**IMAGE DEBLURRING USING DEEP BASED PROCESS**

REVIEW 1:

Deconvolution is the most commonly used image processing method in optical imaging systems to remove blur caused by the point spread function (PSF). Although this method has proven successful in unlocking, it has several drawbacks: B. The multiple iterations required for fusion slow down the processing time and are suboptimal if the experimental operator chosen to represent the PSF is suboptimal. In this article, we present a deep learning-based deblurring method that is fast and applicable to optical microscope imaging systems. We tested the robustness of the proposed deblurring method using publicly available, simulation, and experimental data (including 2D optical microscopy data and 3D optoacoustic microscopy data). All of which showed significantly improved blurring results compared to deconvolution. We compared our results with several existing deployment methods. Our results are superior to previous techniques and do not require multiple iterations or pre-determined experimental operators. Our method has several advantages, such as ease of use, reduced computation time, good deblurring results, and broad application to all kinds of optical microscope imaging systems. Deep learning approaches open new avenues for fuzziness and can be applied to various areas of biomedical imaging.

REVIEW 2:

Recently, several high-performance algorithms have been developed that use deep learning algorithms to derive high-resolution images from low-resolution image inputs. However, problems associated with super-resolution due to blurry or corrupted low-resolution images have received less attention. In this work, we propose a new deep learning approach that simultaneously considers blurring and super-resolution of low-resolution blurry images. We evaluate state-of-the-art super-resolution convolutional neural network (SR-CNN) architectures proposed in [1] for fuzzy reconstruction scenarios and experimentally prove their superiority at both known a priori fuzzy levels. We propose a revised and deeper architecture that and unknown.

REVIEW 3:

Mobile phone images have evolved significantly over the last 20 years. Cameras are one of the main features of new mobile phones. Much research has been done in this area to improve image quality. Due to the small size of mobile phones, there is a limit to the number of camera modules that can be installed, and thick lenses and large image sensors cannot be installed. This affects the amount of light captured and image quality. In low light, smartphones perform Single lens reflex (DSLR) camera and image quality testing. Post-processing then improves the image quality. Low light conditions and fast movements are difficult for mobile imaging. In dark situations, a longer exposure time collects more light, which can cause motion blur on objects. Motion blur artifacts can range from photography to graphic representations of racing cars, and can even be caused by fast moving objects during the day. Motion blur loses sharp information and results in poor image quality. defocusing ring A tool that removes flicker from your photos and makes them look sharper. In the field of signal processing, deep learning-based approaches have become very popular recently. The results are promising because deep learning algorithms can learn and model non-linear and complex relationships. Deep learning algorithms have also been used for several image recovery tasks, as is the case here.

REVIEW 4:

Non-blind image blur is the restoration of a potentially sharp image from a blurred image produced by a known blur kernel. This is a common but difficult inverse imaging problem. The key is to reliably suppress noise amplification during the inversion process. Recent approaches have made breakthroughs in exploiting convolutional neural network (CNN)-based denoising priorities in the image domain or gradient domain, allowing the use of CNNs for denoising. The performance of these approaches is highly dependent on the effectiveness of the denoising CNN in removing the enhanced noise. Its distribution is unknown and depends on iterations of the deblurring process on different images. In this article, we present CNN-based images previously defined in the Gabor domain. Prior not only exploits the optimal spatial frequency resolution and strong directional selectivity of the Gabor transform, but also allows the intermediate processing to use complex-valued (CV) representations for better noise reduction. CV-CNN was developed to take advantage of the CV representation and allow it to better generalize and handle unknown and real-valued sounds. By combining CNN-based Gabor domain CV with unrolling schemes, we propose a deep learning-based approach to unblind image blurring. Extensive experiments have demonstrated that the performance of the proposed approach outperforms state-of-the-art approaches.

REVIEW 5:

We present a simple and effective non-blind image blurring approach that combines classical techniques and deep learning. In contrast to existing methods that defocus images directly in standard image space, we perform an explicit deconvolution process in feature space by integrating the classical Wiener deconvolution framework with learned depth features. I suggest that you A multi-scale feature improvement module then predicts the defocused image from the deconvoluted depth features, gradually restoring details and small-scale structures. The proposed model is continuously trained and evaluated using scenarios involving simulated and real image blur. Our extensive experimental results show that the proposed deep Wiener deconvolution network enables ambiguous results with visibly fewer artifacts. Moreover, our approach is quantitatively much better than state-of-the-art non-blind image blurring techniques.

REVIEW 6:

Many basic image-related problems involve the unfold operator. Due to camera noise, saturation, image compression, etc., to name a few, real blur degradation rarely conforms to the linear convolutional model. Rather than fully model the outliers (which is very difficult from a generative model perspective), we develop deep convolutional neural networks to characterize the degradation. We found that direct application of existing deep neural networks did not yield reasonable results. Our solution is to connect classical optimization-based schemes with neural network architectures, introducing a novel separable structure as a reliable support for robust deconvolution against artifacts. Our network contains two submodules, both monitored and trained with proper initialization. They provide good performance in non-blind image deconvolution compared to previous methods based on generative models.

REVIEW 7:

Modern digital microscopy often uses deconvolution techniques to eliminate many image errors and increase resolution. In this overview, we categorized these techniques into classical techniques, deep learning-based techniques, and optimization-based techniques. In this paper, we discuss key neural network architectures such as convolutional and generative adversarial networks, autoencoders, various forms of iterative networks, and attentional mechanisms used for unfolding problems. Deep learning has received particular attention as the most powerful and flexible modern approach. This paper describes the main neural network architectures used for deconvolution problems. We discuss difficulties in applying them, such as discrepancies between standard loss functions and visual content and image non-uniformity. We then consider how to address this by introducing new loss functions, multi-scale learning, and prior knowledge of visual content. Finally, we provide an overview of promising directions and further development of deconvolution methods in microscopy.

REVIEW 8:

On-orbit optical imaging equipment may deteriorate due to the effects of the space environment and long-term operation. Degradation blurs the image received from the ground. Defects arise from defocus, and spherical aberration leads to blurring of the received image. Image blurring should be done in the preprocessing step to compensate for the bad effects of the sensor. Aberrations are modeled by Zernike polynomials and handled by deep learning deblurring methods. In this article, we show how to deconvolve the acquired data to improve the image quality. A convolutional neural network is trained to estimate point spread function (PSF) parameters with a specific pattern from images acquired on satellite calibration sites. Image deconvolution is performed to improve the signal-to-noise ratio (SNR) and modulation transfer function (MTF) of the image. Technical and imagery data used for modeling and experiments are taken from the VNREDSat-1 satellite, the first operational small optical satellite for Earth observation in Vietnam. Experiments are run on a computer accelerated by a graphics processing unit (GPU) to ensure fast computation.

REVIEW 9:

Existing deep learning methods for image blur usually train models on pairs of sharp and blurry images. However, synthetic blurring of images is not always accurate enough to represent the blurring process in real-world scenarios. To address this problem, we combine two GAN models, Learning-to-Blur GAN (BGAN) and Learning-to-DeBlur GAN (DBGAN), to obtain a better model for learning how to blur images. We propose a new way of serving models. I'm mainly learning how to blur images. The first model, BGAN, learned how to blur sharp images using unpaired sharp and blurry image sets, and then his second model, DBGAN, learned to do so. instruct it to learn how to blur an image properly. Relativistic blur loss is used to reduce the discrepancy between real and synthesized blur. As an additional contribution, this paper also presents the Real-World Blurred Image (RWBI) dataset, which contains various blurred images. Our experiments show that the proposed method consistently achieves excellent quantitative performance and higher perceptual quality on both the newly proposed dataset and the published GOPRO dataset increase.

REVIEW 10:

Most of the traditional frame-by-frame blurring techniques before deep learning use coarse-to-fine schemes that estimate a sharp image at coarse scales and adjust it incrementally at finer scales. Although this scheme has also been adopted by several deep learning-based approaches, a single-scale approach was recently introduced that outperforms previous coarse-fine approaches in terms of quality and computation time. In this article, we review the coarse-to-fine scheme and analyze the shortcomings of previous coarse-to-fine approaches. Based on our analysis, we propose a new deep-learning-based approach, multi-scale stage network (MSSNet), to correct errors and blur single images. MSSNet he will take Stage configurations reflecting blur scales, information propagation schemes between scales

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