DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks

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Abstract

We present an end-to-end learning approach for motion deblurring, which is based on conditional GAN and content loss – DeblurGAN. DeblurGAN achieves state-of-the art in structural similarity measure and by visual appearance.[1] The quality of the deblurring model is also evaluated in a novel way on a real-world problem – object detection on (de-)blurred images. The method is 5 times faster than the closest competitor.

Second, we present a novel method of generating synthetic motion blurred images from the sharp ones, which allows realistic dataset augmentation.

Model, training code and dataset are available at https://github.com/KupynOrest/DeblurGAN

1. Introduction

This work is devoted to removing motion blur from a single photograph, given no information about kernel or camera movement. Large progress is done recently in related areas of image super-resolution [18] and in-painting [40] by applying generative adversarial networks (GANs) [10]. GANs are known for an ability to preserve high texture details in images and create solutions that are close to real image manifold and looks perceptually more convincing. Inspired by recent works on image super-resolution [18] and image-to-image translation by generative adversarial networks [14], we treat deblurring as a special case of such image-to-image translation. We present DeblurGAN – an approach based on Conditional Generative Adversarial Networks [22] and a multi-component loss function. Different from previous works we use Wasserstein GAN [2] with Gra-

Figure 1: DeblurGAN helps object detection. From top to bottom: YOLO [27] detections results on a blurred image, restored by DeblurGAN, ground truth sharp image.

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[1]Previously claimed new sota in peak-signal-to-noise ratio was due to evaluation bug. After fixing the mistake, DeblurGAN is on par with previous sota. Thanks to Huaijin Chen for catching it.
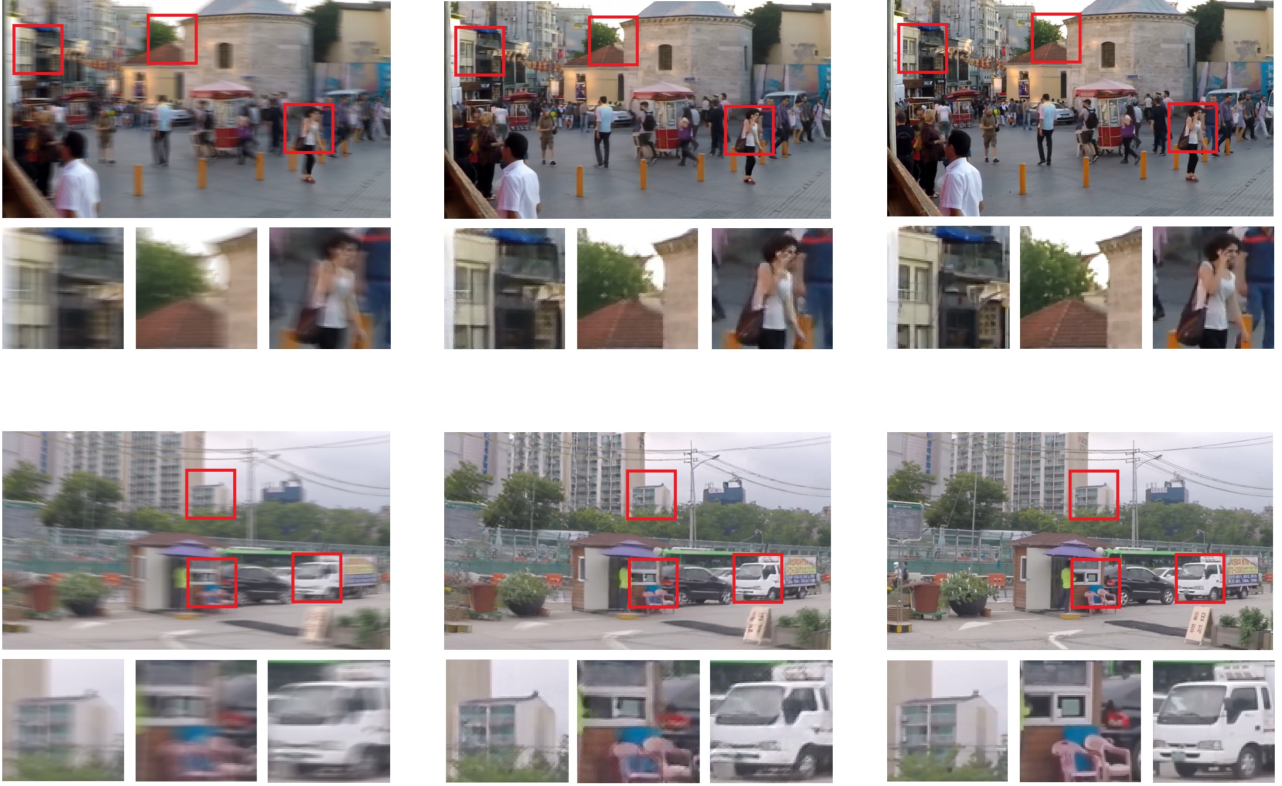
Figure 2: Images processed by DeblurGAN. From left to right: blurred photo, result of DeblurGAN, ground truth sharp image.

dient Penalty [11] and perceptual loss [15]. This encourages solutions which are perceptually hard to distinguish from real sharp images and allows to restore finer texture details in contrast to using traditional MSE or MAE as an optimization target.

Our contribution is three-fold. First, we propose a loss and architecture, which obtains new state-of-the art results in motion deblurring, while being 5x faster than the fastest competitor. Second, we present a method based on random trajectories for generating a dataset for motion deblurring training in an automated fashion from the set of sharp image. We show, that combining it with existing dataset for motion deblurring learning, improves results compared to training on real-world images only. Finally, we present a novel dataset and method for evaluation deblurring algorithms based on how they improve object detection results.

2. Related work

2.1. Image Deblurring

The common formulation of blur model is following:

$$I_B = K * I_S + N \qquad (1)$$

, where I_B is a blurred image, K is a blur kernel, I_S is a sharp latent image, $*$ denotes the convolution operation and N is an additive noise.

The whole family of deblurring methods is divided into two types: blind and non-blind deblurring. Early works [33] mostly focuses on non-blind deblurring, making an assumption that the blur function K is known. Most of them rely on the classical Lucy-Richardson algorithm, Wiener or Tikhonov filter to perform the deconvolution operation and obtain I_S estimate. In practice the blur function is unknown, so the blind deblurring algorithms estimate both latent sharp image I_S and blur kernel K. Finding a blur function for each pixel is an ill-posed problem, so most of the existing algorithms rely on image heuristics and assumptions on the sources of the blur. Those family of methods addresses the blur caused by camera shake by considering blur to be uniform across the image. Firstly, the camera motion is estimated in terms of the induced blur kernel, and then the effect is reversed by performing a deconvolution

operation. Starting with the success of Fergus *et al.* [8], a lot derivative methods [39][37][26][3] has been developed over the last ten years. Some of the methods are based on an iterative approach [8] [39], which improve the estimate of the motion kernel and sharp image on each iteration by using parametric prior models. However, the running time, as well as the stopping criterion, is a significant problem for those kinds of algorithms. Others use assumptions of a local linearity of a blur function and simple heuristics to quickly estimate the unknown kernel. These methods are fast but work well on a small subset of images. With the success of deep learning, over the last few years, there appeared some approaches based on convolutional neural networks (CNNs). Sun *et al.* [32] use CNN to estimate blur kernel, Chakrabarti [6] predicts complex Fourier coefficients of motion kernel to perform non-blind deblurring in Fourier space whereas Gong [9] use fully convolutional network to move for motion flow estimation. All of these approaches use CNN to estimate the unknown blur function. Recently, a kernel-free end-to-end approaches by Noorozi [25] and Nah [23] that uses multi-scale CNN to directly deblur the image. Such methods are able to deal with different sources of the blur.

2.2. Generative adversarial networks

The idea of generative adversarial networks, introduced by Goodfellow *et al.* [10], is to define a game between two competing networks: discriminator and generator. The generator receives noise as an input and generates a sample. A discriminator receives a real and generated sample and is trying to distinguish between them. The goal of the generator is to fool the discriminator by generating perceptually convincing samples that can not be distinguished from the real one. From the theoretical perspective, the game between the generator G and discriminator D is the minimax objective:

$$\min_{G} \max_{D} \mathop{\mathbb{E}}_{x \backsim \mathbb{P}_r} [\log(D(x))] - \mathop{\mathbb{E}}_{\tilde{x} \backsim \mathbb{P}_g} [\log(1 - D(\tilde{x}))]$$

where $\mathbb{P}_r$ is the data distribution and $\mathbb{P}_g$ is the model distribution, defined by $\tilde{x} = G(z), z \backsim P(z)$, the input z is a sample from a simple noise distribution. GANs are known for its ability to generate samples of good perceptual quality, however, training of vanilla version suffer from many problems such as mode collapse, vanishing gradients etc, as described in [29]. Minimizing the value function in GAN is equal to minimizing the Jensen-Shannon divergence between the data and model distributions on x. Arjovsky *et al.* [2] discuss the difficulties in GAN training caused by JS divergence approximation and propose to use the Earth-Mover (also called Wasserstein-1) distance $W(q, p)$. The value function for WGAN is constructed using Kantorovich-Rubinstein duality [35]:

$$\min_{G} \max_{D \in \mathcal{D}} \mathop{\mathbb{E}}_{x \backsim \mathbb{P}_r} [D(x)] - \mathop{\mathbb{E}}_{\tilde{x} \backsim \mathbb{P}_g} [D(\tilde{x})] \quad (2)$$

where $\mathcal{D}$ is the set of $1-$Lipschitz functions and $\mathbb{P}_g$ is once again the model distribution The idea here is that critic value approximates $K \cdot W(P_r, P_\theta)$, where K is a Lipschitz constant and $W(P_r, P_\theta)$ is a Wasserstein distance. In this setting, a discriminator network is called critic and it approximates the distance between the samples. To enforce Lipschitz constraint in WGAN Arjovsky *et al.* add weight clipping to $[-c, c]$. This technique, however, may lead to optimization difficulties such as capacity under-use or exploding/vanishing gradients. Gulrajani *et al.* [11] propose to add a gradient penalty term:

$$\lambda \mathop{\mathbb{E}}_{\tilde{x} \backsim \mathbb{P}_{\tilde{x}}} [(\|\nabla_{\tilde{x}} D(\tilde{x})\|_2 - 1)^2]$$

to the value function as an alternative way to enforce the Lipschitz constraint. This enables stable training of a wide variety of GAN architectures with almost no hyperparameter tuning.

2.3. Conditional adversarial networks

Generative Adversarial Networks have been applied to different image-to-image translation problems, such as super resolution [18], style transfer [20], product photo generation [5] and others. Isola *et al.* [14] provides a detailed overview of those approaches and present conditional GAN architecture also known as *pix2pix*. Unlike vanilla GAN, cGAN learns a mapping from observed image x and random noise vector z, to $y : G : x, z \rightarrow y$. Isola *et al.* also put a condition on the discriminator and use U-net architecture [28] for generator and Markovian discriminator which allows achieving perceptually superior results on many tasks, including synthesizing photos from label maps, reconstructing objects from edge maps, and colorizing images.

3. Proposed method

The goal is to recover sharp image I_S given only a blurred image I_B as an input, so no information about the blur kernel is provided. To do that we train a CNN G_{θ_G}, to which we refer as the Generator. For each I_B it estimates corresponding I_S image. In addition, during the training phase, we introduce critic function D_{θ_D} and train both networks in an adversarial manner.

3.1. Loss function

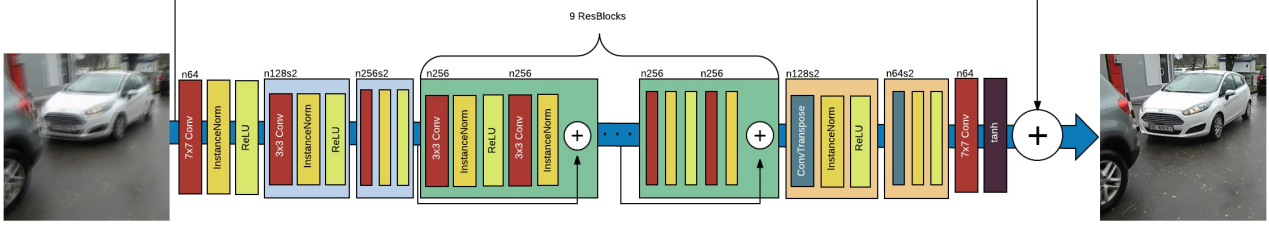We formulate the loss function as a combination of content and adversarial loss:

Figure 3: Architecture of the DeblurGAN generator network. DeblurGAN contains two strided convolution blocks with stride $\frac{1}{2}$, nine residual blocks [12] and two transposed convolution blocks. Each ResBlock consists of a convolution layer, instance normalization layer, and ReLU activation.

$$\mathcal{L} = \underbrace{\underbrace{\mathcal{L}_{GAN}}_{adv\ loss} + \underbrace{\lambda \cdot \mathcal{L}_X}_{content\ loss}}_{total\ loss}$$

where the λ equals to 100 in all experiments. Unlike Isola *et al.* [14] we do not condition the discriminator as we do not need to penalize mismatch between the input and output. **Adversarial loss** Most of the papers related to conditional GANs, use vanilla GAN objective as a loss [18][23]. More recently [41] provides an alternative way of using Least Square GAN [21] which is more stable and generates higher quality results. We use WGAN-GP [11] as the critic function. The critic does not output a probability that the reconstructed image is sharp and the loss is calculated as the following:

$$\mathcal{L}_{GAN} = \sum_{n=1}^{N} -D_{\theta_D}(G_{\theta_G}(I^B)) \qquad (3)$$

Content loss Two classical choices for "content" loss function are **L1** or **MAE** loss, **L2** or **MSE** loss on raw pixels. Instead, we adopted recently proposed **Perceptual** loss [15]. Perceptual loss is a simple L2-loss, but based on the difference of the generated and target image CNN feature maps. It is defined as following:

$$\mathcal{L}_X = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(I^S)_{x,y} - \phi_{i,j}(G_{\theta_G}(I^B))_{x,y})^2$$

where $\phi_{i,j}$ is the feature map obtained by the j-th convolution (after activation) before the i-th maxpooling layer within the VGG19 network, pretrained on ImageNet [7], $W_{i,j}$ and $H_{i,j}$ are the dimensions of the feature maps.

3.2. Network architecture

Generator CNN architecture is shown in Figure 3. It is similar to one proposed by Johnson *et al.* [15] for style transfer task. It contains two strided convolution blocks with stride $\frac{1}{2}$, nine residual blocks [12] (ResBlocks) and two transposed convolution blocks. Each ResBlock consists of

a convolution layer, instance normalization layer [34], and ReLU [24] activation. Dropout [31] regularization with a probability of 0.5 is added after the first convolution layer in each ResBlock.

In addition, we introduce the global skip connection which we refer to as ResOut. CNN learns a residual correction I_R to the blurred image I_B, so $I_S = I_B + I_R$. We find that such formulation makes training faster and resulting model generalizes better.

During the training phase, we define a critic network D_{θ_D}, which is Wasserstein GAN [2] with Gradient Penalty [11], to which we refer as WGAN-GP. The architecture of critic network is identical to PatchGAN [14, 20]. All the convolutional layers except the last are followed by InstanceNorm layer and LeakyReLU [36] with $\alpha = 0.2$.

4. Motion blur generation

There is no easy method to obtain image pairs of corresponding sharp and blurred images for training, in contrast to other popular image-to-image translation problems, such as super-resolution or colorization. A typical approach to obtain image pairs for training is to use a high frame-rate camera to simulate blur using average of sharp frames from video [25, 23]. It allows to create realistic blurred images but limits the image space only to scenes present in taken videos and makes it complicated to scale the dataset. Sun *et al.* [32] creates synthetically blurred images by convolving clean natural images with one out of 73 possible linear motion kernels, Xu *et al.* [38] also use linear motion kernels to create synthetically blurred images. Chakrabarti [6] creates blur kernel by sampling 6 random points and fitting a spline to them.

We take a step further and propose a method, which simulates more realistic and complex blur kernels. We follow the idea described by Boracchi and Foi [4] of random trajectories generation. Then the kernels are generated by applying sub-pixel interpolation to the trajectory vector. Each trajectory vector is a complex valued vector, which corresponds to the discrete positions of an object following 2D

Wasserstein distance

Critic

Perceptual loss +
WGAN loss

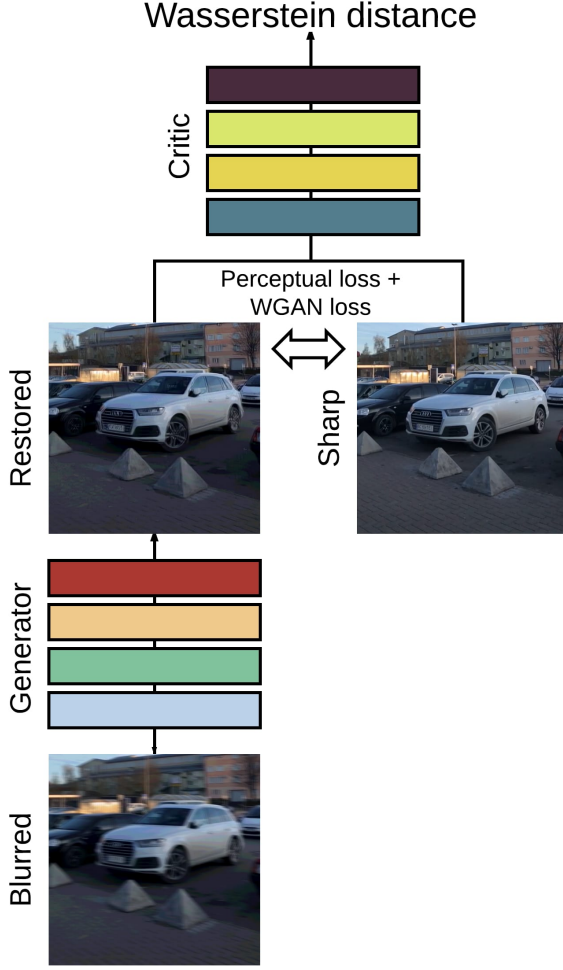Restored   Sharp

Generator

Blurred

Figure 4: Conditional GAN for motion deblurring. Generator network takes the blurred image as an input and produces the estimate of the sharp image. During the training time, the critic network takes restored and sharp image as an input and estimates a distance between them. Total loss consists of WGAN loss from critic and perceptual loss [15] based on the difference in activations of VGG-19 [30] between the feature maps of sharp and restored images. At test time only the generator is kept

random motion in a continuous domain. Trajectory generation is done by Markov process, summarized in Algorithm 1. Position of the next point of the trajectory is randomly generated based on the previous point velocity and position, gaussian perturbation, impulse perturbation and deterministic inertial component

5. Training Details

We implemented all of our models using PyTorch[1] deep learning framework. The training was performed on a

Algorithm 1 Motion blur kernel generation. Initial parameters:
$M = 2000$ – number of iterations, $L_{max} = 60$ – max length of the movement,
$p_s = 0.001$ – probability of impulsive shake.
I = inertia term, uniform from $(0,0.7)$
p_b – probability of big shake, uniform from $(0,0.2)$
p_g – probability of gaussian shake, uniform from $(0,0.7)$
ϕ – initial angle, uniform from $(0,2\pi)$
x – trajectory vector

1: **procedure** BLUR(Img, M, L_{max}, p_s)
2:     $v_0 \leftarrow cos(\phi) + sin(\phi) * i$
3:     $v \leftarrow v_o * L_{max}/(M-1)$
4:     $x = \text{zeros}(M, 1)$
5:     **for** $t = 1$ to $M - 1$ **do**
6:         **if** randn $< p_b * p_s$ **then**
7:             nextDir $\leftarrow 2 \cdot v \cdot e^{i*(\pi+(\text{randn}-0.5))})$
8:         **else**:
9:             nextDir $\leftarrow 0$
10:         $dv \leftarrow \text{nextDir} + p_s * (p_g * (\text{randn} + i * \text{randn}) * I * x[t] * (L_{max}/(M-1))$
11:         $v \leftarrow v + dv$
12:         $v \leftarrow (v/abs(v)) * L_{max}/(M-1)$
13:         $x[t+1] \leftarrow x[t] + v$
14:     Kernel $\leftarrow$ sub pixel interpolation(x)
15:     Blurred image $\leftarrow conv(\text{Kernel}, \text{Img})$
16:     **return** Blurred image

single Titan-X GPU using three different datasets. The first model to which we refer as *DeblurGAN_WILD* was trained on a random crops of size 256x256 from GoPro dataset images [23] downscaled by a factor of two.. The second one *DeblurGAN_Synth* was trained on 256x256 patches from MS COCO dataset blurred by method, presented in previous Section. We also trained *DeblurGAN_Comb* on a combination of synthetically blurred images and images taken in the wild, where the ratio of synthetically generated images to the images taken by a high frame-rate camera is 2:1. As the models are fully convolutional and are trained on image patches they can be applied to images of arbitrary size. For optimization we follow the approach of [2] and perform 5 gradient descent steps on D_{θ_D}, then one step on G_{θ_G}, using Adam [16] as a solver. The learning rate is set initially to 10^{-4} for both generator and critic. After the first 150 epochs we linearly decay the rate to zero over the next 150 epochs. At inference time we follow the idea of [14] and apply both dropout and instance normalization. All the models were trained with a batch size = 1, which showed empirically better results on validation. The training phase took 6 days for training one *DeblurGAN* network.
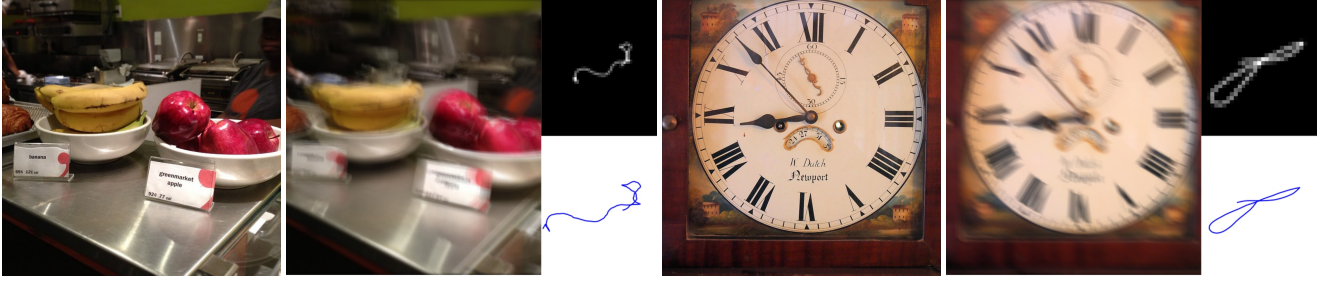
Figure 5: Examples of generated camera motion trajectory and the blur kernel and the corresponding blurred images.
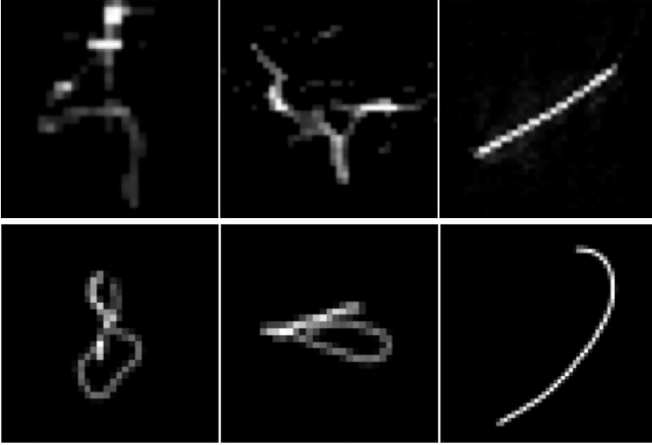

Figure 6: Top row: Blur kernels from real-world images estimated by Fergus *et al.* [8]. Bottom row: Synthetically generated kernels by our method. Our randomized method can simulate wide variety of realistic blur kernels with different level of non-linearity.

6. Experimental evaluation

6.1. GoPro Dataset

Table 1: Mean peak signal-to-noise ratio and structural similarity measure on GoPro test dataset of 1111 images. We took *linear* image subset for testing all models. State-of-art results (∗) by Nah *et al.* [23] obtained with *gamma* subset.

Method	Sun *et al.*	Nah *et al.*	DeblurGAN		
Metric	[32]	[23]	*WILD*	*Synth*	*Comb*
PSNR	24.64	28.34/**29.1***	27.21	23.69	**28.72**
SSIM	0.842	0.916	0.954	0.884	**0.958**
Time	20 min	4.33 s		**0.85 s**	

GoPro dataset[23] consists of 2103 pairs of blurred and sharp images in 720p quality, taken from various scenes. We compare the results of our models with state of the art models [32], [23] on standard metrics and also show the running time of each algorithm on a single **GPU**. Results are in Table1. DeblurGAN shows superior results in terms of structured self-similarity, is close to state-of-the-art in peak signal-to-noise-ratio and provides better looking results by visual inspection.[2] It can handle blur caused by camera shake and object movement, does not suffer from usual artifacts in kernel estimation methods and at the same time has more than 6x fewer parameters comparing to Multi-scale CNN , which heavily speeds up the inference. Deblured images from test on GoPro dataset are shown in Figure 7.

6.2. Kohler dataset

Kohler dataset [17] consists of 4 images blurred with 12 different kernels for each of them. This is a standard benchmark dataset for evaluation of blind deblurring algorithms. The dataset is generated by recording and analyzing real camera motion, which is played back on a robot platform such that a sequence of sharp images is recorded sampling the 6D camera motion trajectory. Results are in Table 2, similar to GoPro evaluation.

Table 2: Mean peak signal-to-noise ratio and structural similarity measure on Kohler benchmark dataset.

Method	Sun *et al.*	Nah *et al.*	DeblurGAN		
Metric	[32]	[23]	*WILD*	*Synth*	*Comb*
PSNR	25.22	26.02	**26.10**	25.67	25.86
MSSIM	0.773	0.811	**0.816**	0.792	0.802

6.3. Object Detection benchmark on YOLO

Object Detection is one of the most well-studied problems in computer vision with applications in different domains from autonomous driving to security. During the last

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[2]Previously reported sota PSNR equal to 33.29 on GoPro dataset was due to mistake in evaluation code. In particular, pixel values were not converted from uint8 to float before calculating mean. Kohler dataset is not impacted by this mistake, because we use reference Matlab implementation.
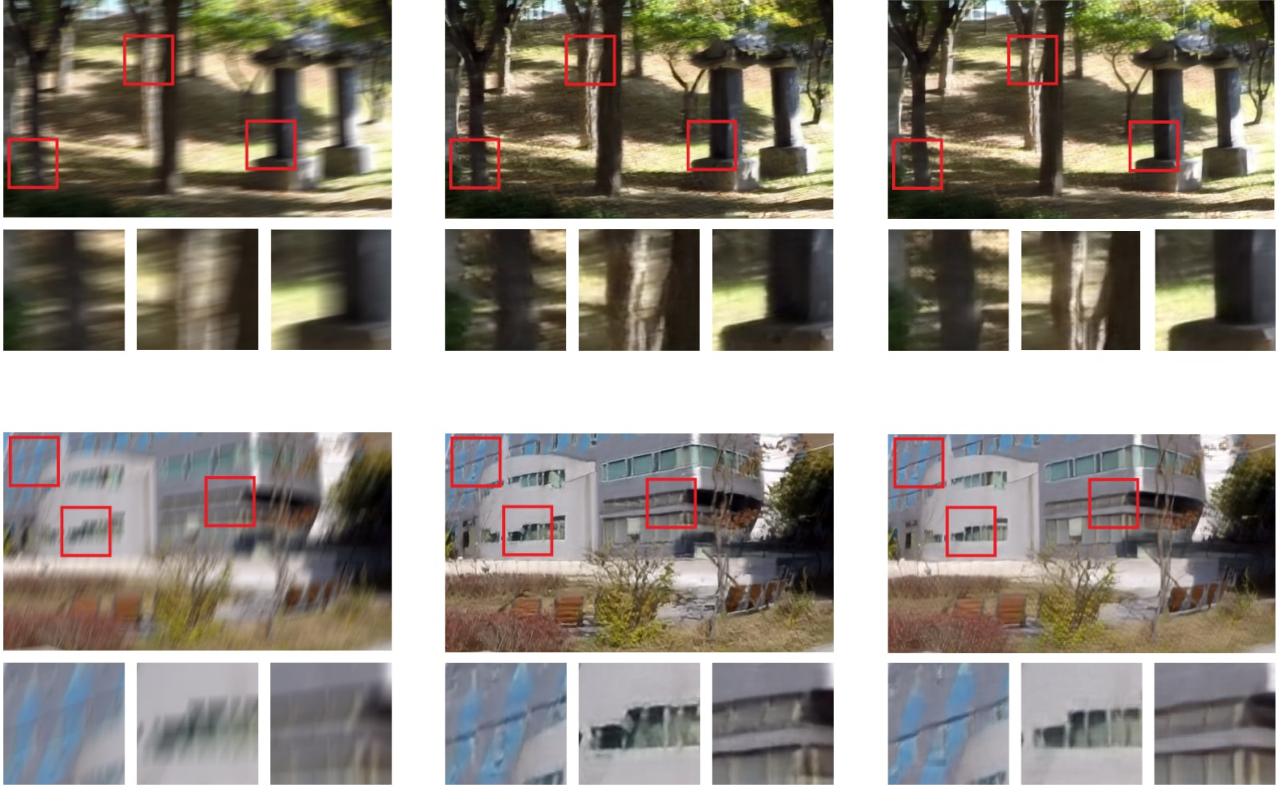
Figure 7: Results of evaluation on GoPro test dataset. From left to right: blurred photo, result of Nah *et al*. [23], result of our algorithm.

few years approaches based on Deep Convolutional Neural Networks showed state of the art performance comparing to traditional methods. However, those networks are trained on limited datasets and in real-world settings images are often degraded by different artifacts, including motion blur, Similar to [19] we studied the influence of motion blur on object detection and propose a new way to evaluate the quality of deblurring algorithm based on results of object detection on a pretrained YOLO [27] network.

For this, we constructed a dataset of sharp and blurred street views by simulating camera shake using a high framerate video camera. Following [13][23][25] we take a random between 5 and 25 frames taken by 240fps camera and compute the blurred version of a middle frame as an average of those frames. All the frames are gamma-corrected with $\gamma = 2.2$ and then the inverse function is taken to obtain the final blurred frame. Overall, the dataset consists of 410 pairs of blurred and sharp images, taken from the streets and parking places with different number and types of cars.

Blur source includes both camera shake and blur caused by car movement. The dataset and supplementary code are available online. Then sharp images are feed into the YOLO network and the result after visual verification is assigned as ground truth. Then YOLO is run on blurred and recovered versions of images and average recall and precision between obtained results and ground truth are calculated. This approach corresponds to the quality of deblurring models on real-life problems and correlates with the visual quality and sharpness of the generated images, in contrast to standard PSNR metric. The precision, in general, is higher on blurry images as there are no sharp object boundaries and smaller object are not detected as it shown in Figure 9.

Results are shown in Table 3. DeblurGAN significantly outperforms competitors in terms of recall and F1 score.

7. Conclusion

We described a kernel-free blind motion deblurring learning approach and introduced DeblurGAN which is a Conditional Adversarial Network that is optimized using a multi-component loss function. In addition to this, we implemented a new method for creating a realistic synthetic motion blur able to model different blur sources. We in-
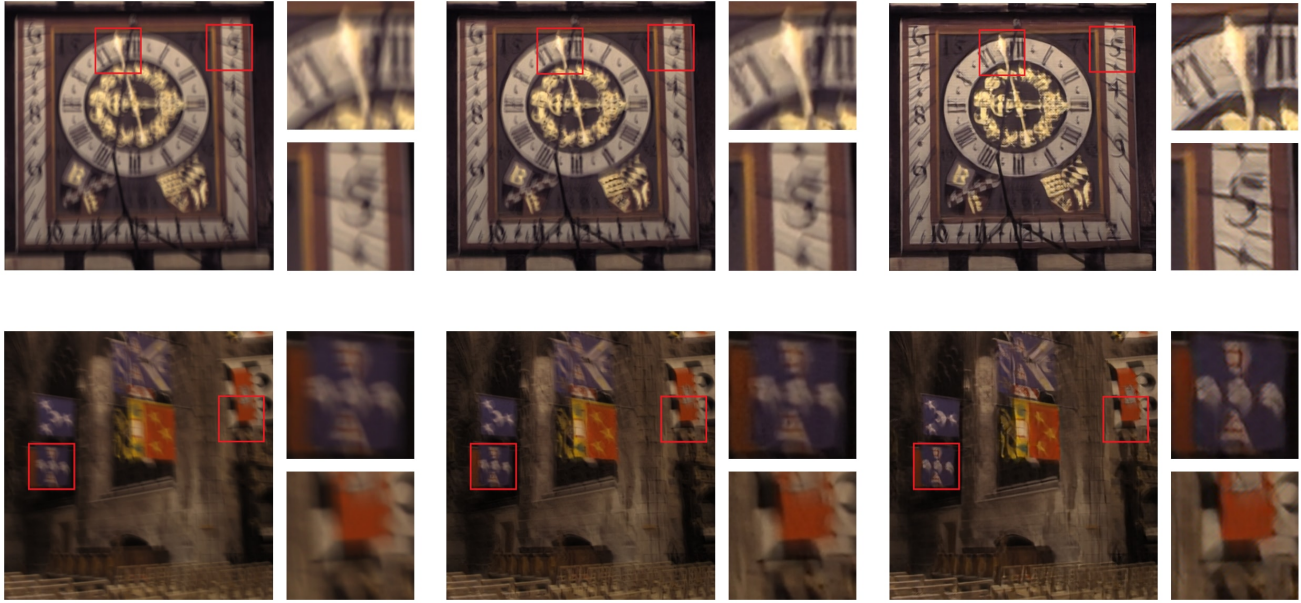
Figure 8: Evaluation on Kohler dataset. From left to right: blurred photo, Nah *et al*. [23], DeblurGAN

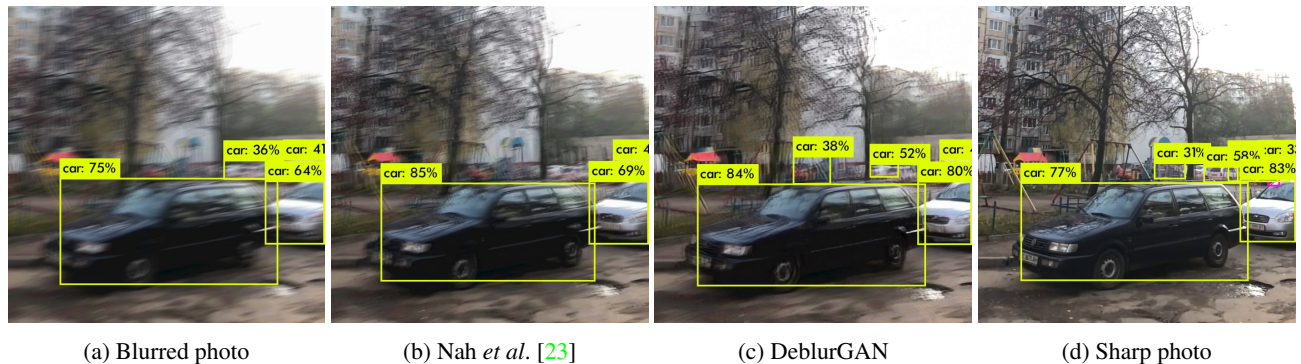(a) Blurred photo   (b) Nah *et al*. [23]   (c) DeblurGAN   (d) Sharp photo

Figure 9: YOLO object detection before and after deblurring

Table 3: Results of object detection on YOLO [27] on blurred and restored photos using our and Nah *et al*. [23] algorithms. We take the results on corresponding sharp images as the ground truth. DeblurGAN has higher recall and F1 score than its competitors.

Method	prec.	recall	F1 score
no deblur	0.821	0.437	0.570
Nah *et al*. [23]	**0.834**	0.552	0.665
DeblurGAN WILD	0.764	0.631	0.691
DeblurGAN synth	0.801	0.517	0.628
DeblurGAN comb	0.671	**0.742**	**0.704**

troduce a new benchmark and evaluation protocol based on results of object detection and show that DeblurGAN significantly helps detection on blurred images.

8. Acknowledgements

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