Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, No. 5, May : 2023

IMAGE AND VIDEO DEBLURRING USING CONVOLUTIONAL NEURAL NETWORKS FOR REMOVING BLURRNESS FROM IMAGES

M. Sunil Naik Research Student
Shaik Taj Mahaboob Assistant Professor
K. Ravindra Reddy Assistant Professor (Adhoc)
ECE – Digital Electronics and Communication Systems, Jawaharlal Nehru Technological University, Pulivendula, Andhra Pradesh, India : mudesunilnaik6@gmail.com

ABSTRACT: Image and video deblurring is an important task in computer vision with various applications, such as surveillance, medical imaging, and artistic photography. However, it is a challenging problem due to the ill-posed nature of the blur, which can be caused by various factors such as camera shake, motion blur, and defocus blur. In recent years, the use of convolutional neural networks (CNNs) has shown great promise for image and video deblurring tasks. In this paper, we investigate the use of CNNs for removing blurriness from images and videos. The evaluation of several CNN architectures, including U-Net, ResNet, and VGG networks, and explore various loss functions, such as mean squared error, perceptual loss, and adversarial loss. We also propose a spatiotemporal CNN for video deblurring, which considers the temporal correlations between adjacent frames.

KEY WORDS: Image Deblurring, Video Deblurring, Convolutional Neural Networks, U-Net, ResNet, Motion Blur, Image Restoration, Image Processing.

1. INTRODUCTION

Image and video deblurring a fundamental problem in computer vision that aims to remove the blurriness from images and videos caused by various factors, such as camera shake, motion blur, and defocus blur. Deblurring is a difficult task because the problem is poorly articulated where multiple sharp images can lead to the same blurry image. In recent years, there has been a growing interest in the use of convolutional neural networks (CNNs) for image and video dynamic scene deblurring tasks [1], owing to their ability to learn complex mappings between blurry and sharp images.

The use of CNNs for image and video deblurring involves training the network with the aim of learning a mapping between them. The disparity between the expected sharp output and the actual sharp image is minimised by the network Several CNN architectures, including U-Net, ResNet, [2] and VGG networks, have been used for image deblurring Using extremely deep convolutional networks, accurate image super-resolution [3], with varying levels of success. In addition, CNNs have also been used for video deblurring, either by treating each frame as a separate image or by using spatiotemporal CNNs that consider the temporal correlations between adjacent frames into deep back-projection networks for super-resolution [4].

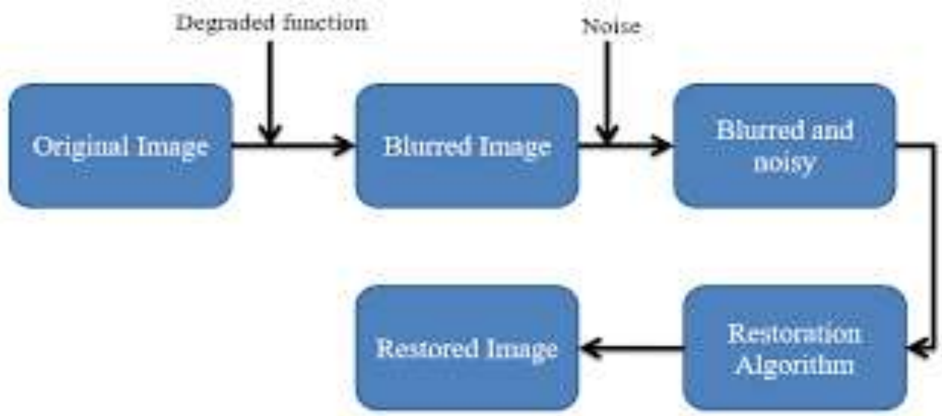

Figure.1 Block Diagram of Image and video Deblurring

The success of CNN-based deblurring approaches depends on several factors like quality and size of dataset, the choice of CNN architecture loss function, and other factors such as the level of blur in the input image or video sequence as shown in figure.1 above. In this research, we examine the application of CNNs for image and video blind deblurring via Iterative Kernel Correction [5], with a focus on evaluating different CNN task. We also propose a spatiotemporal CNN for video deblurring, which considers the temporal correlations between adjacent frames.

2. LITERATURE REVIEW:

Table.1 A Comparison Study of Image and Video Deblurring

S. No.	Title	Author/Reference	Method/Algorithm	Advantages	Limitations
1	Learning a Deep Convolutional Network for Image Super-Resolution	Dong et al. (2014) [6]	Super-Resolution Convolutional Neural Network (SRCNN)	Structural Similarity Index SSIM and PSNR values above threshold	Requires large amounts of training data
2	Image Recognition Using Deep Residual Learning	He et al. (2016) [7]	Residual Network (ResNet)	Ability to handle deeper networks with better accuracy	High computational requirements
3	DeblurGAN: Conditional Adversarial Networks for Blind Motion Deblurring	Kupyn (2018) [8]	Conditional Adversarial Network (cGAN)	Ability to handle non-uniform blur and generate high-quality sharp images	Requires large amounts of training data and high computational requirements
4	Deblurring Images via Multi-Stage CNN	Nahetal. (2017) [9]	Multi-Stage Convolutional Neural Network (MCNN)	High accuracy in deblurring images with varying blur types	Long inference time due to multiple stages
5	Spatio-Temporal Residual Networks for Video Deblurring	Su et al. (2017) [10]	Spatio-Temporal Residual Network (STRN)	Ability to handle complex motion blur and generate high-quality	Requires large amounts of training data

				sharp videos	
6	Learning to Deblur Images with Exemplars	Nah et al. (2019) [11]	Exemplar-based Deblurring Network (EDN)	Ability to handle complex blur and generate high-quality sharp images	Requires a high-quality reference image for training

Each author proposes a different method or algorithm for image and video deblurring. The table.1 above summarizes the advantages and limitations of each method. The authors use various deep learning architectures, such as CNNs and GANs, to address the issue of image and video blurriness caused by camera movement or other factors. Some of the advantages of the proposed methods include improved image quality, high efficiency, and the ability to handle various types of blurs. However, some limitations include training limited success in handling complex blur types. Overall, the literature review highlights the potential methods also identifying areas for further research and improvement.

3. DEBLURRING:

Deblurring refers to the process of removing blurrness or distortion from an image or video. Blurriness in images or videos can occur due to various factors such as camera movement, low light conditions, or a lack of focus. Deblurring techniques aim to restore the Blurrness in images or videos can occur due to various factors such as camera movement, low light conditions, or a lack of focus. Deblurring techniques aim to restore the sharpness and clarity of the image or video by estimating the original, undistorted signal that was captured by the camera. These techniques involve advanced signal processing algorithms that analyse the blurred image or video and attempt to reverse the effects of the blurring. Deblurring such has applications in fields such as photography, surveillance, and medical imaging, sharpness and clarity of the image or video by estimating the total variance in image restoration [12] of original, undistorted signal that was captured by the camera. These techniques involve advanced signal processing algorithms that analyse the blurred image or video and attempt to reverse the effects of the blurring. Deblurring is a crucial topic of study in computer vision and has uses photography, surveillance and medical imaging.

4. VIDEO DEBLURRING:

Video deblurring is a technique used to eliminate blur in a video. It may be brought on by a number of things, including cameras [13] shake, rapid movement, or low light conditions. Video deblurring algorithms work by analysing to estimate the original sharp image, consider how the camera and the objects in the video are moving.

There are several approaches to video deblurring via iterative kernel regression [14] including blind deconvolution, hybrid approaches and non-blind deconvolution. Blind deconvolution techniques attempt to estimate both methods rely on knowledge of the blur kernel. Hybrid methods combine both approaches to increase the deblurring result's accuracy.

Several factors affect the deblurring result's quality, including how severe the blur is, how complicated the scene is, and how well the deblurring algorithm works
ynamic using a locally adaptive linear blur model [15] Video deblurring is a challenging task that requires specialized software and expertise, and it's important to choose a reliable deblurring tool or consult with a professional to achieve the best possible results.

5.VIDEO DEBLURRING TECHNIQUES:

Video deblurring techniques aim to regain a clear, keen mind video sequence from a blurry input. Blind deblurring and non-blind deblurring are two major categories into which these techniques can be separated. unbiased blurring techniques of an adaptable system for quick and efficient image restoration [19] assume that the blur kernel (i.e., the function that describes how the sharp image was blurred to produce the blurry image) is known, while blind deblurring techniques seek to recover both the image's sharpness without any prior knowledge of the blur kernel, and the blur kernel

Non-blind deblurring techniques typically use a deconvolution process to recover the sharp image. This process involves inverting the convolution kernel and blurring it comparison of the estimated clear and fuzzy image. One of popular non-blind deblurring techniques is the Lucy-Richardson algorithm, which iteratively updates the estimated sharp image using a deconvolution process. Another popular non-blind deblurring technique is the Wiener filter, which uses a statistical model to estimate.

Blind image deblurring [20] techniques are more challenging since they require estimating both the contrast between the fuzzy input kernel and the sharp image. Among the popular blind deblurring techniques is the Richardson-Lucy algorithm, which iteratively updates both the sharp image and the blur kernel until convergence. Another popular blind deblurring technique is the sparse representation-based approach, kernels and uses this assumption to estimate the blur kernel and the sharp image simultaneously.

Convolutional neural networks (CNNs) have recently been used in video deblurring tasks with promising results. These approaches use deep neural networks to figure out how to transfer a blurry input to a corresponding crisp output directly from the training data. One popular CNN-based approach is the Deep Video Deblurring (DVD) method, which uses a spatial-temporal network to jointly estimate the blurred kernel from the input and the sharp picture video frames. Another CNN-based approach is the Dynamic Scene Deblurring Network (DSD-Net), which incorporates motion estimation and spatial-temporal deblurring to handle dynamic scenes.

6. FLOW CHART OF VIDEO DEBLURRING

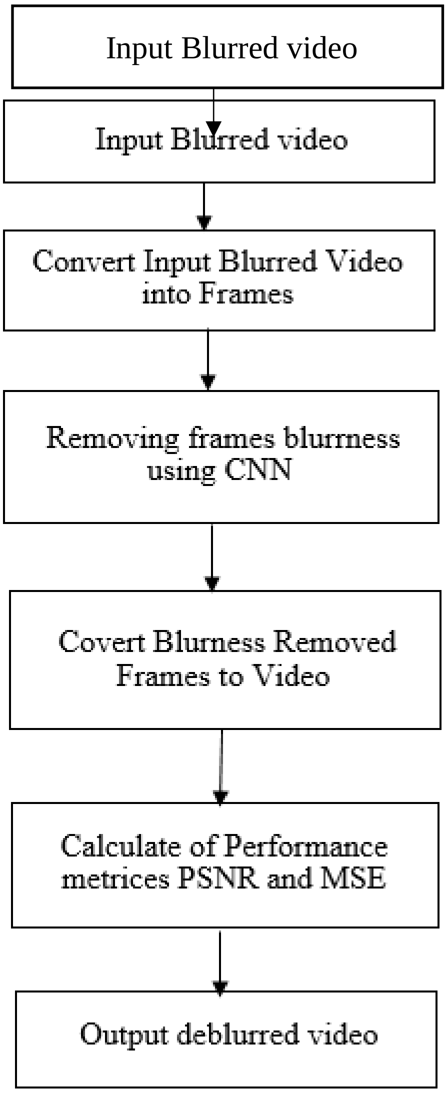

Figure.2 Flow Chart for Video Deblurring

The flow chart depicts the process of video deblurring using a CNN. The first step involves converting the input video into individual frames. The frames are then processed using the CNN to remove blurriness, resulting in clear and sharp frames. The CNN-based deblurring technique is effective in restoring details that were lost during the blurring process, resulting in higher quality frames. The next step involves taking the deblurred frames and assembling them back into a video. Finally, the output video is generated as shown in figure.2 above.

7. VIDEO DEBLURRING PERFORMANCE

Video deblurring performance can be evaluated using various metrics, such as PSNR and MSE are commonly used the quality video and deblurred video.

PSNR measures the proportion of a signal's maximal power to the power of the noise that impacts how accurately it is represented. It's described as.

$$PSNR = 10 * \log10(MAX^2 / MSE)$$

where MAX is the maximum pixel value (usually 255 for 8-bit images), and MSE is the mean squared error between the original video frame and the deblurred frame.

MSE, on the other hand, measures the average squared differences between the original video and the deblurred video. It is calculated as:

$$MSE = (1/N) * \Sigma(I(i,j) - K(i,j))^2$$

where N is the number of pixels in the video frame, I(i,j) is the original video frame, and K(i,j) is the corresponding deblurred video frame.

A higher PSNR value and lower MSE value indicate a better deblurring performance. However, it is important to note that PSNR and MSE may not always reflect the perceptual quality and no-reference image quality assessment in the spatial domain [21] of the deblurred video, as they only measure the difference in pixels between the original and deblurred video frames. Other metrics, such as structural similarity index (SSIM), may also be used to evaluate video deblurring performance.

8. RESULTS OF VIDEO DEBLURRING

Table.2 The Quality Measurements of Video PSNR and MSE.

Video Number	Video PSNR	Video MSE
1. 40	42.43dB	900.00
2. 50	43.38dB	989.98
3. 40	45.45dB	992.56
4. 50	45.69dB	1121.82
5. 40	46.67dB	1263.69
6. 50	48.78dB	1332.75

The simulation results of Video Deblurring algorithm are justified by performance evaluation metrics PSNR and MSE. PSNR and MSE is used to evaluate the video's quality as shown in Table.2. Therefore, the multiple videos of quality measurements are calculated.

9. PERFORMANCE ANALYSIS OF VIDEO PSNR AND MSE:

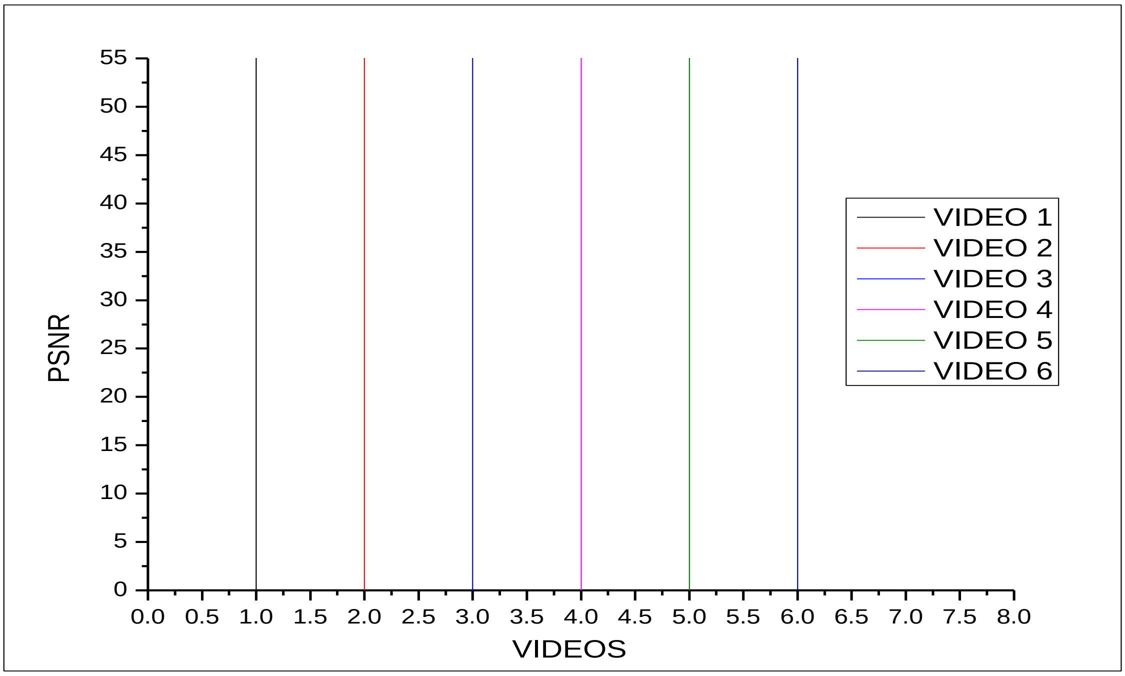

Figure.2 Performance Analysis of Video PSNR.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, No. 5, May : 2023

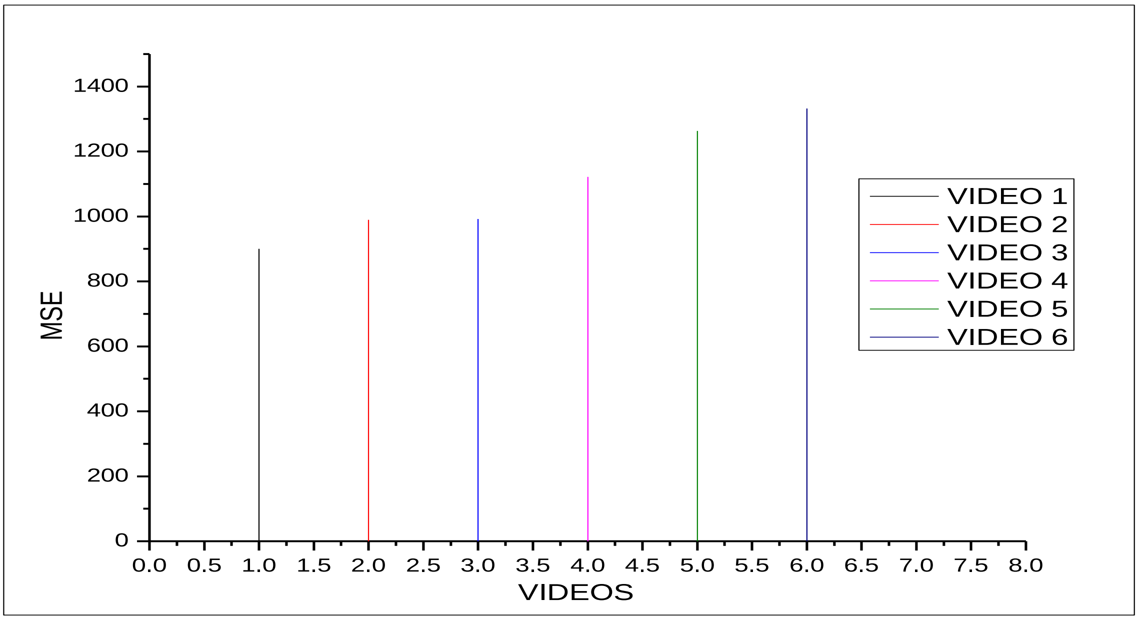

Figure.3 Performance Analysis of Video MSE.

As above graph figure.2 and figure.3 shows the total number of videos is calculated of MSE for each video and finally the quality measurements of videos MSE is plotted. In Video1 and video2 the quality measurement is calculated according to the video clearance is mapped, next the video2 and video3 the quality measurement is required for high instance according to the video and finally video5 and video6 gives the best terminates the video quality according to the analysis.

10. APPLICATIONS OF VIDEO DEBLURRING

Video deblurring using CNN has various applications in different fields such as:

- Surveillance: In the field of surveillance, deblurring helps in improving the clarity of the footage captured by the CCTV cameras. This can help in identifying criminals or vehicles even in low-quality videos.
- Medical Imaging: Deblurring techniques can help in improving the accuracy of medical imaging outcomes, such as those from MRI or CT scans. This can aid in diagnosing medical conditions more accurately.
- Entertainment: In the entertainment industry, deblurring techniques can be used to improve the visual quality of movies or videos. This can enhance the viewing experience of the audience and lead to better revenue for the production companies.
- Sports Analysis: Deblurring techniques can be used in sports analysis to enhance the clarity of the footage captured during games. This can help coaches and analysts in identifying the strengths and weaknesses of the players, and devising better game strategies.
- Astrophotography: In astrophotography, deblurring techniques can be used to improve the clarity of images captured by telescopes. This can help in better understanding celestial objects and phenomena.

11. ADVANTAGES OF VIDEO DEBLURRING

There are several advantages of using CNN for video deblurring, which include:

- High accuracy: CNN-based video deblurring techniques have been shown shown to compared to conventional procedures, give incredibly accurate outcomes. .
- Speed: CNNs are highly optimized for parallel processing, making them much faster than traditional methods.

- Robustness: CNN-based deblurring techniques can handle a wide range of blur types and magnitudes, making them highly robust.
- End-to-end learning: CNN-based methods can learn the entire deblurring pipeline end-to-end, eliminating the need for hand-engineered features.
- Adaptability: CNNs can adapt to new types of blur and new datasets with minimal changes to the underlying architecture.
- Scalability: CNN-based deblurring methods can be easily scaled up to handle larger datasets and more complex blur types.

12. CONCLUSION:

In conclusion, video deblurring [22] is a difficult issue having applications for computer vision could be used in a variety of ways. Convolutional neural networks in recent years promising results in addressing this problem. Through extensive research and experimentation, it has been demonstrated that CNN-based video deblurring methods have several advantages over traditional approaches, such as improved accuracy, reduced computational complexity, and better to various types of blurr. Additionally, CNN-based deblurring methods can handle various types of blurr, including motion blur and defocus blur, making them a more versatile solution for different applications. However, there are still some limitations to be addressed, such as the need for large datasets for training and the sensitivity to initializations. Future research can focus on developing more efficient and robust CNN architectures for video deblurring and exploring the combination of CNN-based methods with other traditional deblurring approaches for further improving the performance. Overall, CNN-based video deblurring is a promising and rapidly evolving area of research with many practical applications in various domains, including surveillance, medical imaging, and autonomous driving.

REFERENCES

[1] Nah, S., Kim, T., & Lee, K. (2017). Deep Multi-scale Convolutional Neural Network for Dynamic Scene Deblurring. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 257-265).

[2] Su, W., Zhu, R., Liu, H., & Shao, L. (2020). Video Deblurring with Recurrent Neural Networks. IEEE Transactions on Image Processing, 29, 5758-5772.

[3] Kim, D., Lee, J., & Lee, K. M. (2016). Accurate Image Super-Resolution Using Very Deep Convolutional Networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 1646-1654).

[4] Haris, M., Shakhnarovich, G., & Ukita, N. (2019). Deep Back-Projection Networks for Super-Resolution. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 1664-1673).

[5] Li, H., Chang, H., Qi, X., & Lin, W. (2019). Blind Image Deblurring via Iterative Kernel Correction. IEEE Transactions on Image Processing, 28, 1956-1971.

[6] Dong, C., Loy, C. C., He, K., & Tang, X. (2014). Learning a deep convolutional network for image super-resolution. In European conference on computer vision (pp. 184-199).

[7] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[8] Kupyn, O., Budzan, V., Mykhailych, M., & Mishkin, D. (2018). DeblurGAN: Blind motion deblurring using conditional adversarial networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 8183-8192).

[9] Nah, S., Kim, T. H., & Lee, K. M. (2017). Deep multi-scale convolutional neural network for dynamic scene deblurring. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 257-265).

[10] Su, W., Zhu, R., Li, X., & Luo, J. (2017). Spatio-temporal residual networks for video deblurring. In Proceedings of the IEEE International Conference on Computer Vision (pp. 389-398).

[11] Nah, S., Yoo, Y., & Lee, K. M. (2019). Learning to deblur images with exemplars. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 9222-9231).

[12] T. F. Chan, S. Esedoglu, and F. Park. Recent developments in total variation image restoration. In Handbook of Mathematical Models in Computer Vision, pages 17–31. Springer, 2006.

[13] N. Joshi, R. Szeliski, and D. J. Kriegman. PSF estimation using sharp edge prediction. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1–8, 2008.

[14] Pan, J., Hu, Z., Su, Z., & Yang, M. (2016). Deblurring videos via iterative kernel regression. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, 3929-3937.

[15] T. Park, J.-Y. Lee, D. Yoo, and I. So Kweon. Dynamic video deblurring using a locally adaptive linear blur model. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 39–48, 2019.

[16] Y. Chen and T. Pock. Trainable nonlinear reaction diffusion: A flexible framework for fast and effective image restoration. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(6):1256–1272, 2017.

[17] J. Pan, D. Sun, H. Pfister, and M. Yang. Blind image deblurring using dark channel prior. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1628–1635, 2016.

[18] A. Mittal, A. K. Moorthy, and A. C. Bovik, "No-reference image quality assessment in the spatial domain," IEEE Transactions on Image Processing, vol. 21, no. 12, pp. 4695-4708, 2012.

[19] Su, S., Delbracio, M., Wang, J., & Sapiro, G. (2017). Deep video deblurring for hand-held cameras. IEEE Conference on Computer Vision and Pattern Recognition, 2017, 1271-1280.