Learning a Convolutional Neural Network for Non-uniform Motion Blur Removal

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Abstract

In this paper,the author address the problem of estimating and removing non-uniform motion blur from a single blurry image. They propose a deep learning approach to predicting the probabilistic distribution of motion blur at the patch level using a convolutional neural network (CNN).They further extend the candidate set of motion kernels predicted by the CNN using carefully designed image rotations. A Markov random field model is then used to infer a dense non-uniform motion blur field enforcing motion smoothness. Finally, motion blur is removed by a non-uniform deblurring model using patch-level image prior. Experimental evaluations show that this approach can effectively estimate and remove complex non-uniform motion blur that is not handled well by previous approaches.

1. Introduction

Image deblurring [1] aims at recovering sharp image from a blurry image due to camera shake, object motion or out-of-focus. In this paper,they focus on estimating and removing spatially varying motion blur.

Non-uniform deblurring has attracted much attention in recent years. Methods in [3] [4] work on non-uniform blur caused by camera rotations, in-plane translations or forward out-of-plane translations. They are effective for removing non-uniform blur consistent with these motion assumptions. Another category of approaches works on non-uniform motion blur caused by object motion. They estimate blur kernels by analyzing image statistics, blur spectrum, or with a learning approach using hand-crafted features [2].Other approaches jointly estimate the sharp image and blur kernels using a sparsity prior. It is still challenging today to remove strongly non-uniform motion blur captured in complex scenes.

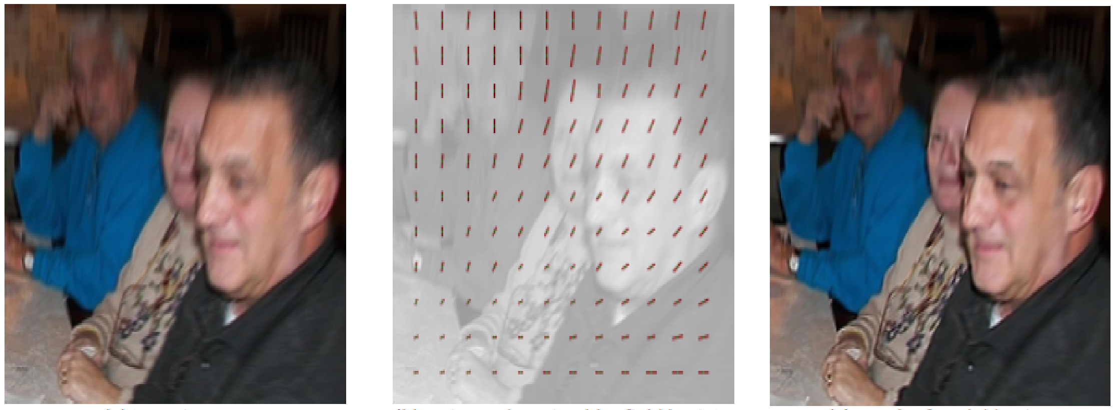
In this work,they propose a novel deep learning-based approach to estimating non-uniform motion blur, followed by a patch statistics-based deblurring model adapted to nonuniform motion blur.They estimate the probabilities of motion kernels at the patch level using a convolutional neural network (CNN), then fuse the patch-based estimations into a dense field of motion kernels using a Markov random field (MRF) model. To fully utilize the CNN,they propose to extend the candidate motion kernel set predicted by CNN using an image rotation technique, which significantly boost its performance for motion kernel estimation. Taking advantage of the strong feature learning power of CNNs,they can well predict the challenging nonuniform motion blur that can hardly be well estimated by the state-of-the-art approaches.

Figure 1 illustrates our approach. Given a blurry image, we first estimate non-uniform motion blur field by a CNN model, then we deconvolve the blurry image. Our approach can effectively estimate the spatially varying motion kernels, which enable us to well remove the motion blur.

2. RelatedWork

Estimating accurate motion blur kernels is essential to non-uniform image deblurring. In [3] [4], nonuniform motion blur is modeled as a global camera motion, which basically estimates an uniform kernel in the camera motion space. Methods jointly estimate the motion kernels and sharp image. They rely on a sparsity prior to infer the latent sharp image for better motion kernel estimation. Different to them, we estimate motion blur kernels directly using the local patches, which does not require the estimation of camera motion or a latent sharp image.

Another category of approaches estimates spatially varying motion blur based on local image features. The method estimates motion blur based on blur spectrum analysis of image patch in Fourier transform space. [5] predicts motion blur kernel using natural image statistics. estimates motion blur by analyzing the alpha maps of image edges. [2] learns a regression function to predict motion blur kernel based on some hand-crafted features. Different to them, we estimate motion blur kernels using a convolutional neural network, followed by a carefully designed motion kernel extension method and MRF model to predict a dense field



(a) Input image (b) Estimated motion blur field by CNN (c) Result after deblurring

Figure 1. An example illustrating our approach. Given an image with non-uniform motion blur (left). We first estimate the field of non-uniform motion blur kernels by a convolutional neural network (middle), then deconvolve the blurred image (right).

of motion kernels.This approach can well estimate complex and strong motion blur, which can hardly be well estimated by the previous approaches.

References

[1] S. Cho, Y. Matsushita, and S. Lee. Removing non-uniform motion blur from images. In *ICCV*, 2007. 1

[2] F. Couzini-Devy, J. Sun, K. Alahari, and J. Ponce. Learning to estimate and remove non-uniform image blur. In *CVPR*, 2013. 1

[3] A. Gupta, N. Joshi, C. L. Zitnick, M. Cohen, and B. Curless. Single image deblurring using motion density functions. In *ECCV*, 2010. 1

[4] M. Hirsch, C. J. Schuler, S. Harmeling, and B. Scholkopf. Fast removal of non-uniform camera shake. In *ICCV*, 2011. 1

[5] B. Sch?lkopf, J. Platt, and T. Hofmann. Blind motion deblurring using image statistics. In *NIPS*, 2006. 1