# PARTIAL IMAGE BLUR DETECTION AND SEGMENTATION FROM A SINGLE SNAPSHOT

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# ABSTRACT

In this paper, we address the problem of detecting and segmenting partial image blur from a single input image. Instead of assuming particular image priors or requiring additional user annotation, we propose a novel learning framework which jointly solves the tasks of blur kernel estimation and image blur segmentation, so that partial image blur can be automatically separated from the remaining parts of the input image. By alternating between the two learning tasks, we show that our proposed method would achieve promising detection and segmentation performance, which would benefit further processing or analysis tasks of interest. We also verify that, via both qualitative and quantitative evaluation, our approach would perform favorably against state-of-the-art blur detection or segmentation works.

Index Terms- Blur detection, image segmentation

### 1. INTRODUCTION

Image blur is a common issue in photography which not only affects the quality of the photo but also reduces user satisfaction. Even if an image is uniformly blurred (e.g., due to camera motion), direct estimation of the blur kernel for image deblurring is an ill-posed problem. This is because that, one would require the estimation of the blur kernel and the associated latent image simultaneously. To tackle this problem, prior knowledge on the image properties is typically required (e.g., natural image gradients [1], local color statistics [2], dark channel [3], and blur kernel sparsity [4, 5]). Recently, deep learning techniques [6] have also been proposed for solving the above problem.

Unfortunately, image blur might result from both camera and moving objects of interest. In other words, multiple blurred regions can be presented in an image. Moreover, camera motion would also result in out-of-plane rotation which also blurs the input image. Thus, how to properly detect each blur region and to distinguish between the corresponding image regions would be a challenging and practical task.

Detecting multiple blurred regions (including partial blur) from a single image has been studied by researchers in the

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**Fig. 1**: Examples of partial image blur presented in an image. Note that the images are adopted from [7].

fields of computer vision and image processing. For example, some require user interaction for producing high-quality alpha mattes for estimation (e.g., foreground and background trimap [8, 9], moving path [10]), while others observe local cues for blur detection and segmentation (e.g., 1-D box filter [11, 12], sparse representation [13]). Some further solve this task by learning the Bayesian models via conforming multi-layer image representation with different smoothness constraints (e.g., Potts prior [14], similarity matrix [15], soft segmentation [16]). Nevertheless, most existing approaches typically require additional information like user interaction or prior knowledge for achieving satisfactory performance.

In this paper, we focus on detecting and segmenting partial blurred regions from a single input image. In our work, we assume that there exists a region of obvious image blur (caused by a single yet unknown uniform kernel) in the input image, while the remaining regions are blur free. For simplicity, we do not consider image blur due to out-of-focus and out-of-plane rotation, which are not within the scope of discussions in this paper. To address the above problem, we propose to solve the joint task of blur kernel estimation and image blur segmentation. Via alternating between the two tasks, refined blur kernels and improved blur detection/segmentation can be simultaneously achieved. Finally, a standard Markov Random Field model is applied to refine the final detection and segmentation output. The main contributions of our work are highlighted below:

• We aim at solving partial image blur from a single input image, without the need of user interaction or prior knowledge/assumption on the type of blur kernel.

- Based on the framework of maximum a posteriori (MAP), we propose to solve the joint task of blur kernel estimation and image blur segmentation, which is shown to benefit partial image blur detection and segmentation.
- Via alternative optimization between the above two tasks, the partial image blur region can be automatically detected and extracted, which can be further refined by MRF for producing the final output.

## 2. OUR PROPOSED METHOD

#### 2.1. Problem Formulation

When an image L is blurred by a single kernel K, the blurred output image I can be formulated as:  $I = K \otimes L$ , where  $\otimes$  denotes the convolution operation. And, due to both latent image and the blur kernel are unknown, direct estimation of them is an ill-posed problem.

When multiple partial blur can be expected, one can extend the equation above as the following form:

$$I = \sum_{t=1}^{N} K_i \otimes (M_i \odot L), \qquad (1)$$

in which  $\mathbf{M} = \{M_1, M_2, ..., M_N\}$  indicates N disjoint masks separating each blurred image segment, each associated with a blur kernel  $K_i$  in  $\mathbf{K} = \{K_1, K_2, ..., K_N\}$  (*i* is the segment index). We have  $\odot$  as element-wise multiplication. It is worth repeating that, in this paper, we assume that there exists a single blur region in the input image which is caused by a single uniform kernel. In other words, we have N = 2 while both **M** and **K** need to be automatically determined.

As highlighted in Section 1, we propose to solve a joint optimization task of blur kernel estimation and image blur segmentation, so that partial image blur can be automatically detected and segmented from the input image. The framework of our proposed method is illustrated in Figure 2, which consists of two major components of blur kernel estimation and image blur segmentation, followed by a MRF-based post-processing stage for producing the final output. As detailed and verified later, alternation between the two proposed components would introduce satisfactory ability in identifying and extracting the partial blur region from the input image, while no prior knowledge of the blur kernel nor user interaction would be needed during the entire process.

## 2.2. Partial Image Blur Detection and Segmentation

## 2.2.1. A Brief Review of MAP for Image Deblurring

Since solving the above image deblurring is an ill-posed problem, priors like gradient sparsity of natural images [17] are



Fig. 2: A flowchart showing the procedures of our algorithm.

typically applied in a maximum a posteriori (MAP) framework as a popular solution. Thus, one can approach the original blur kernel estimation and image recovery tasks by solving the following minimization problem:

$$\underset{\mathbf{M},\mathbf{K},L}{\text{minimize}} \quad \left| \left| I - \sum_{i=1}^{N} K_i \otimes (M_i \odot L) \right| \right|_2^2 + \\ \gamma \sum_{\star = \{x,y\}} ||\nabla_{\star}L||_1^1 + \lambda \sum_{i=1}^{N} ||K_i||_1^1,$$

$$(2)$$

where the first term represents the data fitting term, the second term corresponds to image sparsity prior, and the last term is for kernel normalization. Parameters  $\gamma$  and  $\lambda$  are the weight and Lagrange multiplier, respectively.

We note that, optimization of (2) can be achieved by iteratively solving with each subproblem of determining **M**, **K** and *L*, while each turns into an easier task and would be more efficient to solve [18]. Such alternative optimization would also provide advantages of dealing with image noise caused by local textures over existing methods like [11], which focus on estimating blur kernels for each image patch and choose to perform image segmentation based on the associated kernels.

#### 2.2.2. Blur Kernel Estimation

Instead of assuming that the blur kernel is known from a set of predetermined kernel candidates, we advocate the joint learning of blur kernel and blur image segmentation for partial image blur detection. As depicted in Figure 2, we advance and alternate between two major components for solving this challenging task.

We now detail the first task of blur kernel estimation from an input image with partial blur. For estimating the blur kernels **K** (which also implies the recovery of the latent image L), we assume that the set of disjoint segmentation masks **M** is given and fixed. In other words, the sub-task to be addressed at this stage is to estimate the kernel  $K_i$  for each image segment *i*. Since existing solutions exist for solving such a blur kernel estimation task (and our goal is not to improve its performance), we apply the method proposed in [18] for iteratively deriving **K** and L given **M**. More specifically, the technique of reweighted least squares (IRLS) is utilized for



**Fig. 3**: From left to right: example image, two sets of image edges identified by k-means clustering (shown in red and blue), and the corresponding estimated blur kernels.

solving this task. Nevertheless, once the blur kernels  $\mathbf{K}$  and the resulting latent image L are obtained, we will use such derived information for performing the following task of image blur segmentation.

### 2.2.3. Image Blur Segmentation

Given **K** and *L*, the stage of image blur segmentation aims at learning the segmentation mask **M** for separating the segment of image blur and the remaining image regions with blur free. To determine the binary mask of **M**, we start with an alphamatting like soft mask with each pixel value between [0, 1]. Thus, we solve the first term in (2)), which is a convex optimization problem with respective to **M** (given fixed **K** and *L*). Once the soft mask is derived, a simple threshold of 0.5 can be applied to convert it into the binary segmentation mask.

We note that, when solving the above segmentation task, we do not assume any particular image priors for extracting different image segments from an image with partial blur. Thus, the derived segmentation mask might not be smooth along the the segment boundaries. Therefore, after the alternative optimization between blur kernel estimation and image blur segmentation is complete, we employ an additional MRF-based post processing step to produce the final detection/segmentation output.

#### 2.2.4. Initialization and Refinement

To perform the learning process in Figure 2 for estimating the image partial blur and its associated image regions, we start from the stage of blur kernel estimation with kernel initialization. With an input image I with partial blur, since image blur is typically observed in image regions with long edges, we focus on pixels along strong edges and perform clustering to distinguish the edges associated with blur and non-blur regions. Visualization of the observed strong edges is shown in Figure 3.

As for producing the final detection output from the derived mask  $\mathbf{M}$ , we need to preserve the segment boundary based on the latent image I since such information might not be sufficiently recovered during the stage of joint kernel estimation and blur image segmentation.

To better estimate the detection output from different



**Fig. 4**: An example of MRF refinement. (a) Input image, (b) segmentation ground-truth, (c) estimated mask **M**; (d) refinement output.

types of blur kernels, we utilize an additional set of 20 natural images collected over the Internet, which are blurred by the estimated kernels  $\mathbf{K} = \{K_1, K_2, ..., K_N\}$  (N = 2 in our work). For each patch with the associated kernel, it is described by local binary pattern (LBP) [19], followed by gradient boosting decision trees [20] as the classifiers. Such classifiers will be applied to recognize each overlapping patch in the estimated latent image L, so that the average output would be processed by MRF as the final detection map (see Figure 4 for example). Note that, for refinement purposes, the data term of the MRF determines the mask label for each segment, while the smoothness terms measures the gradient magnitude between adjacent image segments.

### 3. EXPERIMENTS

### 3.1. Datasets and Settings

To evaluate the performance of our proposed method, we apply the dataset of [7] and consider state-of-the-art approaches of blur segmentation [11] and detection [7, 21, 22, 11] for comparisons. To detect the image edges as noted in Section 2.2.4, we utilize [23] for extracting image structural edges with a ridge detector, followed by thresholding the resulting stroke length which is 4 times larger the kernel size. For the refinement stage of our method, we follow [20] and use LBP features [19] to learn the classifiers. As for the MRF model, we apply graph cuts with multi-label energy minimization (GCMEX) [24] for optimization.

## 3.2. Evaluation

We first evaluate the performance of partial blur detection. We compare to the methods noted above, and show the example results in Figure 4. To further assess the ability of our method for partial image blur segmentation, we compare the segmentation results in Figure 6 (note that the segmentation results are produced using the code of [11], which is publicly available). We note that, compared to some recent approaches which tend to result in false positive detection results due to poor kernel estimation, our integration of blur kernel estimation and blur segmentation would suppress noisy estimation from either task.



**Fig. 5**: Performance comparisons of partial image blur detection. Images from left to right: input, ground truth, detection outputs of [11], [21], [7], [13], [22], and ours, respectively.



**Fig. 6**: Comparisons of segmenting partial image blur. From left to right: input, ground truth, outputs of [11], and ours.

In addition to qualitative comparisons, we perform additional quantitative evaluation, and plot the accuracy and precision-recall curves in Figure 7 for the completeness of comparisons. In this figure, we particularly consider the performances of [21], [7], [13], and [22], and we observe that our method consistently performed favorably against these state-of-the-art approaches. Thus, the effectiveness of our approach can be successfully verified.



**Fig. 7**: Comparisons of accumulated accuracy and precision-recall curves for partial image blur detection.

# 4. CONCLUSION

We approached the problem of extracting partial image blur from a single input image by solving the joint tasks of blur kernel estimation and image blur segmentation. The proposed learning framework uniquely integrates the above two fundamental image processing tasks. By utilizing alternative optimization which retrieves and utilizes the information produced by each task, we can automatically identify the partial image blur presented in the input. Followed by standard MRF for refinement purposes, the produced image mask can be viewed as an effective detection and segmentation output, which would be preferable over recent approaches which require additional image assumption or user feedback.

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