture. Our motivation behind these additions is based on high and low- frequency discrepancies between blurry and sharp image pairs.

Image deblurring has been a critical area of research, owing to an increase in the number of image and video datasets. However, the task comes with some challenges. Sharp images usually have an imbalance between low and high-frequency information, with the latter being in high quantity. CNNs, a significant part of ResBlocks, usually have a limited receptive field, especially in the early layers. Hence, a ResBlock might be advantageous in learning high- frequency components, but the low-frequency information will not be appropriately modelled. This challenge is tackled using the FFT Block along with the edge and frequency reconstruction losses.

The NAF Block is used to make the model more computationally efficient by dropping components that do not provide that much of a performance advantage with the amount of computational power they utilize, along with simplifying different components such as the activation function, normalization, and attention. Layer normalization is used to make training much smoother with different variations of learning rates along with preventing gradient explosion caused by the other components.

The main challenges in image deblurring include obtaining real-world motion-blurred datasets, long-range spatial dependency in the blur, wrong estimation of the blur, and suboptimal results when the blur is slight. Blurred images in the real world are usually too complex to be trained upon because of their non-uniformity. Synthetic image generation methods have been utilized to tackle this problem, including the dataset we will be using. We conduct our experiments on the frames of Deep Video Deblurring dataset (DVD) instead of GoPro dataset owing to its diversity in the magnitude of blur and the real-world scenarios depicted in the videos captured.

Our major contributions are listed below:

We aim to improve the existing method used for de-blurring images. We have proposed a new ResBlock, NFResblock, which can be used in place of the simple ResBlock for better results.

Using the proposed ResBlock, we have shown a significant improvement of 3.65% in PSNR, thereby establishing new state-of-the-art metric values for the chosen dataset (Results shown in Fig. 1)

Extensive ablation experiments have been conducted to prove the significance of each of the individual components in theproposed networks. $I_B = K(M) * I_G + S_N$

Blurry Result Our Result Ground Truth

Figure 1: Inference results of the NFResNet+ architecture

The primary objectives of the "Image Deblurring and Restoration" project are multifaceted. Firstly, the project aims to develop and implement robust deblurring algorithms specifically tailored to address the challenges inherent in medical images, including motion artifacts and limitations in imaging equipment. Another key objective is to enhance the fidelity of medical images by mitigating blurriness, ensuring a clearer and more accurate representation of anatomical structures and pathological conditions.

The project will also involve customization of deblurring and restoration techniques to suit the unique characteristics and requirements of various medical imaging modalities. Additionally, comprehensive evaluations and validations of the developed algorithms using diverse medical image datasets are planned to ensure their effectiveness and reliability across different scenarios. Lastly, the project explores the integration of these advanced algorithms into existing medical imaging systems to improve overall diagnostic tools.

The adaptability of the developed algorithms to different healthcare settings will be a key consideration, accounting for variations in equipment, imaging protocols, and patient conditions. The project also aims to explore the feasibility of real-time image deblurring and restoration, ensuring practical applicability in clinical workflows where timely and accurate information is crucial. Moreover, by laying the groundwork for future research endeavours, the project aims to identify areas of improvement, potential extensions, and applications beyond medical imaging, contributing to the broader field of image processing.

II. Literature Review

Image Deblurring has many applications. It can be used for better viewing space vehicles, satellites, and stars; medical imaging such as MRI; Iris recognition for facial verification; radar imaging; removing motion blur due to camera shake, etc. In this paper, we introduce a new NFResblock, which consists of the NAFBlock and the FFT ResBlock. Using these additions, we introduce NFResnet based on MIMO-Unet and NFResnet+ based on the MultiScale Architecture. Our motivation behind these additions is based on high and lowfrequency discrepancies between blurry and sharp image pairs.

The perceptual quality of images directly impacts the process of medical image analysis and decision-making manoeuvres of with respiratory and patient motion impel the medical image acquisition device to capture unclear images with blind-motion blurs. Removing blur from any image is a challenging task. Typically, deblurring refers to a deconvolution operation, where a blurred image comprises a blur kernel with additive sensor noises as follows:

medical practitioners. Contrarily, acquiring a visually plausible and precise representation of repository organs is a strenuous process. It requires a longer scanning time to capture the image of the complex respiratory system. Slower scanning times combined In the above, * represents the convolution operation, K(M) represents the blur kernel, and S_N represents sensor noise. The K(M) for medical images remains blind in most cases. Arguably, the complex structure and texture of the repository systems with blind blurs make the medical image deblurring far more challenging than for generic images.

In recent years, only a few works in the open literature have attempted to address the challenges of deblurring medical images. Most of these methods leverage classical image processing techniques to reduce blurs by applying sharpening filters. Furthermore, only a few recent methods utilize deep learning for learning deblurring from medical images. However, the 8 existing medical image deblurring (MID) methods are domain-oriented and heavily depend on the point spread capacity of the acquisition system.

Therefore, the performance of these methods is limited to specific image types (i.e., CT, MRI) and fails to achieve satisfactory performance in diverse data samples. Oppositely, deep learning-based image deblurring techniques have evolved significantly in the past decade. These methods have illustrated significant improvement in removing deblurs in non-medical images. Notably, the deep deblurring methods outperform traditional counterparts by a considerable margin in diverse data samples.

A. *Quantitative Comparison*

We evaluated the performance of each comparing method by utilizing the evaluation metrics. Moreover, we calculated individual scores (i.e., PSNR, SSIM, and deltaE) for all testing images. We compute the mean performance of each comparing method for a specific dataset to observe their performance on that respective modality. Later, we summarized the performance of each comparing method by calculating the mean PSNR, SSIM, and deltaE scores obtained on the individual modality. In all evaluation criteria, the proposed method outperforms the existing deblurring methods by a notable margin. It also shows that the proposed method is a medical image modality independently and can handle a diverse range of blurry images. As a result, the proposed method demonstrates superior performance across all comparing datasets. On average, our method outperforms its near-performing deep method by 0.86 dB in PSNR, 3% in SSIM, and 0.15 in DeltaE metrics. Overall, the quantitative evaluation confirms that the proposed method can remove blur by recovering structural information, low-noise ratio, and visually plausible sharp medical images compared to existing methods.

OBJECTIVE AND SCOPE

As technology evolves, the project aims to stay at the forefront of innovation by actively engaging with emerging trends in imaging technologies, machine learning, and computational methodologies. This proactive approach will enable the project to not only adapt to evolving healthcare landscapes but also anticipate and address emerging challenges and opportunities.

In this paper, we have explained what is the proper net- work structure for using the "coarse-to-fine" scheme in im- age deblurring. We have also proposed a scale-recurrent network, as well as an encoder-decoder ResBlocks structure in each scale. This new network structure has less parameters than previous multi-scale deblurring ones and is easier to train. The results generated by our method are state- of-the-art, both qualitatively and quantitatively. We believe this scale-recurrent network can be applied to other image processing tasks, and we will explore them in the future.

A. Aim of the Project

The limitation of existing methods, as highlighted in the initial paragraph, served as the catalyst for the motivation behind this study. The goal is to incorporate a robust learning-based Motion-Invariant Deblurring (MID) solution, capable of effectively handling large kernel blurs without explicitly considering image modality. In response to the challenges faced in image deblurring, especially with the proliferation of image and video datasets, this extended aim encompasses three key objectives.

Firstly, the project seeks to address the difficulty associated with large kernel blurs, providing a solution that can navigate and rectify such challenges. Importantly, the approach is modality-agnostic, aiming to transcend limitations by offering a more versatile deblurring technique applicable across various imaging scenarios. Finally, the project aims to tackle the imbalance in frequency information found in sharp images, ensuring a more balanced representation to produce visually more appealing deblurred results.

By achieving these objectives, the study aims to contribute significantly to the advancement of image deblurring techniques, making them more adaptable, versatile, and effective in handling real-world complexities.

B. Scope and Limitations

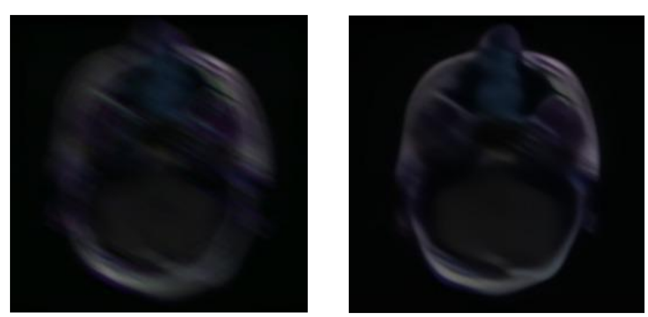
The scope of our project encompasses several key dimensions. Firstly, it addresses the pressing issue of motion artifacts in multi-modal medical images, offering a versatile solution that can enhance diagnostic accuracy across various imaging techniques. The incorporation of a novel residual dense block with spatial-asymmetric attention underscores the project's commitment to recovering salient information, mitigating the impact of respiratory and patient movement artifacts. Moreover, the project extends beyond mere deblurring, exploring the seamless integration of the proposed method into broader medical image analysis tasks such as segmentation and detection. The comprehensive evaluation strategy, covering both quantitative and qualitative metrics, ensures a thorough understanding of the project's effectiveness compared to existing deblurring methods. Additionally, the inclusion of text image deblurring with a simple yet powerful L0-regularized prior showcases the versatility of the proposed approach, making it applicable beyond medical imaging to address deblurring challenges in text-related scenarios.

However, certain limitations should be acknowledged. Firstly, the computational demands of the deep network may restrict its real-time applicability in resource-constrained environments, necessitating careful consideration of hardware requirements. The effectiveness of the proposed method is intricately tied to the diversity and representativeness of the training dataset, potentially limiting its performance in scenarios not well-covered during training. While the project excels in removing common artifacts like motion blur, its efficacy against unforeseen or highly complex artifacts may be constrained. Moreover, robustness in extreme or rare medical imaging cases and the potential impact of residual artifacts on clinical decision-making and user experience represent areas that may require further exploration. It's essential to recognize the subjective nature of image interpretation in clinical settings and its implications, a fact that the study may not comprehensively address. These limitations underscore the need for a nuanced understanding of the practical applicability and potential constraints of the proposed deblurring method in the complex landscape of medical imaging.

I. PROPOSED METHODOLOGY

In this section, we give a detailed description of the individual components used in the network and the overall architecture.

Figure 2: Result of deblurring MID images



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A. NFResblock

The proposed NFResBlock consists of two main components, namely FFT-ResBlock and NAF-Block. The following sub-sections describe them in detail.

1) *FFT-ResBlock:* We propose a new addition to the existing ResBlock, which helps us capture the informationfrom the frequency domain. It is known that CNNs have a limited effective receptive field. As suggested by,it can be said that ResBlock instantiated by CNNs, may lack good abilities in modeling low-frequency information. Also, as mentioned by, blurry images tend to have more low-frequency information than sharp images. Thus, ResBlock's failure to capture low-frequency information is a significant constraint in reducing the inconsistency between the blurry and sharp images.

To tackle this problem, we add another branch basedon a channel-wise Fast Fourier Transform (FFT). This helpsus in capturing the global information in the frequency domain. First, the image is converted from spatial domain to frequency domain using FFT. Then, like a residual branch, frequency domain features are passed to convolution blocks followed by a non-

linear activation function.

1) *NAF-addition:* NAF Block is a novel convolutional building block of Nonlinear Activation Free Network, namely NAFNet [1]. To avoid over-complexity in the architecture, this block avoids using any activation functions like ReLU, GELU, Softmax, etc. hence keeping a check on the intra-block complexity of the network. We have conducted experiments with both the variations of the NAF-block introduced.

Along with that, we have also conducted experiments using just the upper half and the lower half of the NAF-Block as illustrated in Fig. 3 (a) NAF-U and (c) NAF-D.

B. NFResNet

NFResNet is based on MIMO-Unet. It utilizes a coarse-to-fine approach for single image deblurring compared to multi-scale architectures, which stack subnetworks and gradually increase the sharpness of images from bottom to top. It makes use of an encoder to make the training easier. It then uses a decoder similar to a multi-cascaded Unet architecture. Finally, it uses asymmetric fusion to merge these multi-scale features. The architecture consists of a single U-shaped block with 3 encoder and decoder blocks. The encoder is a multi-input block compared to other architectures, which only take a single input at the start. Similarly, the decoder is a multi-output block compared to other architectures that output a single image at the end.

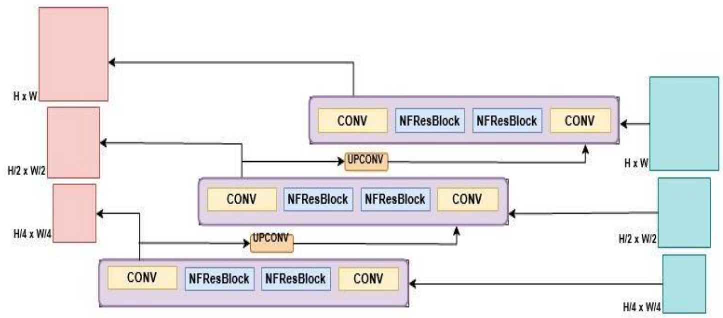

Figure 3: NFResnet+ architecture

The Multi-Input Single Encoder consists of a Convolution Block, a Feature attention module, and a Residual Block. The ResBlock is replaced by the NFResBlock containing the entire NAF structure along with the FFT operation. It allows the model to learn critical information about the frequency domain and reduces the model's computational complexity. Features from the Encoder Block are combined with the blurry image's features. This helps in handling diverse image blurs. Features are first extracted using a shallow convolution module which is then passed to the Feature attention module to emphasize or suppress the features and learn their spatial or channel importance. These are now sent to the NFResBlock for further refinement.

Asymmetric Feature Fusion, inspired by allows information flow between different architecture scales. Each block takes the input of all the encoder blocks and combines the multi-scale features using a convolution layer. The output is then passed to the corresponding decoder block. This helps the decoder block in exploiting multi-scale features.

C. NFResnet+

NFResNet+ is similar to NFResnet. The choice of architecture is devised to solve the problem of dynamic scene deblurring. Conventional deblurring methods fail to solve the problem where the blur kernel is difficult to estimate. This leads to the failure of removing blur in the image. Our method involves a multi-scale architecture that restores sharp images when the blur is multi-sourced. The method also does not suffer from kernel- related problems arising in deblurring. The input and output are in the form of a batch of 3 images; each image is a down sampled version of the previous one. At each level, we have NFResBlocks, containing the NAF-U or the NAF-D structure of the NAF Block, sandwiched between convolution layers to form a ResNet structure.

The central architecture involves using multiple ResNets at different scales where the output of the lower scale network is upconvolved to the input of the upper scale network. We have only included half of the NAF block - either the upper half or the lower half - as we observed that it was sufficient to get better results as compared to NFResNet with lower number of parameters. We also chose to go with multi-scale architecture instead of a U-net architecture as it was a simplified solution ofthe same task.

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D. *Table 1: QUANTITATIVE DEBLURRING PERFORMANCE COMPARISON ON THE DVD*

Method	PSNR	SSIM	Year
DVD	25.44	0.8412	2017
MobileNetv2	28.54	0.8654	2019
Qi *et al.*	28.72	0.8702	2020
Tao *et al.*	29.55	0.8822	2018
Zhang *et al.*	29.01	0.8732	2019
Ye *et al.*	30.81	0.9045	2020
Xia *et al.*	30.92	0.9057	2022
NFResNet (Ours)	31.95	0.9052	2023
NFResNet+ (Ours)	32.05	0.8938	2023

E. *Experimental Settings*

To make the model generalized to different types of scenarios and to prevent overfitting, the images were randomly flipped, horizontally and vertically, and rotated by 90 degrees. For augmentation in color, RGB channels were randomly permuted. To account for cases of image degradation, a number was chosen randomly in the range [0.5, 1,5] and then multiplied by the saturation level in the HSV color space. Gaussian noise was added, wherein the standard deviation of the noise is also randomly sampled using a Gaussian distribution $N\ (0,\ (2/255)^2)$. Values outside [0, 1] wereclipped. To keep the range of input and output between [-0.5, 0.5] so that they are zero-centered, 0.5 was subtracted from their values.

Training of the dataset was carried out till 40 epochs in each setting, after which we observed the convergence of loss values. The model was compiled using the Pytorch backend. Adam optimizer with a learning rate of 10^{-4}, $\beta_1$and β_2 with a value of 0.9 and 0.999 was used. 40 blocksand 19 blocks were used at each level in NFResNet and NFResNet+ respectively.

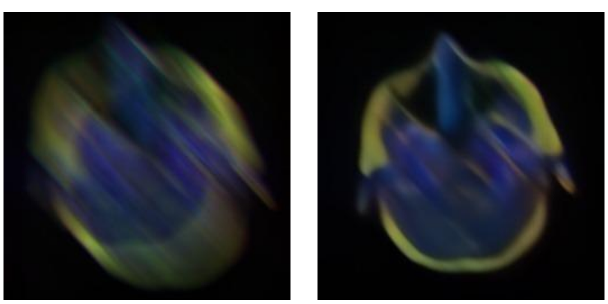

Figure 4: Result of deblurring MID images

B. *Discussion and Comparison*

As seen in TABLE I, our proposed architectures achieve the best and the second-best performance for PSNR and SSIM, respectively, as compared to the previous works. We observea significant increase of 25.98% when compared with theoriginal dataset baseline. Moreover, has an unstable training procedure, which is one of the technical disadvantages of using generative adversarialnetworks. However, we remove the heavy pixel attention and channel attention model and use a simple gate in NAF-D and simple channel attention in NAF-U to capture the long-range dependencies to achieve an 11.59% increase in PSNR value. Our NFResNet alone surpasses the metrics owing to the feature attention and ResBlock modules and the interconnected architecture that shares the information across different feature maps obtained at different scales.

To make our model even more straightforward, we remove feature attention modules, shallow convolutional modules, extra skip connections and the encoder-decoder architecture as proposed in MIMO-Unet. For the remaining multi- input- multi-output network, we use a group of convolution blocks containing normal convolutions and NFResBlocks and term it as NFResNet+. As a result, NFResNet has 13.84M parameters, whereas NFResNet+ (containing NAF-Down block) has 13.60M parameters. We do not utilize the complete NAF structure in our NFResNet+ as we hypothesized that having one feature attention layerwas enough for the model to focus on the blurry areas. We observed that a better value of PSNR was obtained in the case of NFResNet+ with fewer parameters. A slight decrease was also observed in the value of SSIM compared to NFResNet, which could be because of the removal of additional feature attention modules and skip connections.

Conclusion and Future Work

The field of image deblurring and restoration has witnessed significant advancements in recent years, driven by advancements in computational methods, deep learning, and computer vision. In conclusion, the progress made in this area has opened up new possibilities and applications, with implications for various domains. Here's a brief summary of the conclusion and future scope:

Diverse Applications:

The impact of image deblurring and restoration extends across various fields, including medical imaging, satellite imagery, surveillance, photography, and more. The ability to recover clear and detailed information from blurred images is crucial in many real-world scenarios.

Deep Learning Dominance: Deep learning approaches, particularly convolutional neural networks (CNNs), have played a pivotal role in advancing the state-of-the-art in image deblurring. These models can learn intricate patterns and features from large datasets, enabling them to generalize well to different types of blurs.

Computational Efficiency: As computational power continues to increase, there has been a focus on developing more computationally efficient algorithms. Real-time or near-real-time applications, such as video processing and live streaming, benefit greatly from faster and more efficient deblurring techniques.

This study proposed a novel learning-based deep method for mutimodal medical image deblurring. The proposed method demonstrates that medical image deblurring can be generalized for multi-modal medical images with a proper learning strategy. This study also introduced a novel scale-recurrent deep network with residual dense block and spatial asymmetric module. The 33 proposed module aims to learn salient features with local-global attention for recovering detail texture and information while deblurring medical images. The performance of the proposed method has been evaluated with different medical image datasets. The comparison results demonstrated that the proposed method outperforms the existing works in qualitative and quantitative comparisons.

The applicability of the proposed method has been evaluated by incorporating it into numerous medical image analysis tasks. The experimental results reveal that the proposed method can substantially improve the performance of such analysis tasks by removing blind-motion blurs from the given image. It has planned to collect real-world blur-sharp medical image pairs and study
the performance of the proposed method in 3D images in a futurestudy.

Future Scope:

Robustness to Varied Conditions: Ongoing research aims to enhance the robustness of deblurring algorithms to handle a wide range of challenging conditions. This includes addressing complex blur patterns, handling low-light environments, and adapting to various imaging devices. Multimodal Approaches: Integrating information from multiple sources, such as depth data or additional sensor modalities, could further improve deblurring performance. Multimodal approaches can provide richer information for more accurate restoration. Real-Time Applications: The development of algorithms that can operate in real-time or with minimal latency is crucial for applications like autonomous vehicles, robotics, and live video processing. Optimizing existing methods and developing new ones to meet these requirements is a significant research direction. Continued Advances in Deep Learning: The evolution of deep learning techniques, including novel architectures, regularization methods, and transfer learning, will likely contribute to further improvements in deblurring and restoration performance. User- Friendly Tools: Translating these sophisticated techniques into user-friendly tools for photographers, designers, and other professionals will make image deblurring and restoration more accessible and widely applicable.
A number of methods have been developed by various researchers for image deblurring or image restoration. Till now, image deblurring is a challenging issue. By analyzing various methods, we conclude that in the category of Nonblind methods, wiener filter give worst performance, its PSNR 34 (peak signal to noise ratio) value is low as compared to other techniques and LR method is good, its PSNR value is high as compared to other methods.
Blind deconvolution method is gives best result in comparison with non-blind techniques.

Blind deconvolution method can also be used for non-uniform motion deblurring using segmentation and motion blur estimation method. It is a two-step procedure. In the first step, segment the image into foreground and background. Second step is to estimate motion blur parameters and then use those parameters for deblurring. From other techniques, ADSD-AR gives highest PSNR value. Future scope is to design a hybrid technique to get better result.

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