LSD$_2$ – Joint Denoising and Deblurring of Short and Long Exposure Images with Convolutional Neural Networks

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Abstract

The paper addresses the problem of acquiring high-quality photographs with handheld smartphone cameras in low-light imaging conditions. We propose an approach based on capturing pairs of short and long exposure images in rapid succession and fusing them into a single high-quality photograph. Unlike existing methods, we take advantage of both images simultaneously and perform a joint denoising and deblurring using a convolutional neural network. The network is trained using a combination of real and simulated data. To that end, we introduce a novel approach for generating realistic short-long exposure image pairs. The evaluation shows that the method produces good images in extremely challenging conditions and outperforms existing denoising and deblurring methods. Furthermore, it enables exposure fusion even in the presence of motion blur.

1. Introduction

Capturing high-quality images in difficult acquisition conditions is a formidable challenge. Such conditions, which are not uncommon, include low lighting levels and dynamic scenes with significant motion or high dynamic range, e.g. in the presence of both dark shadows and bright highlights. The problems related to low-light imaging affect all cameras but they are most pronounced in smartphones, the currently most commonly used acquisition device, where the camera and optics need to be small, lightweight and cheap.

The situation is particularly challenging if the device is handheld or the scene is dynamic as no satisfactory compromise between short and long exposure times exists. To get rich colors and good brightness with low noise, one should choose long exposure with low sensor sensitivity setting (ISO number). However, this will cause strong motion blur if the camera is moving (shaking) or if there is motion in the scene. On the other hand, a short exposure and high sensitivity setting will produce sharp but noisy images. Examples of such short and long exposure images are shown in Fig. 1.

We propose a novel approach that addresses the aforementioned challenges by taking “the best of both worlds” via computational photography, avoiding the unsatisfactory trade-off between the short and long exposure settings. The method captures pairs of short and long exposure images in almost instantaneous succession and fuses them into a single high-quality image using a convolutional neural network (CNN). The overall capture time is only fractionally longer than the long exposure. Many current mobile devices can be programmed to capture sequences of images with different exposure times in rapid bursts without any extra hardware or notable delay.
The proposed CNN-based method, called LSD$_2$\textsuperscript{1} performs joint image denoising and deblurring, exploiting information from both images, adapting their contributions to the conditions at hand. Thus, it brings significant practical benefits in comparison to conventional denoising and deblurring methods, which are limited by the information in a single image. Furthermore, LSD$_2$ does not rely on existing denoising algorithms unlike previous methods that utilize short-long exposure image pairs for image deblurring [37, 33].

Besides the problems of noise and blur, mobile imaging suffers from the limited dynamic range of camera sensors, which is often more severe in smartphone cameras than in digital single-lens reflex cameras. Even if the user were able to keep the camera perfectly still, the camera might not be able to capture the full dynamic range of the scene with a single exposure. Thus, details are typically lost either in dark shadows or bright highlights. LSD$_2$ approach provides a solution to this problem and produces more faithful colors and brightness values than in single-exposure input images. We note that previous exposure fusion algorithms such as [24] assume that input images are neither blurry nor misaligned.

The approach has the following key ingredients. We train a U-net type deep convolutional neural network that takes a pair of short-long exposure images as input and provides a single image as output. The network is trained using both simulated and real data. A large volume of simulated data is generated from regular high-quality photographs by synthesizing both short- and long-exposure images. Real training data are acquired by capturing image pairs of static scenes with varying exposure times using a tripod. The long exposure image in each real pair is the ground truth target for the network and the blurred input is obtained by adding synthetic blur to it. Additionally, we train a second network for exposure fusion, which takes the short-exposure image and the output of the LSD$_2$ network as input and produces a tone-mapped result as shown in Fig. 1.

The main contributions of the paper are the following:

- We present LSD$_2$, the first joint denoising and deblurring approach based on convolutional neural networks, and show results superior to the state-of-the art. The network will be made public.

- We propose a novel approach for generating realistic training and evaluation data. The data will be published to facilitate future research.

- We show that processing the output of the LSD$_2$ network with an exposure fusion network achieves better reproduction of colors and brightness than a single-exposure smartphone image.

\textsuperscript{1}LSD$_2$ stands for Long-Short Denoising and Deblurring.

2. Related work

Single-image denoising is a classical problem, which has been addressed using various approaches such as sparse representations [7], transform-domain collaborative filtering [5] or nuclear norm minimization [9]. In addition, several deep learning based approaches have been proposed recently [14, 2, 38, 17]. Typically the deep networks are trained with pairs of clean and noisy images [14, 2, 38], but it has been shown that training is possible without clean targets [17]. The raw sensors data has also been used to improve low-light imaging [3]. Besides the end-to-end deep learning approaches there are methods that utilize either conventional feed-forward networks [39] or recurrent networks [4] as learnable priors for denoising. Randomly initialized networks have been used as priors without pretraining [31]. Many of the recent methods can be applied to other restoration tasks, such as inpainting [17, 31] and single-image super-resolution [38, 4]. Nevertheless, in contrast to our approach, the aforementioned methods focus on single image restoration and do not address multi-image denoising and deblurring.

Single-image deblurring is an ill-posed problem and various kind of priors have been utilized to regularize the solutions. For example, the so called dark and bright channel priors [22, 36] have been used with promising results. However, these methods assume spatially invariant blur which limits their practicality. Priors based on deep networks have also been proposed [39]. There are end-to-end approaches, where a neural network takes the blurry image as input and directly outputs a deblurred result [21, 20, 16]. Some methods utilize inertial sensor data in addition to images [19, 11]. Other methods first estimate blur kernels and thereafter perform non-blind deconvolution [29, 8], and some approaches utilize deep networks for removing the deconvolution artifacts [27, 32]. Despite recent progress, single-image deblurring methods often fail to produce satisfactory results since the problem is very challenging and ill-posed. That is, unlike our approach, the aforementioned methods can not utilize a sharp but noisy image to guide the deblurring.

Recently, several multi-image denoising [10, 18] or deblurring approaches [6, 35, 34, 1] have been proposed that are based on processing a burst of input images that are captured consecutively. However, unlike our approach, these methods do not vary the exposure time of the images but use either short or long exposure bursts and, hence, they address either denoising or deblurring, but not both problems jointly like we do. Moreover, since the characteristics of their input images are not as complementary as in our case, we will publish the Android software we developed for acquisition of the back-to-back short and long exposure images, enabling reproducibility of our results and further exploitation of multi-exposure imagery.
they can not get “the best of both worlds” but suffer the
drawbacks of either case. For example, a burst of short
exposure images may suffer from too low light and low signal
to noise ratio in the darkest scene regions, although align-
ment and weighted averaging of multiple frames can allevi-
ate the problem to some extent [10, 18]. On the other hand,
using only relatively long exposure has problems with dy-
namic scenes as there may be severe spatial misalignment
between the images, and the capture time is longer so that
fast-moving objects may disappear from the view. On top
of that, based on our own observations and earlier studies
[18, 1], it seems that due to the non-complementary nature
of constant exposure images it is necessary to use more in-
put frames than two and this may increase the consump-
tion of memory, power, and processing time. Moreover,
with a constant exposure the saturated bright regions can
not be easily avoided and high dynamic range imaging is
not achieved.

A similar problem setting as in our work is considered in
[37, 33]. These methods utilize short-long exposure image
pairs for image deblurring. They first estimate blur kernels
for the blurry image and thereafter use the so-called resid-
ual deconvolution, proposed by [37], to iteratively estimate
the residual image that is to be added to the denoised sharp
image. We note that both methods use [23] for denoising.
It was demonstrated in [33] that the results of [37] could be
improved by introducing a non-uniform blur model. One
limitation of [33] is that their model is not applicable to
non-static scenes and it assumes that the motion of the cam-
era during exposure is limited to rotations about its optical
center, whereas LSD2 generalizes to a more diverse set of
motions. Another drawback of [37] and [33] is that they
require a separate photometric and geometric registration
stage, where the rotation is estimated manually [37]. We
compared our approach to [33] using their images (static
scene, pure rotation) and observed that our results are bet-
ter or comparable despite the fact that the images have un-
known exposure times and they are captured with another
camera having different noise characteristics (see Fig. 6).

3. Method Overview

The short and long exposure images can be captured
with a modern mobile device that supports per-frame cam-
era control. An example is shown in Fig. 1. The short
exposure image is sharp but noisy as it is taken with a high
sensitivity setting of ISO equal to 800. Notice that the col-
ors are distorted w.r.t. the long exposure image with ISO
equal to 200, which is blurry due to camera motion. Fur-
thermore, the images are slightly misaligned even though
they are captured immediately one after the other.

Fig. 2 shows an overview of the proposed LSD2 method.
The goal is to recover the underlying sharp and noise-free
image using a pair of long and short exposure images. The
input images are jointly denoised and deblurred by a con-
volutional neural network similar to U-net [25]. The archi-
tecture of the network and training details are covered in
Sec. 5.

Capturing real pairs of noisy and blurry images together
with the ground truth sharp images is a major challenge. To
train the network, we propose a data generation framework
that produces realistic training data with the help of gyro-
scope readings recorded from handheld movements. De-
tails of the data generation framework are given in the next
section. To further improve the performance, the network
is fine-tuned with real short and long exposure images cap-
tured with a mobile device as described in Sec. 5.3.

4. Data Generation

In order to train the network, we need pairs of noisy
and blurry images together with the corresponding sharp
images. Since there is no easy way to capture such real-
world data, we propose a data generation framework that
synthesizes realistic pairs of short and long exposure im-
ages. By utilizing images taken from the Internet and gyro-
scope readings, we can generate unlimited amount of train-
ing data with realistic blur while covering a wide range of
different scene types.

In the following subsections, we describe the different
stages of our data generation pipeline: synthesis of long
and short exposure image pairs, addition of noise and re-
alistic blur, and simulation of spatial misalignment. The
LSD2 network operates with images having intensity range
[0, 1] and hence we first scale the original RGB values to
that range. Since the aforementioned imaging effects oc-
cur in linear color space, we invert the gamma correction of
the input images. As we do not know the real value of the
gamma, it is assumed that γ = 2.2. Once the images have
been generated, the gamma is re-applied.

4.1. Synthesis of Long Exposure Images

We take a regular high-quality RGB image I from Inter-
net as the starting point of our simulation. We avoid overex-
posed or underexposed photographs. However, at test time
our long exposure input image should be slightly overex-
posed in order to enable high dynamic range and ensure
sufficient illumination of darkest scene regions. Hence, we
need to simulate the saturation of intensities due to overex-
posure. We do that by first multiplying the intensity values
with a random number s uniformly sampled from the inter-
val [1, 3]. The short exposure image is generated from this
intensity-scaled version sI, as described in the next sub-
section. Then, by clipping the maximum intensity to value
of 1, we get the sharp long exposure image, which will be
the ground truth target for network training. That is, we
train the network to predict an output with similar expos-
ure as the long exposure image. This enables us to use the
real long exposure images captured with a tripod as targets when fine-tuning with real data (Sec. 5.3). In practical use, the degree of overexposure can be controlled by utilizing an auto-exposure algorithm to determine the long exposure time. Further, the performance can be improved by selecting the ratio between the short and long exposure time to be always constant even if the absolute time varies, e.g. based on brightness of the scene. Thus, we record the real image pairs so that the short exposure time is always 1/30 of the long exposure time.

4.2. Underexposure and Color Distortion

The underexposed short exposure image is synthesized from the aforementioned long exposure image $sI$, where intensities can exceed 1, by applying affine intensity change $(asI + b)$ with random coefficients $(a, b)$ sampled from uniform distributions, whose parameters are determined by analyzing the intensity distributions of real short and long exposure pairs, captured with a constant exposure time ratio (1/30).

Our analysis of real image pairs showed that the colors are often distorted in the noisy short exposure image as show in Fig. 1. Hence, in order to simulate the distortion, we randomly sample different affine transformation parameters $(a_i, b_i)$ for each color channel $i$. Moreover, the parameters of the uniform distributions for $a_i$ and $b_i$ are determined independently for each color channel and they are such that $a_i < 0.3$ and $b_i < 0.01$ always. By introducing random color distortions, we encourage the network to learn the colors and brightness mainly from the (blurry) long exposure image.

The final short exposure image for network training is obtained by adding noise after the affine intensity change. An example of synthetic short exposure image is shown in Fig. 3 and details of added noise are described in Sec. 4.5.

4.3. Motion Blur

The motion blur is simulated only to the long exposure image $sI$. Synthetically blurred images are generated with help of gyroscope measurements. Similar to prior work [11, 26], we assume that motion blur is mainly caused by the rotation of the camera. We start by recording a long sequence of gyroscope readings with a mobile device. The device is kept more or less steady during the recording to simulate a real life imaging situation with a shaking hand.

Let $t_1$ denote the starting time of the synthetic image exposure. It is randomly selected to make each of the blur fields different. The level of motion blur is controlled by the exposure time parameter $t_e$, which defines the end time of the exposure $t_2 = t_1 + t_e$. The rotation of the camera $R(t)$ is obtained by solving the quaternion differential equation driven by the angular velocities and computing the corresponding direction cosine matrices [30]. Assuming that the translation is zero (or that the scene is far away), the motion blur can be modelled using a planar homography

$$H(t) = KR(t)K^{-1},$$

where $K$ is the intrinsic camera matrix. Let $x = (x, y, 1)^T$ be a projection of the 3D point in homogeneous coordinates. The point-spread-function (PSF) of the blur at the given location can be computed by $x' = H(t)x$.

Since mobile devices are commonly equipped with a rolling shutter camera, each row of pixels is exposed at slightly different time. This is another cause of spatially-variant blur [28]. When computing the PSFs, the start time of the exposure needs to be adjusted based on the y-coordinate of the point $x$. Let $t_r$ denote the camera readout time, i.e. the time difference between the first and last row exposure. The exposure of the $y$th row starts at $t_1(y) = t_f + t_r y / N$, where $t_f$ corresponds to the starting time of the first row exposure and $N$ is the number of pixel rows. To take this into account, we modify Eq. 1 so that

$$H(t) = KR(t)K^T (t_1)K^{-1}.$$
An example of computed PSFs is shown in Fig. 2. The blurred image is produced by performing a spatially-variant convolution between the sharp image and the blur kernels (PSFs). To speed-up the convolution, we only store and process the nonzero elements of each blur kernel.

4.4. Spatial Misalignment

It is assumed that the blurry image is captured right after the noisy image. Still, the blurry image might be misaligned with respect to the noisy image due to camera or scene motion. Let us consider a horizontal blur kernel with the length of 5 pixels \((1/5) \ast [11111]\). Normally, the origin would be at the center of the kernel (middle of the exposure). To introduce the effect of spatial misalignment, we set the origin of each PSF kernel to be at the beginning of the exposure. In the previous example, that would correspond to the first or last position of the kernel depending on the motion direction. The effect of misalignment is visualized in Fig. 3. Although we assumed that the images can be taken immediately one after the other, this approach also extends to cases when there is a known gap between the two exposures.

4.5. Realistic Noise

As a final step, we add shot noise to both generated images. The shot noise is considered to be the dominant source of noise in photographs, modeled by a Poisson process. The noise magnitude varies across different images since it depends on the (ISO) sensitivity setting of the camera. In general, the noise will be significantly more apparent in the short exposure image, and we model this by setting the noise magnitude for the short exposure image larger by a constant factor of 4. Later in Sec. 5.3, the network is fine-tuned with real examples of noisy images. This way the noise characteristics can be learned directly from the data.

Finally, after adding the noise, we ensure that the maximum intensity of the blurry long exposure image does not exceed the maximum brightness value of 1. That is, we clip larger values at 1.

5. Network and Training Details

5.1. Architecture

The network is based on the popular U-Net architecture [25]. This type of network has been successfully used in many image-to-image translation problems [13]. It was chosen because of its simplicity and because it produced excellent results for this problem.

In our case, the input of the network is a pair of blurry and noisy images (stacked). Since the network is fully convolutional, the images can be of arbitrary size. The architecture of the network is shown in Fig. 2. First, the input goes through a series of convolutional and downsampling layers. Once the bottleneck, i.e. the lowest resolution is reached, this process is reversed. The upsampling layers expand the low-resolution image back into a full resolution image. The feature maps from the encoder are concatenated with equally sized feature maps of the decoder. The number of feature maps is shown below the layers in Fig. 2. All convolutional layers use a 3x3 window, except the last layer, which is a 1x1 convolution. Downsampling layers are 2x2 max-pooling operations with a stride of 2.

5.2. Training

The LSD$_2$ network was trained on 100k images taken from an online image collection [12]. The synthetically corrupted images have resolution of 270 × 480 pixels. We used the Adam [15] optimizer with the L2 loss function. The learning rate was initially set to 0.00005 and it was halved after every 10th epoch. The network was trained for 50 epochs.

5.3. Fine-tuning

The method is targeted for real-world images that have gone through unknown image processing pipeline of the camera. To this end, we fine-tune the network with real images captured with the NVIDIA Shield tablet. This way, the network can learn the noise and color distortion models directly from the data. Examples of real noise are shown in Fig. 4. Notice the relatively coarse appearance of the noise. Our synthetic noise model assumes that the noise is independent for each pixel. This clearly does not hold because of the camera’s internal processing (demosaicing, etc.).

We capture pairs of short and long exposure images while the camera is on a tripod. The long exposure image is used as the ground truth sharp image and the short exposure image directly corresponds to the noisy image. The blurred
image is generated from the sharp image as described in Sec. 4.3. To increase the amount of training samples, we capture several image pairs at once while varying the long exposure between 30 - 330 milliseconds. The ratio of exposure times remains fixed so that the short exposure is always 1/30 of the long exposure. The ISO settings for the long and short exposure images are set to 200 and 800, respectively. The original images are divided to four sub-images to further increase the training data. The network was fine-tuned on 3500 images (480 x 960 pixels) for 30 epochs. The rest of the details are the same as in Sec. 5.2.

6. Experiments

We capture pairs of noisy and blurry images in rapid succession with the NVIDIA Shield tablet and the Google Pixel 3 smartphone. The image acquisition setup is the same as in Sec. 5.3, except this time the camera and/or scene is moving. The resolution of the images is 800 × 800 pixels (cropped from the original images). For the quantitative comparison, we use synthetically blurred and noisy image pairs taken from the validation set. An example of such pair is shown in Fig. 2.

6.1. Single-Image Approaches

The proposed approach is first compared against the state-of-the-art denoising methods BM3D [5] and FDN CNN [38]. Their noise standard deviation parameters have been manually tuned to achieve a good overall balance between noise removal and detail preservation. The results are shown in Figs 4 and 5. The short exposure image (noisy) has been normalized so that its intensity matches the blurry image for visualization. The most apparent weakness of BM3D and FDN CNN is that the color information is partly lost and cannot be recovered using a noisy image alone. LSD2 does a good job at extracting the colors from the blurry image. There is significantly less noise compared to BM3D and FDN CNN, which tend to over-smooth some of the details.

The importance of using real data for fine-tuning is demonstrated in Fig. 4. The fine-tuning clearly helps as the output is significantly less noisy and the colors are better. Furthermore, the fine-tuning does not make the network device specific. In our synthetic noise model, the noise is assumed to be independent for each pixel. We argue that if we only use synthetic data the coarse appearance of the real noise "fools" the network to conclude that these fine structures (noise) are details that should not be removed.

Fig. 5 show a comparison against the state-of-the-art deblurring method [16]. The results of DeblurGAN are unsatisfactory as it fails to remove most of the blur. Note that saturated image regions, such as light streaks, do not cause problems for LSD2. Furthermore, LSD2 performs surprisingly well on a dynamic scene even though it has not been trained for this type of situations. However, fine details such as the bike wheels remain blurry.

A quantitative comparison of the methods is presented in Table 1. LSD2 outperforms the other methods by a fair margin. DeblurGAN [16] generates a "grid-like" pattern over the blurry images, which partly explains the poor results. See the supplementary material for more results.

6.2. Multi-Image Approches

The implementation of Yuan et al. [37] or the more recent method by Whyte et al. [33] are not publicly available. For comparison, we use a pair of blurry and noisy images provided by the authors of [33]. As the exposure and ISO settings are different, we skip the fine-tuning of LSD2. A comparison against the original result by [33] is shown in Fig. 6. Even though the setup is not ideal for LSD2, it produces equally good if not better results. The output of [33] shows a little bit of ringing and slightly less details. Note that [33] and [37] perform a separate denoising step and their inputs are manually registered.

A recent burst deblurring method by Aittala and Durand [1] takes an arbitrary number of blurry images as input. Using their implementation, we compare the methods in Fig. 7. Their results clearly improve as more images are added. Nevertheless, the final result appears less sharp compared to ours, which is obtained with only two images (blurry and noisy). Furthermore, the saturated regions such as the over-exposed windows, cannot be recovered using the long exposure images alone. We also tried feeding a pair of noisy and blurry images to [1] but the results were poor. This is not surprising as their method is designed for blurry images only. Similar to [33, 37], the input images need to be registered in advance.

6.3. Exposure Fusion

As described in previous sections, LSD2 network performs joint denoising and deblurring and outputs a sharp version of the long exposure image that is aligned with the short exposure image. Thus, the short exposure image and

| Method   | PSNR   | SSIM  |
|----------|--------|-------|
| Noisy    | 16.43  | 0.51  |
| Blurred  | 16.88  | 0.57  |
| DeblurGAN [16] | 15.78 | 0.54  |
| BM3D [5] | 23.48  | 0.79  |
| FDN CNN [38] | 23.83 | 0.81  |
| LSD2     | 25.67  | 0.89  |

Table 1. The average peak-signal-to-noise ratio (PSNR) and structural similarity (SSIM) computed for 30 synthetically corrupted image pairs (shown in the supplementary material). For fairness, the outputs of [5] and [38] have been adjusted so that the colors match the blurred images before computing the scores as the color distortions may have a significant impact to the scores.
Figure 4. A comparison of LSD$_2$ and single-image denoising methods BM3D [5] and FDnCNN [38]. The second column from the right shows the results without fine-tuning (synthetic data only). Note that the LSD$_2$ network was fine-tuned using NVIDIA Shield data but the input images on the second row were captured with Google Pixel 3.

Figure 5. A low light performance in the presence of saturated pixels (top) and a dynamic scene performance (bottom).

Figure 6. A comparison of LSD$_2$ and Whyte et al. [33]. Note that [33] requires manual alignment and a separate denoising step.
the output of LSD$_2$ network would be suitable inputs to exposure fusion methods, such as DeepFuse [24], which assume that the input images are not blurry or misaligned. Fig. 8 shows the result of DeepFuse when using a pair of noisy and blurry images as input. The results are significantly improved when DeepFuse is used with LSD$_2$.

Note that DeepFuse [24] does not take into account that the short exposure image can be extremely noisy and that colors may be distorted. Therefore, we also trained a second network for exposure fusion. Details of the network architecture and training are given in the supplementary material. The training was done using similar synthetic long and short exposure image pairs as described in Sections 4.1 and 4.2. This time the random number $s$ was uniformly sampled from the interval $[1/3, 3]$ and the ground truth target is the original image, which has not been scaled by $s$ and is presumably taken with “good exposure”. This type of approach differs from existing methods, which often use hand-crafted features and assume that ground truth targets are not available.

In order to demonstrate high-dynamic range imaging, we process the short exposure image and the output of the LSD$_2$ with our exposure fusion network. The results in Figs 1 and 8 show that we get higher dynamic range and better reproduction of colors and brightness than in either one of the single-exposure input images. Our method provides more vivid colors than DeepFuse. Notice also the lack of details in the dark areas of the DeepFuse output (see e.g. the curtains).

The main purpose of this experiment is to demonstrate the suitability of LSD$_2$ approach for handheld high-dynamic range imaging with smartphones. A more comprehensive evaluation of different exposure fusion techniques is left for future work.

7. Conclusion

We proposed a CNN-based joint image denoising and deblurring method called LSD$_2$. It recovers a sharp and noise-free image given a pair of short and long exposure images. Its performance exceeds the conventional single-image denoising and deblurring methods on both static and dynamic scenes. Furthermore, LSD$_2$ compares favorably with existing multi-image approaches. Unlike previous methods that utilize pairs of noisy and blurry images, LSD$_2$ does not rely on any existing denoising algorithm. Moreover, it does not expect the input images to be pre-aligned. Finally, we demonstrated that the LSD$_2$ output makes exposure fusion possible even in the presence of motion blur and misalignment.
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Supplementary material (LSD\(_2\))

This document contains additional examples from the same datasets shown in the paper. Images are best viewed electronically and zoomed-in. Figures 1 - 3 show the results on realworld images (real motion blur and noise). Figures 4 - 6 show the results on synthetically corrupted images. Additional details of the exposure fusion method are given at the end of this document.

1. Additional results

| Noisy | Blurry | BM3D [5] | FDnCNN [38] | DeblurGAN [16] | LSD\(_2\) |
|-------|--------|----------|-------------|----------------|-----------|
![Images](image1.png)

Figure 1. Static scene performance (sparrow, capercaillie, weasel).
Figure 2. Static scene performance (bear, duck, fox, frog).
Figure 3. Dynamic scene performance and low-light performance including saturated pixels (cars, church, clock, street).
Figure 4. Results on synthetically corrupted images (1-10). Noisy images and the results of BM3D [5] and FDnCNN [38] have been normalized so that the mean intensity of each color channel matches the blurred image.
Figure 5. Results on synthetically corrupted images (11-20). Noisy images and the results of BM3D [5] and FDnCNN [38] have been normalized so that the mean intensity of each color channel matches the blurred image.
| Sharp | Noisy | Blurred | BM3D [5] | FDNnCNN [38] | DeblurGAN [16] | LSD$_2$ |
|-------|-------|---------|----------|--------------|----------------|---------|

Figure 6. Results on synthetically corrupted images (21-30). Noisy images and the results of BM3D [5] and FDNnCNN [38] have been normalized so that the mean intensity of each color channel matches the blurred image.
2. Exposure Fusion

The proposed exposure fusion network takes a pair of short and long exposure images as input. Let $I_S$ and $I_L$ denote the short and long exposure images, respectively. In our case, $I_L$ is produced by the LSD$_2$ method. The output of the exposure fusion network is a weight map $W$, which is used to produce the fused image

$$
\hat{I}_F(i, j, k) = W(i, j) \cdot I_L(i, j, k) + [1 - W(i, j)] \cdot I_S(i, j, k),
$$

where $(i, j, k)$ refers to pixel $(i, j)$ in the $k$-th color channel. We then compute the mean squared error loss given the ground truth image $I_F$, presumably taken with "good exposure". In the following sections, we provide details of the network architecture and training.

2.1. Architecture

The network consists of 7 convolutional layers connected in a sequential manner. The input of the network is a pair of short and long exposure images $I_S$ and $I_L$ (stacked). The output is a weight map $W$ with the same size as the input images (single channel). All convolutional layers use a $3 \times 3$ window, except the last layer, which is a $1 \times 1$ convolution. The number of feature maps is 16 for the layers 1, 2, 5 and 6, and 32 for the layers 3 and 4. Even though the network is very simple, it produces surprisingly good results as shown in Fig. 8 of the main paper. We note that alternative network architectures might provide further improvements.

2.2. Training

The network was trained on 50k images taken from an online image collection [12]. The training was done using synthetic long and short exposure image pairs as described in Sections 4.1 and 4.2 of the main paper. The resolution of the images was $270 \times 480$ pixels. We used the Adam [15] optimizer. The learning rate was set to $0.00002$ and the network was trained for 5 epochs.