Dynamic Video Deblurring using a Locally Adaptive Linear Blur Model

Tae Hyun Kim, Seungjun Nah, and Kyoung Mu Lee

Abstract—State-of-the-art video deblurring methods cannot handle blurry videos recorded in dynamic scenes since they are built under a strong assumption that the captured scenes are static. Contrary to the existing methods, we propose a new video deblurring algorithm that can deal with general blurs inherent in dynamic scenes. To handle general and locally varying blurs caused by various sources, such as moving objects, camera shake, depth variation, and defocus, we estimate pixel-wise varying non-uniform blur kernels. We infer bidirectional optical flows to handle motion blurs, and also estimate Gaussian blur maps to remove optical blur from defocus. Therefore, we propose a single energy model that jointly estimates optical flows, defocus blur maps and latent frames. We also provide a framework and efficient solvers to minimize the proposed energy model. By optimizing the energy model, we achieve significant improvements in removing general blurs, estimating optical flows, and extending depth-of-field in blurry frames. Moreover, in this work, to evaluate the performance of non-uniform deblurring methods objectively, we have constructed a new realistic dataset with ground truths. In addition, extensive experimental results on publicly available challenging videos demonstrate that the proposed method produces qualitatively superior performance than the state-of-the-art methods which often fail in either deblurring or optical flow estimation.

Index Terms—video deblurring, non-uniform blur, motion blur, defocus blur, optical flow, Gaussian blur map, non-uniform blur dataset

1 INTRODUCTION

Motion blurs are the most common artifacts in videos recorded from hand-held cameras. In low-light conditions, these blurs are caused by camera shake and object motions during exposure time. In addition, fast moving objects in the scene cause blurring artifacts in a video frame even when the light conditions are acceptable. For decades, this problem has motivated considerable works on deblurring and different approaches have been sought depending on whether the captured scenes are static or dynamic.

Early works on a single image deblurring problem were based on assumptions that the captured scene is static and has constant depth \([1, 2, 3, 4, 5, 6, 7]\) and they estimated uniform or non-uniform blur kernel by camera shake. These approaches were naturally extended to video deblurring methods. Cai et al. \([8]\) proposed a deconvolution method with multiple frames using sparsity of both blur kernels and clear images to reduce errors from inaccurate registration and render a high-quality latent image. However, this approach removed only uniform blur caused by 2-dimensional translational camera motion, and the proposed approach could not handle non-uniform blur from rotational camera motion around the z-axis, which is the main cause of motion blurs \([7]\). To solve this problem, Li et al. \([9]\) adopted a method parameterizing spatially varying motions with 3x3 homographies based on the previous work of Tai et al. \([10]\), and could handle non-uniform blurs by rotational camera shake. In the work of Cho et al. \([11]\), camera motion in 3-dimensional space was estimated without any assistance of specialized hardware, and spatially varying blurs caused by projective camera motion were obtained.

Moreover, in the works of Paramanand et al. \([12]\) and Lee and Lee \([13]\), spatially varying blurs caused by depth variation in a static scene were estimated and removed.

However, these previous methods, which assume static scenes, suffer from spatially varying blurs from various sources in dynamic scenes. Moreover, as it is difficult to parameterize the pixel-wise varying blur kernel in a dynamic scene with simple homography, kernel estimation becomes a more challenging task. Therefore, several researchers have studied on removing blurs in dynamic scenes, which are grouped into two approaches: segmentation-based deblurring approaches, and exemplar-based deblurring approaches.

Segmentation-based approaches usually estimate multiple motions, kernels, and associated segments. In the work of Cho et al. \([13]\), a method that segments homogeneous motions and estimates segment-wise different (1-dimensional) Gaussian blur kernels, was proposed. However, it could not handle complex motions by rotational camera shakes due to the limited capacity of Gaussian kernels. In the work of Bar et al. \([15]\), a layered model was proposed that segments images into foreground and background layers, and estimates a linear blur kernel within the foreground layer. By using the layered model, explicit occlusion handling was possible, but the kernel was restricted to linear. To overcome these limitations, Wulff and Black \([16]\) improved the previous layered model of Bar et al. by estimating the different motions of both foreground and background layers. However, these motion models are restricted to affine models and it is difficult to extend to multi-layered scenes because such task requires depth order reasoning of the layers. To sum up, segmentation-based deblurring approaches have the advantage of removing blurs caused by moving objects in dynamic scenes. However, segmentation itself is a very difficult problem and remains still a challenging issue as reported in \([17]\). Moreover, they fail to segment complex motions like different movements of non-rigid
localized. Similarly, Zhuo and Sim [24] propagated the amount based approach and depends on the detected edges that can be blur map is inaccurate where the blurs are strong since it is image-
propagated the results to other regions. However, the estimated rand [21] estimated defocus blur map at the edges first, and then
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defocus blur kernel. Most of them have approximated the kernel problem. Thus many types of research have studied to estimate the
estimation of no-uniform defocus blur map is also a difficult
when the motion is large and fast. Moreover, depth variation in
the scene generates spatially varying defocus blurs, and accurate estimation of no-uniform defocus blur map is also a difficult problem. Thus many types of research have studied to estimate the defocus blur kernel. Most of them have approximated the kernel as Gaussian or disc model, thus the kernel estimation problem becomes a parameter (e.g. standard deviation of Gaussian blur or disc radius) estimation problem [21], [22], [23], [24].

Specifically, to magnify focus differences, Bae and Durand [21] estimated defocus blur map at the edges first, and then propagated the results to other regions. However, the estimated blur map is inaccurate where the blurs are strong since it is image-based approach and depends on the detected edges that can be localized. Similarly, Zhuo and Sim [24] propagated the amount of blur at the edges to elsewhere, that obtained by measuring the ratio between the gradients of the defocused input and re-blurred input with a Gaussian kernel. To reduce reliance on strong edges in the defocused image, Zhu et al. [23] utilized statistics of blur spectrum within the defocused image, since statistical models can be applicable where there are no strong edges. To be specific, local image statistics is used to measure the probability of defocus scale and determine the locally varying defocus blur map in a single image. However, local image statistics-based methods do not work when there are motion blurs as well as defocus blurs within a single image; Our key observations is that motion blurs change local statistics and yield much complex blurs combined with defocus blurs usually.

As GVD is based on piece-wise linear kernel approximation, GVD cannot handle non-linear blurs combined with motion and defocus blurs which are common in videos captured from handheld cameras. Therefore, in this work, we propose an extended and more generalized method of GVD that can handle not only motion blur but also defocus blur which further improves the deblurring quality significantly. Under an assumption that, the complex non-linear blur kernel can be decomposed into motion and defocus blur kernels, we estimate bidirectional optical flows to approximate motion blur kernel, scales of Gaussian blurs to approximate defocus blur kernel, and the latent frames jointly. The result of our system is shown in Fig[1] in which the motion blurs by differently moving body parts (e.g., head, arms, and legs) as well as camera shake and Gaussian defocus blurs are successfully removed, and accurate optical flows are jointly estimated.

Finally, we provide a new realistic blur dataset with ground truth sharp frames captured with a high-speed camera to overcome the lack of realistic ground truth dataset in this field. Although there have been some evaluation datasets for the deblurring problem, they are not appropriate to carry out a meaningful evaluation for deblurring of spatially varying blurs. First, synthetically generated uniform blur kernels and blurry images from sharp images were provided in the work of Levin et al. [25]. Next, 6D camera motion in 3D space was recorded with a hardware-assisted camera to represent blur from camera shake during exposure time in the work of Köhler et al. [25]. Moreover, there have been some recent approaches to generate synthetic datasets for the sake of machine learning algorithms. To benefit from large training data, lots of blur kernels and blurry images were synthetically generated. In the work of Xu et al. [27], more than 2500 blurry images are generated using decomposable symmetric kernels. Schuler et al. [28] sampled naturally looking blur kernels with

Fig. 1: (a) A real blurry frame in a dynamic scene. (b) Our deblurring result. (c) Our color coded optical flow result. (d) Our (Gaussian) defocus blur map.

body parts, because simple parametric motion models used in [15], [16] cannot fit the complex motions accurately.

Exemplar-based approaches were proposed in the works of Matsushita et al. [18] and Cho et al. [19]. These methods usually do not rely on accurate segmentation and deconvolution. Instead, the latent frames are rendered by interpolating lucky sharp frames that frequently exist in a long video, thus they have less ringing artifacts. However, the work of Matsushita et al. [18] cannot remove blurs caused by moving objects. In addition, the work of Cho et al. [19] allows only slow-moving objects in dynamic scenes because it searches sharp patches corresponding to blurry patch within a small window after registration with homography. Therefore, it cannot handle fast moving objects which have distinct motions from those of backgrounds. Moreover, since it does not rely on conventional deconvolution technique with spatial priors but simple interpolation, it degrades mid-frequency textures such as grasses and trees, and renders smooth results.

To alleviate these problems, in our previous work [20], we proposed a generalized video deblurring (GVD) method that estimates latent frames without using global motion assumption or segmentation to remove motion blurs in dynamic scenes. In GVD, bidirectional optical flows are estimated and used to parametrize pixel-wise varying kernels. Therefore, GVD naturally handles coexisting motion blurs by camera shake and moving objects with complex motions by simultaneously estimating optical flows and the latent frames with a single energy model.

In addition to motion, defocus from limited depth-of-field (DOF) of conventional digital cameras also results in blurry effects in videos. Although shallow DOF is often used to render aesthetic images and highlight the focused objects, frequent defocus or misfocus of moving objects in video yields quality degradation when the motion is large and fast. Moreover, depth variation in the scene generates spatially varying defocus blurs, and accurate estimation of no-uniform defocus blur map is also a difficult problem. Thus many types of research have studied to estimate the defocus blur kernel. Most of them have approximated the kernel as Gaussian or disc model, thus the kernel estimation problem becomes a parameter (e.g. standard deviation of Gaussian blur or disc radius) estimation problem [21], [22], [23], [24].
Gaussian Process, and Sun et al. [29] used a set of linear kernels to synthesize blurry images. However, all these datasets are generated under an assumption that the scene is static and cannot capture complex blurs in the real world. Real blurs in dynamic scenes are complicated and spatially varying, thus synthesizing a realistic dataset is a difficult problem. To solve this problem, we construct a new blur dataset that provides pairs of realistically blurred videos and sharp videos with the use of a high-speed camera.

Using not only the proposed dataset but also real challenging videos as shown in Fig. 2, we demonstrate the significant improvements of the proposed deblurring method in both quantitatively and qualitatively. Moreover, we show that more accurate optical flows are estimated by our method compared with conventional approaches including a state-of-the-art optical flow method that can handle blurry images.

2 MORE GENERALIZED VIDEO DEBLURRING

Most conventional video deblurring methods suffer from the coexistence of various motion blurs from dynamic scenes because the motions cannot be fully parameterized using global or segment-wise blur models. To make things worse, frequent defocus or misfocus of moving objects in dynamic scenes yields more complex (non-linear) blurs combined with motion blurs.

To handle these motion and defocus blurs, we propose a new blur model that estimates locally (pixel-wise) different blur kernels without using the global or segment-wise kernel estimation. In this work, we propose a single energy model consists of not only data and spatial regularization terms but also a temporal term and the proposed model is expressed as follows:

\[ E = E_{data} + E_{temporal} + E_{spatial}. \]  (1)

The detailed models of each term are given in the following subsections.

2.1 A New Data Model based on Kernel Parametrization

Motion blurs are generally caused by camera shake and moving objects, and defocus blurs are mainly due to the aperture size, focal length, and the distance between the camera and focused object. When these two different blurs are combined, more complex blurs are yielded in real frames. For example, Fig. 3 shows how different the blurred images are when point light sources are captured by a single moving camera with and without focus. We observe that the light streak of the defocused light source is much smoother and complex in comparison with that of the focused one. Notably, the light streaks indicate the blur kernel shapes.

However, it is difficult to directly remove the complex blur in Fig. 3 (c). Thus, to alleviate the problem, we assume that the combined blur kernel can be decomposed into two different kernels, which are defocus blur kernel and motion blur kernel. Our assumption holds when the depth change in the scene during the exposure period is relatively small, and it is acceptable since we treat video of rather short exposure time. Thus, the underlying blurring-procedure can be modeled as a sequential process of defocus blurring followed by motion blur as illustrated in Fig. 4.

Under the assumption that the latent frames are blurred by defocus, and subsequently blurred by motion, our blur model is expressed as follows:

\[ B_i(x) = (k_{i,x} \otimes g_{i,x} \otimes L_i)(x), \]  (2)

where \( B_i \) and \( L_i \) denote the \( i_{th} \) blurry and latent frames respectively, and \( x \) denotes pixel location on 2D image domain. At \( x \), the motion blur kernel is denoted as \( k_{i,x} \), and the defocus blur kernel is denoted as \( g_{i,x} \), and the operator \( \otimes \) means convolution.

In general, spatially varying defocus blur \( g_{i,x} \) is approximated by using Gaussian or disc model in conventional works [22], [23]. Therefore, the defocus blur maps are determined by simply estimating the standard deviations of Gaussian models or the radii of disc models. Particularly, local image statistics is widely used to
estimate spatially varying defocus blur map. To be specific, within a uniformly blurred patch, local frequency spectrum provides information on the blur kernel and can be used to determine the likelihood of specific blur kernel \[23\]; thus scales of defocus blurs can be estimated by comparing the fidelities of the likelihood model. However, it is difficult to apply this statistics-based technique when the blurry image has motion blurs in addition to defocus blurs. In Fig. 5 we observe that the maximum likelihood (ML) estimator used in \[23\] finds the optimal defocus blur kernel when a patch is blurred by only defocus blur, however, ML cannot estimate true defocus blur kernel when a blurry patch contains motion blur as well as defocus blur. Therefore we cannot adopt local image statistics to remove defocus blurs in dynamic scenes with severe motion blurs. In this study, we approximate the pixel-wise varying defocus blur using the Gaussian model as shown in Fig. 6 (a), and determine the locally varying standard deviation \(\sigma_i(x)\) of the Gaussian kernel \(g_i(x)\).

Meanwhile, motion blurs are usually approximated by global motion models such as homographies and affine models in conventional video deblurring works \[9, 15, 16, 19\]. However, these global motion models are valid only when the motions are globally or segment-wise rigid, and thus cannot cope with general and pixel-wise varying motion blurs in dynamic scenes. By contrast, to deal with pixel-wise varying motion blurs, we approximate and parameterize the locally different blur kernel, because the solution space of spatially varying kernel in video is extremely large: the dimension of unknown kernel is \(W \times H \times T \times w \times h\) when the size of image is \(W \times H\), length of the image sequence is \(T\), and the size of local kernel is \(w \times h\). Therefore, we approximate the motion blur kernel as piece-wise linear using bidirectional optical flows by extending suggestions in previous works \[17, 30, 31\].

The proposed linearly approximated kernel is illustrated in Fig. 6 (b), and the pixel-wise kernel \(k_{i,x}\) using bidirectional flows can be written by,

\[
k_{i,x}(u, v) = \begin{cases} \frac{\delta(u_{i+1}v_{i+1} - uv)}{2\tau_i\|u_{i+1}v_{i+1} - u_{i-1}v_{i-1}\|}, & \text{if } u \in [0, \tau_i u_{i-1} + 1], v \in [0, \tau_i v_{i-1} + 1] \\
\frac{\delta(u_{i-1}v_{i-1} - uv)}{2\tau_i\|u_{i-1}v_{i-1} - u_{i+1}v_{i+1}\|}, & \text{if } u \in (0, \tau_i u_{i-1} - 1], v \in (0, \tau_i v_{i-1} - 1] \\
0, & \text{otherwise}
\end{cases}
\]

(3)

where \((u, v)\) denotes a location in 2-dimensional kernel space, and

\[u_{i+1}(x) = (u_{i-1} + 1, v_{i-1}), \quad \text{and} \quad u_{i-1}(x) = (u_{i-1} - 1, v_{i-1} - 1)\]

denote pixel-wise bidirectional optical flows at \(x\) on the \(i_{th}\) frame. Camera duty cycle of the frame is \(\tau_i\) and it denotes relative exposure time as used in \[9\]. Kronecker delta is denoted as \(\delta\).

Now, the proposed data model that handles both motion and defocus blurs is expressed as follows:

\[
E_{data}(L, u, \sigma, B) = \lambda \sum_i \sum_{\partial_{\sigma}} \|\partial_{\sigma} K_i(\tau_i, u_{i+1}, u_{i-1})G_i(\sigma_i)L_i - \partial_{\sigma} B_i\|^2,
\]

(4)

where the row vector of the motion blur kernel matrix \(K_i\), which corresponds to the motion blur kernel at pixel \(x\), is the discretized vector form of \(k_{i,x}\), and its elements are non-negative and their sum is equal to one. Similarly, the row vector of the defocus blur kernel matrix \(G_i\) is associated with \(g_{i,x}\) and \(\sigma_i\), denotes the locally varying scale (standard deviations of Gaussian kernel) of defocus blur. Linear operator \(\partial_{\sigma}\) denotes the Toeplitz matrices corresponding to the partial (e.g., horizontal and vertical) derivative filters. Parameter \(\lambda\) controls the weight of the data term, and \(L\), \(u\), \(\sigma\), and \(B\) denote the set of latent frames, optical flows, scales of defocus blurs and blurry frames, respectively.

Fig. 5: (a) A sharp patch. (b) A patch blurred by defocus blur (Gaussian blur with standard deviation 5). (c) A patch blurred by defocus blur (Gaussian blur with standard deviation 5) and motion blur (linear kernel with length 11). (d) Comparisons of fidelities at the centers of the blurry patches by changing the scale of defocus blur. The ground truth scale of the defocus blur is 5 and the arrows indicate peaks estimated by ML estimator.

Fig. 6: Defocus and motion blur kernels. (a) Gaussian defocus blur kernel with standard deviation \(\sigma\) at a pixel location \(x\). (b) Bidirectional optical flows and corresponding piece-wise linear motion blur kernel at a pixel location \(x\).

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conventional optical flow constraints such as brightness constancy and gradient constancy cannot be utilized directly, since such constraints are not valid between two blurry frames. Thus a blur-aware optical flow estimation method among blurry images has been proposed by Portz et al. [31], and this method is based on the commutative law of shift-invariant kernels such that the brightness of the corresponding points is constant after convolving the blur kernel of each image with the other image. However, the commutative law does not hold when the motion is not translational and when the blur kernels vary spatially. Therefore, this approach only works when the motion is smooth.

To address this problem, we propose a new model that estimates optical flow between two latent sharp frames to enable abrupt changes in motions and the blur kernels. Specifically, our model is based on the conventional optical flow constraint between latent frames, that is, brightness constancy. By doing so, we need not restrict our motion blur kernels to be shift invariant, and the formulation of the proposed model is given by,

$$ E_{\text{temporal}}(L, u) = \mu \sum_i \sum_{n=-N}^N |L_i(x) - L_{i+n}(x + u_{i+i+n})|, \quad (5) $$

where $n$ denotes the index of neighboring frames of the frame at $i$, and the parameter $\mu$ controls the weight. We apply the robust $L_1$ norm for robustness against outliers and occlusions.

Notably, a major difference between the proposed model and the conventional optical flow estimation methods is that our method is a joint solution. That is, the latent frames and optical flows should be solved simultaneously in our model. Therefore, the proposed model in (5) restores the latent frames which are temporally coherent, and estimates optical flows among neighboring frames, jointly. Thus we can estimate accurate flows at the motion boundaries as shown in Fig. 10.

### 2.3 Spatial Regularization

To alleviate the difficulties of highly ill-posed deblurring, optical flow estimation, and defocus blur map estimation problems, it is important to adopt well-suited spatial regularizers. In this work, we enforce spatial coherence to penalize spatial fluctuations while allowing discontinuities in the latent frames, flow fields and defocus blur maps. With an assumption that spatial priors for the latent frames, optical flows, and defocus blur maps are independent, we can formulate for the spatial regularization as follows:

$$ E_{\text{spatial}}(L, u, \sigma) = \sum_i |\nabla L_i| + \nu_{\sigma} \sum_i \sum_x \zeta_i(x)|\nabla \sigma_i(x)| + $$

$$ \nu_u \sum_i \sum_x \sum_{n=-N}^N \zeta_i(x)|\nabla u_{i+i+n}(x)|, \quad (6) $$

where parameters $\nu_{\sigma}$ and $\nu_u$ control the weights of the second and third terms.

The first term in (6) denotes the spatial regularization term for the latent frames. Although more sparse regularizer fits the gradient statistics of natural sharp images better [33], [34], [35] and reduces deconvolution artifacts [3], we use conventional total variation (TV) based regularization [17], [36], [37], as TV model is computationally less expensive and easy to minimize. The second and third terms enforce spatial smoothness for defocus blur maps and optical flows, respectively. These regularizers are
also based on TV model, and coupled with an edge-map to preserve discontinuities at the edges of both vector fields. Similar to the edge-map used in conventional optical flow estimation method [38], our edge-map is expressed as follows:

\[ \zeta_i(x) = \exp(-\frac{\|
abla L_0^0(x)\|^2}{v_I}) \],

(7)

where the fixed parameter \( v_I \) controls the weight of the edge-map, and \( L_0^0 \) is an initial latent image in the iterative optimization framework in Sec. [3]

### 3 Optimization Framework

Under the condition that the camera duty cycle \( \tau_i \) is known, by combining \( E_{data} \), \( E_{temporal} \), and \( E_{spatial} \), we have the final objective function as follows:

\[
\begin{align*}
\min_{\mathbf{L}, \mathbf{u}, \sigma} & \quad \lambda \sum_i \sum_{n=-N}^N \| \partial_x K_i(u_{i\rightarrow i+1} + u_{i\rightarrow i-1}) G_i(\sigma_i) L_i - \partial_x B_i \|^2 + \\
& \mu \sum_i \sum_{n=-N}^N \| L_i(x) - L_{i+n}(x + u_{i\rightarrow i+n}) \| + \\
& \sum_i \| \nabla L_i \| + \nu \sum_i \sum_{x} \zeta_i(x) |\nabla \sigma_i| + \\
& \nu u \sum_i \sum_{n=-N}^N \zeta_i(x) |\nabla u_{i\rightarrow i+n}|.
\end{align*}
\]

(8)

Notably, in contrast to the work of Cho et al. [19] that performs multiple approaches in sequential manner, our model finds a solution by minimizing the proposed single objective function in (8). However, due to its non-convexity, our model needs to adopt a practical optimization method to obtain an approximated solution. Therefore, we divide the original problem into easier sub-problems and then use conventional iterative and alternating optimization techniques [2], [16], [17] to minimize the original non-convex objective function. Notably, our alternating minimization technique cannot guarantee to find a globally optimal solution. However, each sub-problem is either convex or approximately well convexified, and thus can be easily minimized. In the following subsections, we introduce efficient solvers and describe how to estimate unknown \( \mathbf{L}, \mathbf{u}, \) and \( \sigma \) alternatively.

#### 3.1 Sharp Video Restoration

While the motion blur kernels \( \mathbf{K} \) and the defocus blur kernels \( \mathbf{G} \) are fixed, the objective function becomes convex with respect to \( \mathbf{L} \), and it can be expressed as follows:

\[
\begin{align*}
\min_{\mathbf{L}} & \quad \lambda \sum_i \sum_{n=-N}^N \| \partial_x K_i G_i L_i - \partial_x B_i \|^2 + \sum_i |\nabla L_i| + \\
& \mu \sum_i \sum_{x} \sum_{n=-N}^N | L_i(x) - L_{i+n}(x + u_{i\rightarrow i+n}) |.
\end{align*}
\]

(9)

To restore the latent frames \( \mathbf{L} \), we adopt the conventional convex optimization method proposed in [39], and derive the primal-dual update scheme as follows:

\[
\begin{align*}
\mathbf{s}^{m+1} &= \frac{\mathbf{s}^m + \eta L \mathbf{A} \mathbf{s}^m}{\max(\mathbf{T}, \text{abs}(\mathbf{s}^m + \eta L \mathbf{A} \mathbf{s}^m))} \\
\mathbf{q}^{m+1} &= \frac{\mathbf{q}^m + \eta L \mu \mathbf{B} \mathbf{q}^m}{\max(\mathbf{T}, \text{abs}(\mathbf{q}^m + \eta L \mu \mathbf{B} \mathbf{q}^m))} \\
\mathbf{L}^{m+1} &= \arg \min_{\mathbf{L}^{m+1}} \lambda \sum_i \sum_{n=-N}^N \| \partial_x K_i G_i \mathbf{L}_i^{m+1} - \partial_x \mathbf{B}_i \|^2 + \\
& \| \mathbf{L}^{m+1} - (\mathbf{L}^m - \mathbf{u}^m (\mathbf{T}^m + 1 + \mu \mathbf{D}^m \mathbf{q}^m)) \|^2, \\
& \quad \frac{2\mathbf{e}_L}{2\mathbf{e}_L}.
\end{align*}
\]

(10)

where \( m \geq 0 \) indicates the iteration number, and \( \mathbf{L}^{m} \) denotes concatenation of all latent frames in a vector form. And \( \mathbf{s} \) and \( \mathbf{q} \) denote the dual variables. Parameters \( \eta L \) and \( \epsilon L \) denote the update steps. The linear operator \( \mathbf{A} \) calculates the spatial difference between neighboring pixels, and the operator \( \mathbf{D} \) calculates the temporal differences among neighboring frames using fixed optical flows. The last formulation in (10) is to update and optimize the primal variable \( \mathbf{L}^{m+1} \), and we apply the conjugate gradient method to minimize it, since it is a quadratic function. Notably, division operators used in the update steps denote the element-wise division.

#### 3.2 Optical Flows Estimation

While the latent frames \( \mathbf{L} \) and the defocus blur kernels \( \mathbf{G} \) are fixed, the objective function in (8) becomes motion estimation model. However, this function is non-convex, because the temporal coherence term \( E_{temporal} \) and the data term \( E_{data} \) are non-convex. For simplicity, we denote those two terms as a non-convex function \( \rho_u(.) \) as follows:

\[
\rho_u(u) = \mu \sum_i \sum_{x} \sum_{n=-N}^N | L_i(x) - L_{i+n}(x + u_{i\rightarrow i+n}) | + \\
\quad \lambda \sum_i \sum_{n=-N}^N | \partial_x K_i(u_{i\rightarrow i+1}, u_{i\rightarrow i-1}) G_i L_i - \partial_x \mathbf{B}_i |^2,
\]

(11)

and we convexify the non-convex function \( \rho_u(.) \) by applying the first-order Taylor expansion to find the optimal optical flows \( \mathbf{u} \). Similar to the technique used in [17], [40], [41], we linearize the function near an initial \( \mathbf{u}_0 \) in the iterative process as follows:

\[
\rho_u(u) \approx \rho_u(u_0) + \nabla \rho_u(u_0)^T (u - u_0),
\]

(12)

where \( \nabla \rho_u(u_0) \) calculates the finite difference (i.e., \( \nabla \rho_u(u_0) = \rho_u(u_0+0.5) - \rho_u(u_0-0.5) \)) to approximately compute the spatial gradients near \( u_0 \) in practice.

In doing so, (6) can be approximated as a convex function w.r.t \( u \) for being fixed \( \mathbf{G} \) and \( \mathbf{L} \) as follows:

\[
\begin{align*}
\min_{\mathbf{u}} \rho_u(u_0) + \nabla \rho_u(u_0)^T (u - u_0) + \\
& \nu u \sum_i \sum_{x} \sum_{n=-N}^N \zeta_i(x) |\nabla u_{i\rightarrow i+n}|.
\end{align*}
\]

(13)

Now, we can apply the convex optimization technique in [39] to the approximated convex function, and the primal-dual update
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Fig. 9: Temporally consistent optical flows over three frames.

process is expressed as follows:

\[
\begin{align*}
\mathbf{p}^{m+1} &= \frac{\mathbf{p}^m + \eta_u (\nabla_x \mathbf{A}_u \mathbf{u}^m)}{\max(\mathbf{T}, \abs{\mathbf{p}^m + \eta_u (\nabla_x \mathbf{A}_u \mathbf{u}^m)})} \\
\mathbf{u}^{m+1} &= (\mathbf{u}^m - \epsilon_u (\nabla_x \mathbf{A}_u \mathbf{u}^m)^T \mathbf{p}^{m+1}) - \epsilon_u \nabla \rho_u (\mathbf{u}_0),
\end{align*}
\]

where \( \mathbf{p} \) denotes the dual variable of \( \mathbf{u} \). Weighting matrix \( \mathbf{W}_u \) is diagonal, and its sub-matrix associated with \( \mathbf{u}_{i-n+i} \) is defined as \( \text{diag}(\zeta_i) \). The linear operator \( \mathbf{A}_u \) calculates the spatial difference between four nearest neighboring pixels, and parameters \( \eta_u \) and \( \epsilon_u \) denote the update steps. Notice that, division operators in the formulation denote the element-wise division.

3.3 Defocus Blur Map Estimation

While the latent frames \( \mathbf{L} \) and the motion blur kernels \( \mathbf{K} \) are fixed, we can estimate the defocus blur maps. As our data term is non-convex, an approximation technique is also required to solve the sub-problem. Similar to our optical flows estimation technique, we approximate and convexify the function using linearization.

First, we define a non-convex data function \( \rho_\sigma(\cdot) \) and approximate it near an initial \( \sigma_0 \) as follows:

\[
\rho_\sigma(\sigma) = \lambda \sum_i \sum_x \left\| \nabla_x \mathbf{K}_i \mathbf{G}_i(\sigma) \mathbf{L}_i - \nabla_x \mathbf{B}_i \right\|^2 \\
\approx \rho_\sigma(\sigma_0) + \nabla \rho_\sigma(\sigma_0)^T (\sigma - \sigma_0),
\]

and then, the approximated convex function for defocus blur map estimation is given by,

\[
\min_{\sigma} \rho_\sigma(\sigma_0) + \nabla \rho_\sigma(\sigma_0)^T (\sigma - \sigma_0) + \nu_\sigma \sum_x \sum_i \zeta_i(x) \left\| \nabla \sigma_i \right\|.
\]

Similarly, (16) can be optimized by using (39), and the primal-dual update formulation is given by,

\[
\begin{align*}
\mathbf{p}^{m+1} &= \frac{\mathbf{p}^m + \eta_\sigma (\nabla_x \mathbf{W}_\sigma \mathbf{A}_\sigma \mathbf{u}^m)}{\max(\mathbf{T}, \abs{\mathbf{p}^m + \eta_\sigma (\nabla_x \mathbf{W}_\sigma \mathbf{A}_\sigma \mathbf{u}^m)})} \\
\mathbf{u}^{m+1} &= (\mathbf{u}^m - \epsilon_\sigma (\nabla_x \mathbf{W}_\sigma \mathbf{A}_\sigma \mathbf{u}^m)^T \mathbf{p}^{m+1}) - \epsilon_\sigma \nabla \rho_\sigma (\mathbf{u}_0),
\end{align*}
\]

where \( \mathbf{r} \) denotes the dual variable of \( \mathbf{u} \) on the vector field. Weighting matrix \( \mathbf{W}_\sigma \) is diagonal, and its sub-matrix associated with \( \mathbf{u}_i \) is defined as \( \text{diag}(\zeta_i) \). Parameters \( \eta_\sigma \) and \( \epsilon_\sigma \) denote the update steps, and division operator means the element-wise division.

4 IMPLEMENTATION DETAILS

To handle large blurs and guide fast convergence, we implement our algorithm on the conventional coarse-to-fine framework with empirically determined parameters. In the coarse-to-fine framework, we build image pyramids with 17 levels for a high-definition (1280x720) video, and use the scale factor 0.9.

Moreover, to reduce the number of unknowns in optical flows, we only estimate \( \mathbf{u}_{i-n+i+1} \) and \( \mathbf{u}_{i-n+i} \). For example, we approximate \( \mathbf{u}_{i-n+i+2} \) using \( \mathbf{u}_{i-n+i+1} \) and \( \mathbf{u}_{i-n+i+1} \), and since it satisfies \( \mathbf{u}_{i-n+i+2} = \mathbf{u}_{i-n+i+1} + \mathbf{u}_{i-n+i+1} \) as illustrated in Fig. 7. We can easily apply this for \( n \neq 1 \).

The overall process of our algorithm is in Algorithm 1. Further details on initialization, estimating the duty cycle and post-processing step that reduces artifacts are given in the following subsections.

**Algorithm 1 Overview of the proposed method**

**Input:** Blurry frames \( \mathbf{B} \)

**Output:** Latent frames \( \mathbf{L} \), optical flows \( \mathbf{u} \), and defocus blur maps \( \sigma \)

1: Initialize \( \mathbf{u}, \tau_i, \) and \( \sigma \). (Sec. 4.1)
2: Build image pyramid.
3: Restore \( \mathbf{L} \) with fixed \( \mathbf{u} \) and \( \sigma \). (Sec. 3.1)
4: Estimate \( \mathbf{u} \) with fixed \( \mathbf{L} \) and \( \sigma \). (Sec. 3.2)
5: Estimate \( \sigma \) with fixed \( \mathbf{L} \) and \( \mathbf{u} \). (Sec. 3.3)
6: Detect occlusion and perform post-processing. (Sec 4.2)
7: Propagate variables to the next pyramid level if exists.
8: Repeat steps 3-7 from coarse to fine pyramid level.

4.1 Initialization and Duty Cycle Estimation

In this study, we assume that the camera duty cycle \( \tau_i \) is given for every frame. However, when we conduct deblurring with conventional datasets, which do not provide exposure information, we apply the technique proposed in [19] to estimate the duty cycle. Contrary to the original method in [19], we use optical flows instead of homographies to obtain initially approximated blur kernels. Therefore, we first estimate flow fields from blurry images with (12), which runs in near real-time. We then use them as initial flows and approximate the kernels to estimate the duty cycle. Moreover, we use \( \sigma_i(x) = 0.25 \) for the initial scale of defocus blur in the coarsest level. Notably, we observe that our method renders reliable deblurring results between 0.1 \( \leq \sigma_i(x) \leq 0.5 \), thus we used empirically determined initial value (\( \sigma_i(x) = 0.25 \)).

4.2 Occlusion Detection and Refinement

Our pixel-wise kernel estimation naturally results in approximation error and it causes problems such as ringing artifacts. Specifically, our data model in (4), and temporal coherence model in (5) are invalid at occluded regions.

To reduce such artifacts from kernel approximation errors and occlusions, we use spatio-temporal filtering as a post-processing:

\[
\mathbf{L}_{i}^{m+1}(x) = \frac{1}{Z(x)} \sum_{n=-N}^{N} \sum_{y} w_{i,n}(x,y) \cdot \mathbf{L}_{i+n}^{m}(y),
\]

where \( y \) denotes a pixel in the 3x3 neighboring patch at location \( x + \mathbf{u}_{i-n+n} \) and \( Z \) is the normalization factor (e.g. \( Z(x) = \sum_{n=-N}^{N} \sum_{y} w_{i,n}(x,y) \)). Notably, we enable \( n = 0 \) in (18) for spatial filtering. Our occlusion-aware weight \( w_{i,n} \) is defined as follows:

\[
w_{i,n}(x,y) = a_{i,n}(x,y) \cdot \exp\left( -\frac{\| F_i(x) - F_{i+n}(y) \|^2}{2\sigma_w^2} \right),
\]
where occlusion state $o_{i,n}(x, y) \in \{0, 0.01, 1\}$ is determined by cross-checking forward and backward flows similar to the occlusion detection technique used in [43]. The 5x5 patch $P_i(x)$ is centered at $x$ in frame $i$. The similarity control parameter $\sigma_w$ is fixed as $\sigma_w = 25/255$.

5 MOTION BLUR DATASET

Because conventional evaluation datasets for deblurring [25], [26] are generated under static scene assumption, complex and spatially varying blurs in dynamic scenes are not provided. Therefore, in this section, we provide a new method generating blur dataset for the quantitative evaluation of non-uniform video deblurring algorithms and later studies of learning-based deblurring approaches.

5.1 Dataset Generation

As we assume motion blur kernels can be approximated by using bidirectional optical flows in (4), we can generate blurry frames adversely by averaging consecutive sharp frames whose relative motions between two neighboring frames are smaller than one pixel. In doing so, we use GOPRO Hero4 hand-held camera which supports taking a 240 fps video of 1280x720 resolution. A similar approach was introduced in [44], which uses a high-speed camera to generate blurry images. However, they captured only linearly moving objects with the fixed (static) camera.

Our captured videos include various dynamic scenes as well as static scenes. We calculate the average of $k$ successive frames to generate a single blurry frame. By averaging $k$ successive frames, realistic motion blurs from both moving objects and the camera shake can be rendered in the blurry frame, and the $240/k$ fps blurry video can be generated (i.e. 16 fps video is generated by averaging every 15 frames). Notably, the ground truth sharp frame is chosen to be the mid-frame used in averaging, since we aim to restore the latent frame captured in the middle of exposure time as shown in fig. 6. Thus the duty cycle is $\tau_i = 0.5$, in our whole dataset. The videos are recorded with caution so that the motions should be no greater than 1 pixel between two neighboring frames to render more smooth and realistic blurry frame.

Our dataset mainly captured outdoor scenes to avoid the flickering effect of fluorescent light which occurs when we capture indoor scenes with the high-speed camera. We captured numerous scenes in both dynamic and static environments, and each frame has HD (1280x720) size. In Fig. 10, some examples of our ground truth frames and rendered blurry frames are shown. We can see that the generated blurs are locally varying according to the depth changes and moving objects.

6 EXPERIMENTAL RESULTS

In this section, we demonstrate the superiority of our method over conventional methods. For evaluation, we use fixed parameters and the values are $\lambda = 250$, $\mu = 2$, $\nu_{\theta} = \nu_{\sigma} = 0.08 \lambda$, $v_I = (\frac{25}{255})^2$, and $N = 2$. Notably, all parameters used in our algorithm are determined empirically.

First, in Table 1 our deblurring results are quantitatively evaluated with the proposed motion blur dataset. Since the source codes of other video deblurring methods that can handle non-uniform blur are not available except for that of our previous work [20], we quantitatively compare our method with [20] in...
terms of the PSNR and SSIM values. To demonstrate the good performance of the proposed method in removing defocus blurs as well as motion blurs, we added different strengths of Gaussian blurs ($\sigma = 1, 1.5, 2$) to the original sharp videos before averaging. Using these datasets including both motion and defocus blurs, we verify that, the proposed approach improves the deblurring results significantly in terms of PSNR and SSIM by removing defocus blurs as well as motion blurs. Notably, our previous work [20] can not handle defocus blurs (i.e. $G_2 = identity matrix$). In Fig. [11] qualitative comparisons using our dataset are shown. Ours restores the edges of buildings, letters, and moving persons, clearly. However, we observe some failure cases in our results. In Fig. [12] we could not estimate accurate motions of the fast moving hand, and thus fail in deblurring. Notice that, it is difficult to estimate motion flows of the small structure with distinct motions in the coarse-to-fine framework as in [45].

In Table. [2] we also evaluate our method with MPI SINTEL dataset [46] which contains spatially varying defocus blurs unlike our high-speed camera dataset. As the proposed method could handle spatially varying defocus blurs, ours still outperforms the baseline method [20]. Notably, we use randomly chosen 10 sequences in the dataset for evaluation, and measure only SSIM values as fog effects are applied to blurry images and they make big intensity differences between blurry and sharp images in MPI SINTEL dataset. Moreover, in Table. [3] to evaluate deblurring qualities of our method for different blurs, we compare our method with conventional methods by changing blur types (i.e. motion blur, defocus blur, and both motion and defocus blurs). For evaluations, we additionally synthesize bi-layered blurry videos (10 sequences) which contain non-uniform motion blurs and/or spatially varying defocus blurs as suggested in [16]. To be specific, we make blurry backgrounds and foregrounds with different Gaussian blurs whose standard deviations are randomly chosen between [0, 2.5]. Then bi-layered blurry videos are generated using the method in [16]. In particular, we employ different translational models for each layer to generate locally varying motion blurs by randomly choosing the horizontal and vertical motion vectors between [7, 31]. As shown in Table. [3] ours shows competitive results against conventional methods when only motion blur or only defocus blur exists in the dataset. Moreover, ours outperforms conventional methods when both blurs are in the dataset. Notably, a naive two-stage approach (denoted as [20]+ [24]) which deblurs motion and defocus blurs in a sequential manner does not render better results, since it is not easy to handle motion and defocus blurs independently.

Next, we qualitatively compare our deblurring results with those of the state-of-the-art exemplar-based method [19] with the test videos used in their work. As shown in Fig. [15] the captured scenes are dynamic and contain multiple moving objects. The method [19] fails in restoring the moving objects because the object motions are large and distinct from the backgrounds. By contrast, our results show better performances in deblurring moving objects and backgrounds. Notably, the exemplar-based approach also fails in handling large blurs, as shown in Fig. [14] as the initially estimated homographies in the largely blurred images are inaccurate. Moreover, this approach renders excessively smooth results for mid-frequency textures such as trees, since the method is based on interpolation without spatial prior for latent frames. We also visually compare our method with the state-of-the-art segmentation-based deblurring approach [16]. The test video is shown in Fig. [15] which is a bilayer scene used in their original work. Although the bi-layer scene is a good example to verify the performance of the layered model, inaccurate segmentation near the boundaries causes serious artifacts in the restored frame. By contrast, since our method does not need segmentation, ours restores the clean boundaries much better than the layered model.

In Table. [3] we quantitatively compare the optical flow accuracies with blur-aware method [31] on MPI SINTEL dataset [46]. We measure average end point error (EPE) values to compare optical flow accuracies with 10 video sequences in SINTEL dataset. Although the method of Portz et al. [31] was proposed to handle blurry images in optical flow estimation, its assumption does not hold at the motion boundaries, which is very important for deblurring, thus ours achieves more accurate optical flows. Moreover, we also compare with traditional optical flow estimation methods [41], [47] which are based on brightness constancy and TV minimization similar to ours, and demonstrate our performance.

In Fig. [16] our color coded optical flows and defocus blur maps are compared with state-of-the-art methods. As we expect, optical flows from Portz et al. [31] are inaccurate at the motion boundaries of moving objects. By contrast, our model can cope with abrupt motion changes and thus performs better than the conventional model. Notably, in Fig. [16] (a), ours estimates depth-related defocus blur map very accurately even when motion blurs co-exist. In addition, in Fig. [15] (b), moving cars are focused, thus ours estimates defocus blur map which has the smaller value in the foreground. By contrast, state-of-the-art blur maps from [32] are very inaccurate due to motion blurs.

Moreover, we show the deblurring results with and without using the temporal coherence term $\gamma$, and verify that our temporal coherence model clearly restores edges and significantly reduces ringing artifacts near the edges in Fig. [17].

Finally, other deblurring results from numerous real videos are shown in Fig. [18]. Notice that, our model successfully restores the face which has highly non-uniform blurs because the person moves rotationally (e.g. Fig. [18] (e)).

The video demos are provided in the supplementary material. For additional results, please see our supplementary material. Moreover, our source code and new blur dataset are also available on our website: 1.

7 Conclusion

In this study, we introduced a novel method that removes general blurs in dynamic scenes which conventional methods fail to. We inferred bidirectional optical flows to parametrize motion blur kernels and estimated the scales of Gaussian blurs to approximate defocus blur kernels. Therefore the proposed method could handle general blurs, by estimating a pixel-wise different blur kernel. In addition, we proposed a new single energy model that estimates optical flows, defocus blur maps and latent frames, jointly. We also provided a framework and efficient solvers to minimize the proposed energy function and it has been shown that our method yields superior deblurring results to several state-of-the-art deblurring methods through intensive experiments with real challenging blurred videos. Moreover, we provided the publicly available benchmark dataset to evaluate the non-uniform deblurring methods and we quantitatively evaluated the performance of the proposed method using the proposed dataset. Nevertheless, our model has its limitations in handling large displacement fields.

TABLE 1: Deblurring performance evaluations in terms of PSNR (SSIM) with our synthetic dataset.

<table>
<thead>
<tr>
<th>Seq.</th>
<th>Motion blur + Gaussian blur (σ = 1.0)</th>
<th>Motion blur + Gaussian blur (σ = 1.5)</th>
<th>Motion blur + Gaussian blur (σ = 2.0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>28.02 (0.8552) 27.97 (0.8608)</td>
<td>27.53 (0.8374) 27.85 (0.8473)</td>
<td>26.84 (0.8135) 27.25 (0.8250)</td>
</tr>
<tr>
<td>#2</td>
<td>26.62 (0.8407) 26.97 (0.8519)</td>
<td>25.18 (0.7809) 25.61 (0.7982)</td>
<td>23.91 (0.7160) 24.28 (0.7334)</td>
</tr>
<tr>
<td>#3</td>
<td>32.89 (0.9182) 34.07 (0.9353)</td>
<td>31.27 (0.8849) 32.49 (0.9063)</td>
<td>29.94 (0.8501) 30.75 (0.8680)</td>
</tr>
<tr>
<td>#4</td>
<td>36.77 (0.9684) 36.60 (0.9675)</td>
<td>36.50 (0.9665) 36.61 (0.9698)</td>
<td>36.12 (0.9639) 36.38 (0.9649)</td>
</tr>
<tr>
<td>#5</td>
<td>24.15 (0.7260) 24.01 (0.7306)</td>
<td>23.05 (0.6598) 24.29 (0.7252)</td>
<td>24.03 (0.6989) 24.18 (0.7077)</td>
</tr>
<tr>
<td>#6</td>
<td>27.04 (0.8577) 27.51 (0.8712)</td>
<td>25.18 (0.7880) 25.70 (0.8078)</td>
<td>23.80 (0.7187) 24.20 (0.7374)</td>
</tr>
<tr>
<td>#7</td>
<td>29.07 (0.8863) 29.62 (0.8986)</td>
<td>27.31 (0.8360) 27.93 (0.8529)</td>
<td>25.87 (0.7809) 26.35 (0.7973)</td>
</tr>
<tr>
<td>#8</td>
<td>27.93 (0.8828) 28.46 (0.8940)</td>
<td>26.05 (0.8320) 26.62 (0.8468)</td>
<td>24.52 (0.7768) 24.96 (0.7914)</td>
</tr>
<tr>
<td>#9</td>
<td>30.38 (0.8793) 30.90 (0.8919)</td>
<td>29.05 (0.8427) 29.79 (0.8593)</td>
<td>27.81 (0.8028) 28.43 (0.8188)</td>
</tr>
<tr>
<td>#10</td>
<td>29.13 (0.8843) 29.61 (0.8961)</td>
<td>27.61 (0.8432) 28.23 (0.8587)</td>
<td>26.25 (0.7982) 26.76 (0.8131)</td>
</tr>
<tr>
<td>#11</td>
<td>32.42 (0.9471) 32.77 (0.9519)</td>
<td>30.47 (0.9283) 31.64 (0.9383)</td>
<td>28.81 (0.9064) 29.74 (0.9171)</td>
</tr>
</tbody>
</table>

Avg. 29.49 (0.8769) 29.86 (0.8863) 28.11 (0.8363) 28.80 (0.8553) 27.08 (0.8023) 27.57 (0.8158)

TABLE 2: Deblurring performance evaluations in terms of SSIM with MPI SINTEL dataset [46].

<table>
<thead>
<tr>
<th>Blur type</th>
<th>Motion</th>
<th>Defocus</th>
<th>Motion + Defocus</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>20.20</td>
<td>22.26</td>
<td>20.53</td>
</tr>
<tr>
<td>20</td>
<td>19.01</td>
<td>19.34</td>
<td>19.21</td>
</tr>
<tr>
<td>20</td>
<td>25.03</td>
<td>21.74</td>
<td>21.50</td>
</tr>
<tr>
<td>20 + 24</td>
<td>23.18</td>
<td>21.67</td>
<td>21.08</td>
</tr>
<tr>
<td>Ours</td>
<td>24.93</td>
<td>22.00</td>
<td>21.60</td>
</tr>
</tbody>
</table>

TABLE 3: Deblurring performances for removing defocus blur, motion blur, and both blurs, respectively are compared. PSNR and (SSIM) values are measured for evaluations. Bi-layered synthetic dataset which contains motion and/or defocus blurs is used for comparisons.

<table>
<thead>
<tr>
<th>Method</th>
<th>EPE</th>
<th>16.25</th>
<th>17.74</th>
<th>21.54</th>
<th>15.95</th>
<th>15.87</th>
</tr>
</thead>
<tbody>
<tr>
<td>42</td>
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<td>47</td>
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<td>31</td>
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<tr>
<td>20</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ours</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

TABLE 4: Optical flow evaluations in terms of end point error (EPE) with MPI SINTEL dataset [46]. Our initial optical flows from Wedel et al. [42], and flows from Zach et al. [47], Portzl et al. [31], Kim and Lee [20], and ours are compared.

REFERENCES

Fig. 11: Comparative deblurring results using our blur dataset. (a) Ground truth sharp frames. (b) Generated blurry frames including both motion and defocus blurs. (c) Deblurring results from [20]. (d) Our deblurring results.

Fig. 12: A failure case. (a) A blurry frame in the proposed dataset. (b) Our deblurring result.

Fig. 13: **Left to right:** Blurry frames of dynamic scenes, deblurring results of [19], and our results.

Fig. 14: **Left to right:** Blurry frame, deblurring result of [19], and ours.

Fig. 15: Comparison with segmentation-based approach. **Left to right:** Blurry frame, result of [16], and ours.
Fig. 16: **Left to right:** A real blurry frames with both motion and defocus blurs. Color coded optical flows from Portz et al. [31], and our optical flow results. Defocus blur maps of Shi et al. [32], and ours.

Fig. 17: (a) A blurry frame of a video. (b) Our deblurring result without using $E_{\text{temporal}}$. (c) Our deblurring result with $E_{\text{temporal}}$.

Fig. 18: **Top to bottom:** Numerous real blurry frames and our deblurring results.
Tae Hyun Kim received the BS and the MS degrees in the department of electrical engineering from KAIST, Daejeon, Korea, in 2008 and 2010, and Ph. D. degree in Electrical and Computer Engineering from Seoul National University (SNU), Seoul, Korea in 2016. He is currently working as a postdoctoral researcher with Bernhard Schölkopf at Max Planck Institute for Intelligent Systems. His research interests include low level computer vision and computational photography. He is a member of the IEEE.

Seungjun Nah received the BS degree in Electrical and Computer Engineering from Seoul National University (SNU), Seoul, Korea in 2014. He is currently working towards PhD degree in Electrical and Computer Engineering at Seoul National University. He is interested in computer vision problems including deblurring and visual saliency. He is a student member of the IEEE.

Kyoung Mu Lee received the B.S. and M.S. Degrees in Control and Instrumentation Eng. from Seoul National University (SNU), Seoul, Korea in 1984 and 1986, respectively, and Ph. D. degree in Electrical Engineering from the University of Southern California in 1993. He is currently with the Dept. of ECE at Seoul National University as a professor. Prof. Lee has received several awards, in particular, the Most Influential Paper Award in 2006, the Distinguished Professor Award from the college of Engineering of SNU in 2010. He is currently serving as an Area Editor of the IEEE TPAMI, the Machine Vision Application Journal and the IPSJ Transactions on Computer Vision and Applications, and the IEEE Signal Processing Letters. He also has served (or will serve) as a General Chair of ICCV2019, ACM MM2018, Program Chair of ACCV2015, a Track Chair of ICPR2012, Area Chair of CVPR2012, CVPR2013, CVPR2015, ECCV2014, ECCV2016 and a Workshop Chair of ICCV2013. He was a Distinguished Lecturer of the Asia-Pacific Signal and Information Processing Association (APSIPA) for 2012-2013. More information can be found on his homepage http://cv.snu.ac.kr/kmlee.