

Burst Denoising of Dark Images

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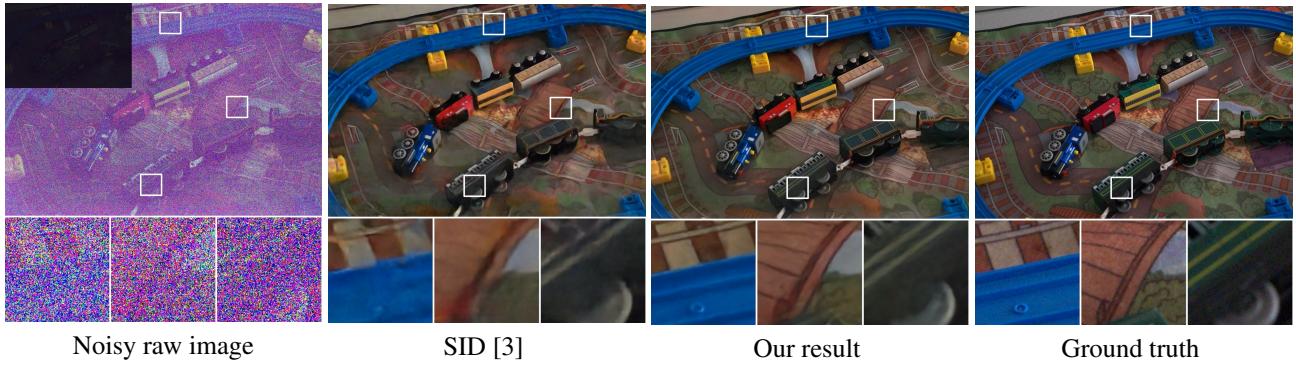


Figure 1: Example denoising results for an extremely dark image. The standard camera output is provided at the top left corner of the raw input image. We compare our approach against SID [3]. Our method allows for much sharper and artifact-free images with better color accuracy (best viewed in color and zoom-in).

Abstract

Capturing images under extremely low-light conditions poses significant challenges for the standard camera pipeline. Images become too dark and too noisy, which makes traditional image enhancement techniques almost impossible to apply. Very recently, researchers have shown promising results using learning based approaches. Motivated by these ideas, in this paper, we propose a deep learning framework for obtaining clean and colorful RGB images from extremely dark raw images. The backbone of our framework is a novel coarse-to-fine network architecture that generates high-quality outputs in a progressive manner. The coarse network predicts a low-resolution, denoised raw image, which is then fed to the fine network to recover fine-scale details and realistic textures. To further reduce noise and improve color accuracy, we extend this network to a permutation invariant structure so that it takes a burst of low-light images as input and merges information from multiple images at the feature-level. Our experiments demonstrate that the proposed approach leads to perceptually more pleasing results than state-of-the-art methods by producing much sharper and higher quality images.

1. Introduction

Capturing images in low-light illumination conditions is an important task in digital photography for several reasons. First, generating higher quality images by digital cameras leads to higher end-user satisfaction. Hence, a number of camera and mobile-device companies recently developed different imaging pipelines to address low-light image enhancement problem [15]. Second, these illumination conditions introduce certain challenges for high-level vision tasks such as object detection [16, 24]. Because of this, enhancing dark images is not only valuable for obtaining visually satisfying images but can also improve the performance of other approaches that are effective for images captured in ideal illumination environments.

Improving the quality of images captured in the dark or low-light conditions is a challenging task. The main difficulty is that the level of the signal measured by the camera sensors is generally much lower as compared to the noise in the measurements [15]. The factors causing the noise are the variations in the number of photons entering the lens and sensor-based measurement errors occurred when reading the signal [2, 10]. Noise present in a low-light image also affects various image characteristics such as fine-scale structures and color balance.

Direct approaches for low-light image enhancement consist of opening the camera’s aperture, increasing the exposure duration or using camera flash [11, 15]. These methods, however, do not solve the problem completely as each of these hacks has some drawbacks. Opening the camera’s aperture is limited by the hardware constraints, and when camera flash is used, objects closer to the camera are brightened more than the objects or the scene elements that are far away [23]. Images captured with long exposure might have unwanted motion blur if the scene contains movement or they demonstrate camera blur because of the small movements of the camera [26]. Hence, in the literature, there has been a wide range of studies which try to improve the quality of low-light images ranging from traditional contrast enhancement methods to learning based approaches.

In this paper, we propose a framework that takes a burst of raw low-light images of a scene as input and generates an enhanced RGB image. Our method is motivated by the learning-based framework by [3] called SID (See-in-the-Dark) in which the authors proposed to train a convolutional neural network (CNN) model to produce enhanced RGB images from raw low-light inputs by using a dataset containing dark images and their corresponding long-exposure references.

As shown in Figure 1, despite the competitive performance of SID [3], there are still some issues that are open to improvements such as unwanted blur, noise and color inaccuracies in the end results, especially for the input images where the input images are extremely dark. To alleviate these issues, we propose a coarse-to-fine network architecture which allows for simultaneous processing of a burst of raw dark images as input to obtain a high quality RGB image.

Our main contributions are summarized as follows:

- We suggest a multi-scale deep architecture containing coarse and fine networks for image enhancement under extremely dark lighting conditions.
- We further extend our coarse-to-fine architecture to develop a new permutation invariant CNN model that predicts an enhanced RGB image by integrating the features from a burst of images of a dark scene.
- Our experiments demonstrate that our approach outputs RGB images which contain less noise and sharper edge details than the state-of-the-art. These are also validated quantitatively based on several quality measures in both single-frame and burst settings.

2. Related Work

Low light image enhancement is a widely studied problem in the image processing literature. Images generally

show different characteristics due to lighting conditions of the environments, and noise and motion blur they contain. Darkness of an image is directly related to the illuminance of a scene, which is measured in terms of lumens per meter squared (lux). Extremely low light images refer to the images that are photographed in the scenes with 0.2-5 lux.

For partially under-exposed images, the traditional strategy is to use general-purpose enhancement methods. However, as mentioned above, image enhancement under extreme low light situations is a more challenging problem due to the inherent severe noise. In this section, we review both these generic methods and the image enhancement approaches that are specifically designed for low-light settings.

Generic approaches that can be used for low-light image enhancement can be divided into three groups: (i) contrast enhancement methods, (ii) techniques based on Retinex Theory, and (iii) learning-based approaches. Most well-known methods for contrast enhancement are histogram equalization and its variants [12, 13, 34]. These methods stretch the image histogram to obtain a visually more pleasing image. Retinex theory assumes that the perceived images can be decomposed into illumination and reflectance components where illumination represents the light intensity and reflectance reflects the characteristics of the objects in the image [14]. Many methods use this human color perception theory for enhancing low light images [6, 9, 22]. Lastly, there are also learning based approaches such as [17, 18, 27, 29], which are typically trained on synthetically created low-light datasets which are limited in perfectly reflecting the real low-light scenes. Although these low-light image enhancement methods provide good results under certain conditions, they usually suffer from color inaccuracies and noise when fed with extremely dark images.

As discussed in the introduction section, the recently proposed SID model [3] specifically aims for enhancing extremely dark images. In this approach, raw Bayer pattern input images are packed into 4-channels which are then scaled with the desired amplification ratio. These packed and amplified inputs are given to a U-Net like architecture for enhancement, which is trained with the L_1 loss function. Very recently, there have been a few attempts to further improve the performance of SID. For instance, Maharjan et al. [19] have proposed residual learning to boost the final quality and to reduce the computational cost. For a similar purpose, Zamir et al. [31] have used a hybrid loss function which is a combination of pixel-wise and perceptual losses. Our single-frame enhancement method differs from these works in that we consider a novel coarse-to-fine architecture that better handles the extremely low-light images by giving much sharper and more vivid colors.

Our work is also related to image denoising. General denoising approaches such as BM3D [5] method and per-pixel

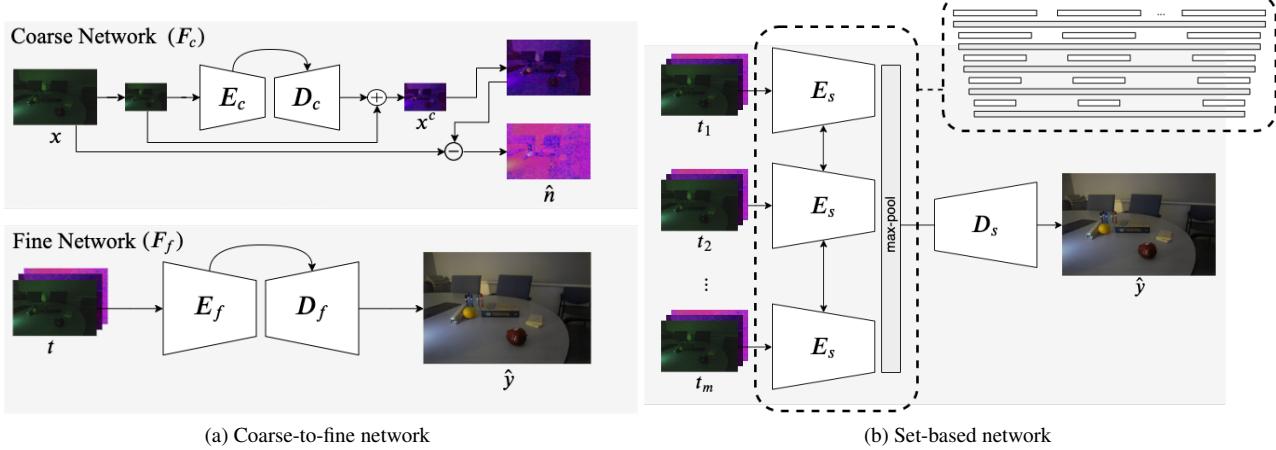


Figure 2: Network architectures of the proposed (a) single-frame coarse-to-fine and (b) set-based burst models.

median denoising of burst images can be also used to enhance extremely low-light images, though as shown in [3], their performances are limited as compared to more specialized approaches. Recently, more sophisticated approaches such as Kernel Prediction Networks [20] or Recurrent Fully Convolutional Networks [8] have been proposed which process a burst of noisy images through deep CNN architectures for denoising purposes. Interestingly, Zhao et al. [33] have suggested to use recurrent convolutional neural networks for denoising a burst of low-light images. Similarly, Liba et al. [15] and Hasinoff et al. [11] also use a burst of low-light images but they focus on improving the individual steps of camera processing pipeline such as auto white balancing or motion metering. In our work, specifically motivated by these recent deep denoising approaches, we also develop a set-based permutation invariant CNN architecture that gives equal importance to each low-light input image, as compared to recurrent models which treat each input in the sequence differently.

3. Our Approach

Table 1 summarizes the notations used in the paper. Our aim is to learn a mapping between the input domain X which consists of raw low-light images to the target domain Y containing long-exposure reference images. To achieve this, we propose both a single-frame model and its set-based extension to process burst images, as illustrated in Figure 2.

3.1. Coarse-to-fine Model

In order to obtain outputs with fine-grained details, we propose to employ a two-step coarse-to-fine training procedure. Similar strategies have been successfully used in various other tasks such as deblurring [21] and image synthesis [28]. Different than these approaches, our coarse

Table 1: Notations used in the paper.

x_1, x_2, \dots, x_m	Burst of raw low-light input images
$F_c(\cdot), F_f(\cdot), F_s(\cdot)$	Coarse, fine and set-based networks
$x_1^c, x_2^c, \dots, x_m^c$	Raw, low-resolution outputs of the coarse network
$\hat{n}_1, \hat{n}_2, \dots, \hat{n}_m$	Noise approximations for x_1, x_2, \dots, x_m
t_1, t_2, \dots, t_m	Tensors containing raw inputs, upsampled coarse outputs and noise approximations
$R_d(\cdot), R_u(\cdot)$	Downsampling and upsampling functions

network outputs a raw (denoised) image. This helps us to decouple the problem of learning the mapping between the raw domain and the RGB domain. Some of the recent denoising methods use the noise level as an additional input channel [2]. Predicting the coarse outputs in the raw domain also allows us to compute the approximate noise levels which can be used in residual learning.

In our model, first, raw low-light images and the corresponding long-exposure images are downsampled by a factor of two. Our coarse network, which is illustrated in Figure 2(a) is trained on this downsampled data and gives denoised outputs in low-resolution.

$$F_c(R_d(x)) = x^c \quad (1)$$

Then, the difference between the high-resolution raw low-light inputs and the upsampling of the output of the coarse network is computed. This difference is used to encode the approximate noise into the network.

$$\hat{n} = x - R_u(x^c), \quad t = (x, \hat{n}, R_u(x^c)) \quad (2)$$

Finally, a fine network is trained with the concatenation of the low-light raw input image, the raw output from the

coarse network and the noise approximation as inputs to obtain the RGB output.

$$F_f(t) = \hat{y} \quad (3)$$

Both coarse and fine networks are optimized with L_1 loss function. They consist of 10 convolution layers where the number of filters are doubled and the resolution is halved after every 2 convolution layers in the encoder part. The initial number of filters are 32. Decoder part consists of the symmetric transposed convolutions which are concatenated with earlier corresponding convolution layers.

3.2. Set-Based Extension

Recently, there have been some attempts on studying invariance and equivariance properties of neural networks [4, 7, 25]. Interestingly, Zaheer et al. [30] provided a generic algorithm to train neural networks that operate on sets via a simple parameter sharing scheme, which allows for information exchange with a commutative operation. Based on this idea, Aittala and Durand [1] have proposed a permutation invariant CNN model for burst image deblurring. In particular, the authors add additional layers to the existing architectures, which results in an increase in the number of model parameters and thus the computational cost. In a similar vein, in this study, we develop a permutation invariant CNN architecture but without increasing the number of parameters and requiring less computational cost by using multiple encoders and a single decoder.

Multiple inputs can help denoising the low-light input images. Nonetheless, simply averaging the multiple inputs or taking the average of the predictions from multiple inputs do not always give satisfactory results in these situations. Hence, we extend our coarse-to-fine method to a novel permutation invariant CNN architecture which takes multiple images of the scene as input and predicts an enhanced image.

In particular, first, low-resolution coarse outputs are obtained for each frame x_i in the burst sequence:

$$x_i^c = F_c(R_d(x_i)) \quad (4)$$

Then, an approximate noise component n_i is computed for each frame, and concatenated with x_i and $R_u(x_i^c)$ as follows:

$$\hat{n}_i = x_i - R_u(x_i^c) \quad (5)$$

$$t_i = (x_i, \hat{n}_i, R_u(x_i^c)) \quad (6)$$

Finally, the set-based network is trained using the set containing the outputs of our coarse network, $\{t_i\}$, as input:

$$\hat{y} = F_s(\{t_1, \dots, t_m\}) \quad (7)$$

Here, F_s represents a permutation invariant CNN, which has m convolutional networks which allows for information exchange between the features of burst frames. This

is achieved by using a max-pooling over the set of features after each convolution layer in the encoder part of the network. Then, in the decoder part, instead of concatenating the deconvolution features with the corresponding earlier features, we concatenate them with the corresponding global max-pooled features computed in the encoder part. So, without even changing the parameter size, we integrate the advantage of multiple observations to the network.

Implementation Details. We take 512×512 random patches for each input and downsample these into 256×256 patches with bilinear interpolation. Patch sizes used for the coarse and fine networks are 256×256 and 512×512 , respectively. We first train the coarse network F_c by using Adam optimizer with a learning rate of 10^{-4} for 2000 epochs and 10^{-5} for 2000 epochs. Then, set-based fine network F_s is trained with the same hyperparameters without fixing the parameters of the coarse network. During training of F_s , we randomly choose the number of burst input frames between 1 and 10. We implement our model with Tensorflow library on an NVIDIA Tesla v100 GPU. Training our network for 10 frames inputs lasts about 3 days.

4. Experimental Evaluation

We train and evaluate our models on SID dataset [3], which consists of short-exposure burst raw images with long-exposure reference images taken under extremely dark indoor or outdoor illumination settings. In particular, we test the performance of our models on Sony subset. There are a total of 93 test images, where the number of burst images varies from 2 to 10. In our experiments, we compare our models with the state-of-the-art methods including SID [3], Maharjan et al. [19], Zhao et al. [33] and Zamir et al. [31]. Among these, only Zhao et al. [33] propose to process burst images. For quantitative evaluation, we employ the popular PSNR, SSIM metrics as well as the LPIPS metric [32], which measures similarity in a more semantic level (lower is better).

Table 2 presents our comparisons with the competing methods. In our quantitative evaluation, we left [31, 33] out since their implementations are not public and the details regarding their experimental analysis are missing. For this reason, we instead qualitatively compare our results against theirs by considering the images presented in their papers. Overall, our single-frame model outperforms the existing methods on all metrics. Our burst model further improves upon our results, achieving the best performance.

Figure 3 shows visual comparison between our single-frame model and SID [3]. We also provide the outputs of the coarse network, which are then refined and enhanced by the fine network. For the first image, noise is reduced in dark regions in a much better manner. For the second image, the color of the yellow book is better recovered and the text of the blue book is more clear when compared to

Table 2: Quantitative results on the SID dataset. Best performing model is indicated with a bold typeface.

Method	PSNR	SSIM	LPIPS
SID [3]	28.97	0.885	0.482
Maharjan et al. [19]	29.16	0.885	-
Ours (single-frame)	29.43	0.891	0.455
Ours (burst)	29.93	0.899	0.429

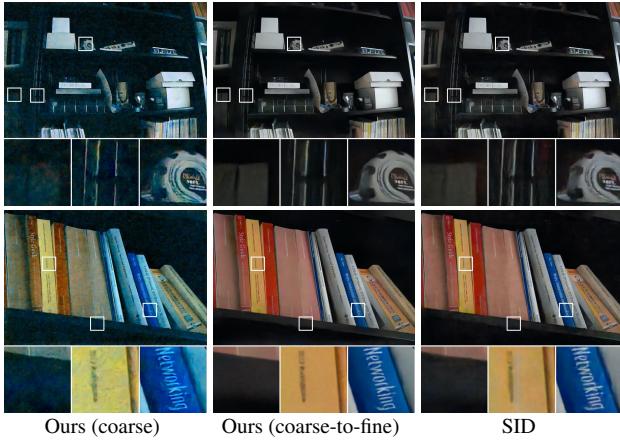


Figure 3: Comparison of our coarse and coarse-to-fine models with SID [3].

SID. It is also apparent that our approach better preserves the edges without introducing any artifacts.

In Figure 4, we present additional comparisons with SID [3] and Maharjan et al. [19]. Zoomed-in regions clearly show that both SID and Maharjan et al. [19] cannot correctly recover thin and elongated structures (e.g. edges of the bench, yellow lane lines) and they suffer from over-smoothing of textured regions (e.g. tree leaves in the two outdoor images). Our single-frame and burst models, on the other hand, better cope up with these issues and greatly reduce the noise as well. Especially, our burst model produces outputs which are very close to the ground truth.

We also compare our methods with Zamir et al. [31] and Zhao et al. [33] qualitatively. In Figure 5, we provide a comparison with Zamir et al. [31]. As can be seen, the details captured with our burst method (e.g. the lines on the wall and the cable) are much sharper and our single-frame model performs on par or better than Zamir et al. [31]. Figure 6 presents visual comparisons between our burst model and Zhao et al. [33], an RNN-based burst model. For the indoor image, our method succeeds in generating the letters of the book and the texture of the sticky notes, whereas Zhao et al. [33] produces a blurry result. Similarly, for the outdoor image, our method produces much finer details – devoid

Table 3: Ablation study. For our coarse network, we show the two alternative output types as RAW or RGB within parentheses. For the ensemble versions of SID [3] and our coarse-to-fine model, and our proposed set-based architecture, we show the corresponding number of burst images in parentheses.

Method	PSNR	SSIM	LPIPS
SID [3]	28.97	0.886	0.482
Ours (coarse(RGB)-to-fine)	29.40	0.891	0.463
Ours (coarse(RAW)-to-fine)	29.43	0.891	0.455
SID (4 frames)	29.36	0.891	0.483
SID (10 frames)	29.38	0.892	0.484
Ours (coarse-to-fine, 4 frames)	29.71	0.895	0.463
Ours (coarse-to-fine, 10 frames)	29.73	0.895	0.465
Ours (set-based, 4 frames)	29.87	0.898	0.435
Ours (set-based, 10 frames)	29.93	0.899	0.429

of any of the brown color artifacts introduced by Zhao et al. [33].

Ablation Study. To evaluate the effectiveness of our approach in more detail, we performed a series of ablation tests. The results of these experiments are shown in Table 3. We first analyze how the output type of the coarse network (RAW or RGB) affects the overall performance of the fine network. It turns out that predicting the coarse output in RAW slightly increases PSNR and decreases LPIPS. Next, we analyze the benefit of using a set-based approach. One might argue that the sole reason behind the success of our burst model is to exploit multiple observations. Hence, we compare our burst model with the ensemble versions of SID [3] and our coarse-to-fine model, which both process multiple frames separately and then combine the outputs by simple averaging. Our set-based approach performs better as it carries out integration at the feature level. It is important to note that the ensemble version of our coarse-to-fine model also outperforms the SID ensemble. Moreover, the performance of our set-based method with 4 frames is better than the ensembles with 10 individual frames. We provide some qualitative results in Figure 7. Our set-based model better preserves texture details and thin structures like letters. As expected, increasing the burst size reduces the noise for both approaches.

5. Conclusion

In this study, we tackle the problem of learning to generate long-exposure images from a set of low-light burst images. We developed a new deep method that incorporates a coarse-to-fine strategy to better enhance the details of the output. Moreover, we extended this network architecture to work with a burst of images by a novel a permuta-

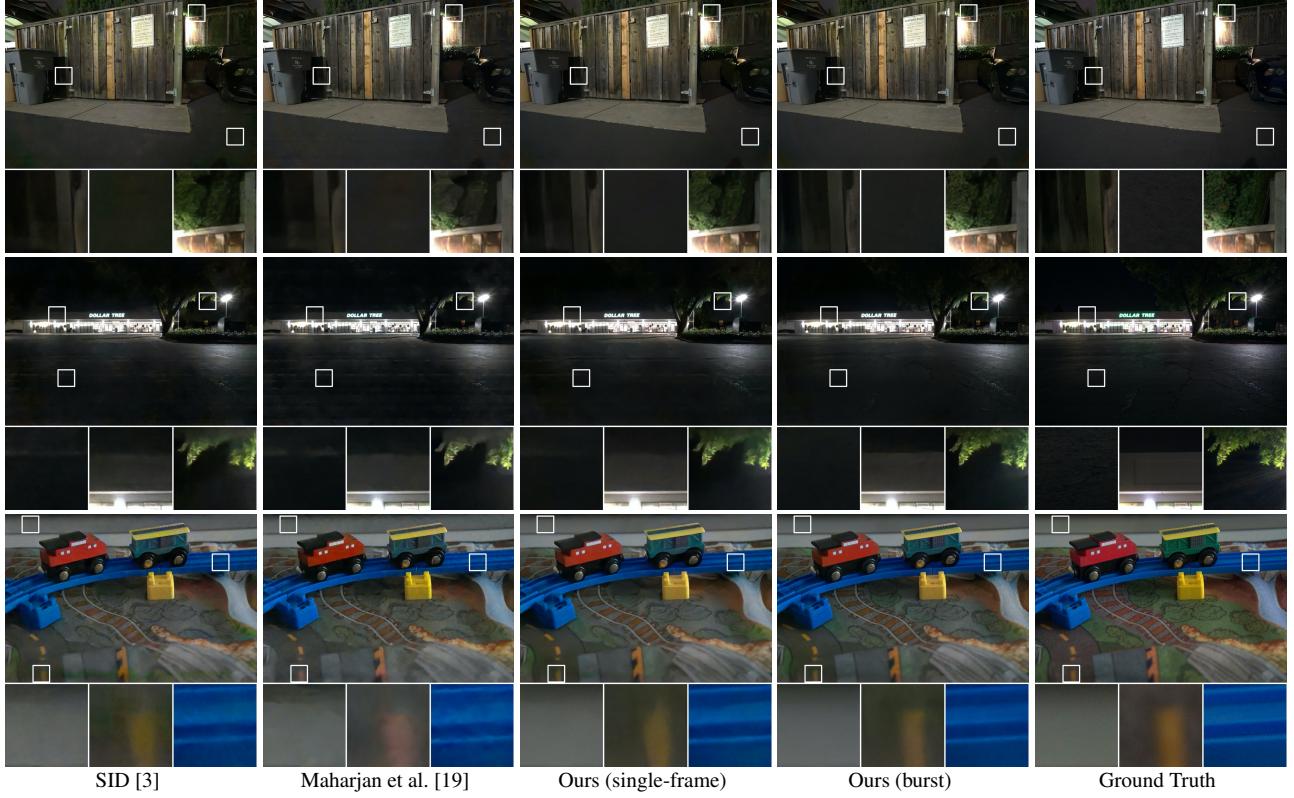


Figure 4: Comparison with state-of-the-art approaches.

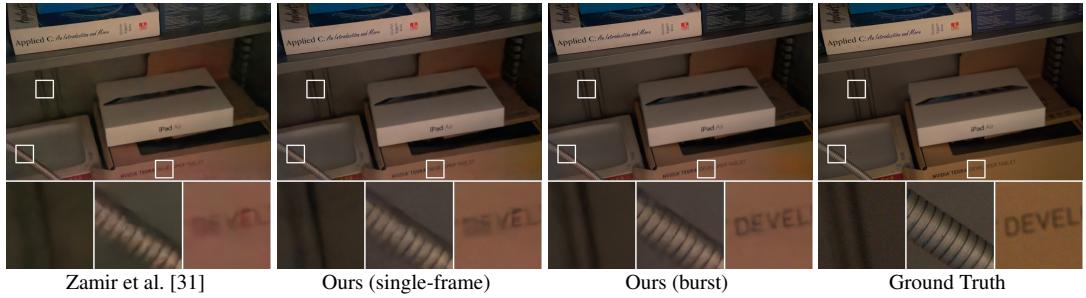


Figure 5: Comparison with Zamir et al. [31].

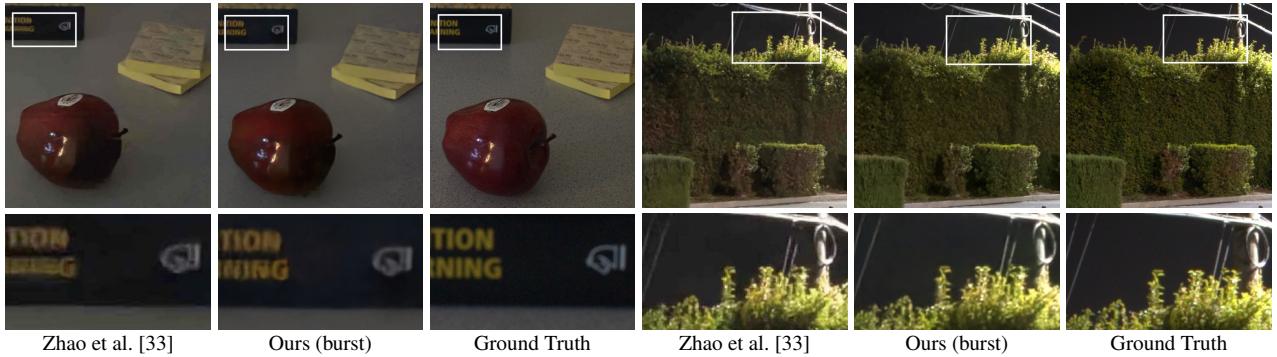


Figure 6: Comparison with burst-based method of Zhao et al. [33].

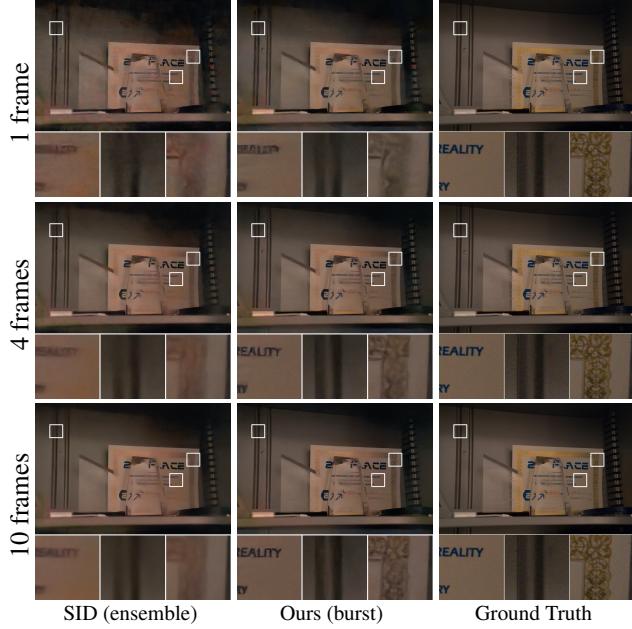


Figure 7: Influence of burst size. We compare our approach with ensemble version of SID [3] for different burst sizes.

tion invariant CNN architecture, which consists of multiple encoders with shared parameters and a single decoder that can exchange information between the features of the burst frames. Our experiments show that our set-based method achieves higher quality results than the existing state-of-the-art models, better capturing finer details, texture and color information and reducing noise level.

Our approach has some limitations though. First, computation time increases with the burst size. Second, our results are still not perfect and there is room for improvement, especially for the scenes with extremely dark illumination conditions. Third, our set-based approach might struggle with sequences involving large motion changes or camera-shake without any modification. In the future, we intend to explore ways to further improve the image quality and the runtime performance. Another interesting line of future research is to extend our work to videos.

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