



Event-guided Multi-patch Network with Self-supervision for Non-uniform Motion Deblurring

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Abstract

Contemporary deep learning multi-scale deblurring models suffer from many issues: (I) They perform poorly on non-uniformly blurred images/videos; (II) Simply increasing the model depth with finer-scale levels cannot improve deblurring; (III) Individual RGB frames contain a limited motion information for deblurring; (IV) Previous models have a limited robustness to spatial transformations and noise. Below, we propose several mechanisms based on the multi-patch network to address the above issues: (I) We present a novel self-supervised event-guided deep hierarchical Multi-patch Network (MPN) to deal with blurry images and videos via fine-to-coarse hierarchical localized representations; (II) We propose a novel stacked pipeline, StackMPN, to improve the deblurring performance under the increased network depth; (III) We propose an event-guided architecture to exploit motion cues contained in videos to tackle complex blur in videos; (IV) We propose a novel self-supervised step to expose the model to random transformations (rotations, scale changes), and make it robust to Gaussian noises. Our MPN achieves the state of the art on the GoPro and VideoDeblur datasets with a 40× faster runtime compared to current multi-scale methods. With 30 ms to process an image at 1280×720 resolution, it is the first real-time deep motion deblurring model for 720p images at 30 fps. For StackMPN, we obtain significant improvements over 1.2 dB on the GoPro dataset by increasing the network depth. Utilizing the event information and self-supervision further boost results to 33.83 dB.

Keywords Motion deblurring · Deep learning · Multi-patch · Event camera · Self-supervision

1 Introduction

The objective of non-uniform blind image deblurring is to remove the undesired blur caused by the camera motion and the scene dynamics (Nah et al., 2017; Tao et al., 2018; Pan et al., 2017). Prior to the success of deep learning, conventional deblurring methods used to employ a variety of constraints or regularizations to approximate the motion blur filters, involving an expensive non-convex non-linear optimization, and

overly restrictive assumption of spatially-uniform blur kernel, resulting in a poor deblurring of complex blur patterns.

Deblurring methods based on deep Convolutional Neural Networks (CNNs) (Krizhevsky et al., 2012; Simonyan and Zisserman, 2014) learn the regression between a blurry input image and the corresponding sharp image in an end-to-end manner (Nah et al., 2017; Tao et al., 2018). To exploit deblurring cues at varying processing levels, the “coarse-to-fine” scheme has been extended to deep CNN scenarios by a multi-scale network architecture (Nah et al., 2017) and a scale-recurrent architecture (Tao et al., 2018). Under the “coarse-to-fine” scheme, a sharp image is gradually restored at different resolutions in a pyramid. Nah et al. (2017) demonstrated the ability of CNN models in removing motion blur from multi-scale blurry images, where a multi-scale loss function is devised to mimic conventional coarse-to-fine approaches. Following a similar pipeline, Tao et al. (2018) shared network weights across scales to improve training and model stability, thus achieving highly effective deblurring compared with (Nah et al., 2017). However, there still exist major challenges in current deep deblurring methods:

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