Abstract

The UG\textsuperscript{2+} challenge in IEEE CVPR 2019 aims to evoke a comprehensive discussion and exploration about how low-level vision techniques can benefit the high-level automatic visual recognition in various scenarios. In its second track, we focus on object or face detection in poor visibility enhancements caused by bad weathers (haze, rain) and low light conditions. While existing enhancement methods are empirically expected to help the high-level end task, that is observed to not always be the case in practice. To provide a more thorough examination and fair comparison, we introduce three benchmark sets collected in real-world hazy, rainy, and low-light conditions, respectively, with annotate objects/faces annotated. To our best knowledge, this is the first and currently largest effort of its kind. Baseline results by cascading existing enhancement and detection models are reported, indicating the highly challenging nature of our new data as well as the large room for further technical innovations. We expect a large participation from the broad research community to address these challenges together.

1. Introduction

Background. Many emerging applications, such as unmanned aerial vehicles (UAVs), autonomous/assisted driving, search and rescue robots, environment monitoring, security surveillance, transportation and inspection, hinge on computer vision-based sensing and understanding of outdoor environments [134]. Such systems concern a wide range of target tasks such as detection, recognition, segmentation, tracking, and parsing. However, the performances of visual sensing and understanding algorithms will be largely jeopardized by various challenging conditions in unconstrained and dynamic degraded environments, e.g., moving platforms, bad weathers, and poor illumination. They can cause severe visual input degradations such as reduced contrasts, detail occlusions, abnormal illumination, faulted surfaces and color shift.

While most current vision systems are designed to perform in clear environments, i.e., where subjects are well observable without (significant) attenuation or alteration, a dependable vision system must reckon with the entire spectrum of complex unconstrained outdoor environments. Taking autonomous driving for example: the industry players have been tackling the challenges posed by inclement weathers; however, a heavy rain, haze or snow will still obscure the vision of on-board cameras and create confusing reflections and glare, leaving the state-of-the-art self-driving cars in struggle (see a Forbes article). Another illustrative example can be found in city surveillance: even the commercialized cameras adopted by governments appear fragile in challenging weather conditions (see a news article). Therefore, it is highly desirable to study to what extent, and in what sense, such challenging visual conditions can be coped with, for the goal of achieving robust visual sensing and understanding in the wild, that benefit security/safety, autonomous driving, robotics, and an even broader range of signal and image processing applications.

1.1. Challenges and Bottlenecks

Despite the blooming research on removing or alleviating the impacts of those challenges, such as dehazing [9, 89, 48, 34], deraining [15, 74, 58, 125, 11, 23, 22, 119] and illumination enhancement [54, 93, 117, 73, 98], the current solutions see significant gaps from addressing the above-mentioned pressing real-world challenges. A collective effort for identifying and resolving those bottlenecks that they commonly face has also been absent.

One primary challenge arises from the Data aspect. Those challenging visual conditions usually give rise to nonlinear and data-dependent degradations that will be much more complicated than the well-studied noise or motion blur. The state-of-the-art deep learning methods are typically hungry for training data. The usage of synthetic training data has been prevailing, but may inevitably lead to domain shifts [71]. Fortunately, those degradations often follow some parameterized physical models a priori. That will naturally motivate a combination of model-based and data-driven approaches. In addition to training, the lack of
real world test sets (and consequently, the usage of potentially oversimplified synthetic sets) have limited the practical scope of the developed algorithms.

The other main challenge is found in the Goal side. Most restoration or enhancement methods cast the handling of those challenging conditions as a post-processing step of signal restoration or enhancement after sensing, and then feed the restored data for visual understanding. The performance of high-level visual understanding tasks will thus largely depend on the quality of restoration or enhancement. Yet it remains questionable whether restoration-based approaches would actually boost the visual understanding performance, as the restoration/enhancement step is not optimized towards the target task and may bring in misleading information and artifacts too. For example, a recent line of researches [48, 127, 62, 65, 66, 16, 99, 105, 59, 95, 84] discuss on the intrinsic interplay relationship of low-level vision and high-level recognition/detection tasks, showing that their goals are not always aligned.

1.2. Overview of UG²+ Track 2

UG²+ Challenge Track 2 aims to evaluate and advance object detection algorithms robustness in specific poor-visibility environmental situations including challenging weather and lighting conditions. We structure Challenge 2 into three sub-challenges. Each challenge features a different poor-visibility outdoor condition, and diverse training protocols (paired versus unpaired images, annotated versus unannotated, etc.). For each sub-challenge, we collect a new benchmark dataset captured in realistic poor-visibility environments with real image artifacts caused by rain, haze, insufficiency of light are observed.

- **Sub-Challenge 2.1: (Semi-)Supervised Object Detection in the Haze.** We provide 4,322 real-world hazy images collected from traffic surveillance, all labeled with object bounding boxes and categories (car, bus, bicycle, motorcycle, pedestrian), as the main training and/or validation sets. We also release another set of 4,807 unannotated real-world hazy images collected from the same sources (and containing the same classes of traffic objects, though not annotated), which might be used at the participants discretization. There will be a held-out test set of 3,000 real-world hazy images, with the same classes of object annotated.

- **Sub-Challenge 2.2: (Semi-)Supervised Face Detection in the Low Light Condition.** We provide 6,000 real-world low light images captured during the nighttime, at teaching buildings, streets, bridges, overpasses, parks etc., all labeled with bounding boxes for human face, as the main training and/or validation sets. We also provide 10,400 unlabeled low-light images collected from the same setting. Additionally, we provided a unique set of 1,022 paired low-light/normal-light images captured in controllable real lighting conditions (but unnecessarily containing faces), which can be used as parts of the training data at the participants discretization. There will be a held-out test set of 4,000 low-light images, with human face bounding boxes annotated.

- **Sub-Challenge 2.3: Zero-Shot Object Detection with Raindrop Occlusions.** We provide 1,010 pairs of raindrop images and corresponding clean ground-truths (collected through physical simulations), as the training and/or validation sets. Different from Sub-Challenges 2.1 and 2.2, no semantic annotation will be available on training/validation images. A held-out test set of 2,496 real-world raindrop images are collected from high-resolution driving videos, in diverse real locations and scenes during multiple drives. We label bounding boxes for selected traffic object categories: car, person, bus, bicycle, and motorcycle.

The ranking criteria will be the Mean average precision (mAP) on each held-out test set, with default Intersection-of-Union (IoU) threshold as 0.5. If the ratio of the intersection of a detected region with an annotated face region is greater than 0.5, a score of 1 is assigned to the detected region, and 0 otherwise. When mAPs with IoU as 0.5 are equal, the mAPs with higher IoUs (0.6, 0.7, 0.8) will be compared sequentially.

2. Related Work

2.1. Datasets

Most datasets used for image enhancement/processing mainly targets at evaluating the quantitative (PSNR, SSIM, etc.) or qualitative (visual subjective quality) differences of enhanced images w.r.t. the ground truths. Some earlier classical datasets include Set5 [6], Set14 [123], and LIVE [97]. The numbers of images are small with only limited. Subsequent datasets come with more diverse scene content, such as BSD500 [75] and Urban100 [56]. The popularity of deep learning methods has increased demand for training and testing data. Therefore, many newer and larger datasets are presented for image and video restoration, such as DIV2K [101] and MANGA109 [26] for image super-resolution, PolyU [115] and Darmstadt [83] for denoising, RawInDark [12] and LOL dataset [113] for low light enhancement, HazeRD [132], OHAZE [3] and IHAZE [2] for dehazing, rain100L/H [119] and rain800 [126] for rain streak removal, and RAINDROP [85] for raindrop removal. However, these datasets provide no integration with subsequent high-level tasks.

A few works [31, 96, 136] make preliminary attempts for event/action understanding, video summarization, or face...
Dehazing methods proposed in an early stage rely on the exploitation of natural image priors and depth and deraining, as in the UG [122]. Here we focus on dehazing, low-light condition, super-resolution [112, 111, 63, 64] and denoising/inpainting [109, 51, 87, 110, 67], deblurring and the novel task-driven evaluation. Those datasets and metrics, to no-reference metrics, to subjective evaluation are generated by Multi-Exposure image Fusion (MEF) or image pairs, in which the reference normal-contrast images are synthesized by applying random gamma transformation on natural normal light images. Some recent works aim to build paired training data from real scenes. In [12], Chen et al. introduced a dataset See-in-the-Dark (SID) of short-exposure low-light raw images with corresponding long-exposure reference raw images. Cai et al. [10] built a dataset of under/over-contrast and normal-contrast encoded image pairs, in which the reference normal-contrast images are generated by Multi-Exposure image Fusion (MEF) or High Dynamic Range (HDR) algorithm.

2.2. Poor Visibility Enhancement

There are numerous algorithms aiming to enhance visibility of the degraded imagery, such as image and video denoising/inpainting [109, 51, 87, 110, 67], deblurring [116, 50], super-resolution [112, 111, 63, 64] and interpolation [122]. Here we focus on dehazing, low-light condition, and deraining, as in the UG3+ Track 2 scope.

Dehazing. Dehazing methods proposed in an early stage rely on the exploitation of natural image priors and depth statistics, e.g. locally constant constraints and decorrelation of the transmission [20], dark channel prior [34], color attenuation prior [135], nonlocal prior [5] et al. Lately, Convolutional Neural Network (CNN)-based methods bring in the new prosperity for dehazing. Several methods [9, 89] rely on various CNNs to learn the transmission fully from data. Beyond estimating the haze related variables separately, successive works make their efforts to estimate them in a unified way. In [45, 80], the authors use a factorial Markov random field that integrates the estimation of transmission and atmosphere light. Some researchers focus on the more challenging night-time dehazing problem [57, 128], [133, 78] try to utilize Retinex theory to approximate the spectral properties of object surfaces by the ratio of the reflected light. AOD-Net [48, 47] re-formulates the haze generation model to realize one-step estimation of the inverse recovery and consider the joint interplay effect of dehazing and object detection. The idea is further applied to video dehazing by extending the model into a light-weighted video hazing framework [49]. In another recent work [92], the semantic prior is also injected to facilitate video dehazing.

Low Light Enhancement. All low-light enhancement methods can be categorized into three ways: hand-crafted methods, Retinex theory-based methods and data-driven methods. Hand-crafted methods explore and apply various image priors to single image low-light enhancement, e.g. histogram equalization [82, 1]. Some methods [53, 131] regard the inverted low-light images as hazy images, and enhance the visibility by applying dehazing. Retinex theory-based method [46] is designed to regard the signal components, reflectance and illumination, differently to simultaneously suppress the noises and preserve high-frequency details. Different ways [40, 39] are used to decompose the signal and diverse priors [107, 24, 32, 25] are applied to realize better light adjustment and noise suppression. Li et al. [54] further extends the traditional Retinex model to a robust one with an explicit noise term, and made the first attempt to estimate a noise map out of that model via an alternating direction minimization algorithm. A successive work [93] develops a fast sequential algorithm. Learning based low-light image enhancement methods [117, 73, 98] have also been studied. In these works, low-light images used for training is synthesized by applying random gamma transformation on natural normal light images. Some recent works aim to build paired training data from real scenes. In [12], Chen et al. introduced a dataset See-in-the-Dark (SID) of short-exposure low-light raw images with corresponding long-exposure reference raw images. Cai et al. [10] built a dataset of under/over-contrast and normal-contrast encoded image pairs, in which the reference normal-contrast images are generated by Multi-Exposure image Fusion (MEF) or High Dynamic Range (HDR) algorithm.

Deraining. Single image deraining is a highly ill-posed problem. To address it, many models and priors are used to perform signal separation and texture classification. These models include sparse coding [41], generalized low rank model [15], nonlocal mean filter [43], discriminative sparse coding [74], Gaussian mixture model [58], rain direction prior [125], transformed low rank model [11]. The presence of deep learning has promoted the development of single image deraining. In [23, 22], deep networks take the image detail layer as their input. Yang et al. [119] propose a deep joint rain detection and removal method to remove heavy rain streaks and accumulation. In [125], a novel density-aware multi-stream densely connected CNN is proposed for
joint rain density estimation and removal. Video deraining can additionally make use of the temporal context and motion information. The early works formulate rain streaks with more flexible and intrinsic characteristics, including rain modeling [29, 27, 30, 28, 130, 69, 4, 94, 8, 7, 15, 38]. The presence of learning-based method [13, 103, 104, 91, 55, 14, 44], with improved modeling capacity, brings new progress. The emergence of deep learning-based methods push performance of video deraining to a new level. Chen et al. [4] integrate superpixel segmentation alignment, and consistency among these segments and CNN-based detail compensation network into a unified framework. [68] presented a recurrent network integrating rain degradation classification, deraining and background reconstruction.

2.3. Visual Recognition under Adverse Conditions

A real-world visual detection/recognition system needs to handle a complex mixture of both low-quality and high-quality images. It is commonly observed that, mild degradations, *e.g.* small noises, scaling with small factors, lead to almost no change of recognition performance. However, once the degradation level passes a certain threshold, there will be an unneglected or even very significant effect on system performance. In [102], Torralba et al. showed that, there will be a significant performance drop in object and scene recognition when the image resolution is reduced to 32×32 pixels. In [137], the boundary where the face recognition performance is largely degraded is 16×16 pixels. Karahan et al. [42] found the threshold of standard deviation of Gaussian noise which will cause a rapid decline range from 10 to 20. In [19], more impacts of contrast, brightness, sharpness, and out-of-focus on face recognition are analyzed.

In the era of deep learning, some methods [21, 118, 17] attempt to first enhance the input image and then forward the output into a classifier. However, this separate consideration of enhancement may not benefit the successive recognition task, because the first stage may incur artifacts which will damage the second stage recognition. In [137, 35] class-specific features is extracted as a prior to incorporate into the restoration model. In [127], Zhang et al. developed a joint image restoration and recognition method based on sparse representation prior, which constrains the identity of the test image and guide better reconstruction and recognition. [43] considers dehazing and object detection jointly. These two stage joint optimization methods achieve better performance than previous one-stage methods. [108, 62] examine the joint optimization pipeline for low-resolution recognition. [66, 65] discuss and the impact of denoising for semantic segmentation and advocates their mutual optimization. Lately, [106] thoroughly examines the algorithmic impact of enhancement algorithms for both visual quality and automatic object recognition, on a real image set with highly compound degradations. In our work, we take a further step to consider the joint enhancement and detection in bad weather environment. Three large-scale datasets are collected to inspire new ideas and develop novel methods in the related fields.

| Training/validation | #images | #bounding boxes |
|---------------------|---------|-----------------|
| test (held-out)     | 2,987   | 24,201          |

| Categories | Car | Person | Bus | Bicycle | Motorcycle |
|------------|-----|--------|-----|---------|------------|
| RTTS       | 25,317 | 11,366 | 2,590 | 698     | 1,232      |
| test (held-out) | 18,074 | 1,562  | 536  | 225     | 3,804      |

### 3. Introduction of UG^{2+} Track 2 Datasets

#### 3.1. (Semi-)Supervised Object Detection in the Haze

In Sub-challenge 2.1, we use the 4,322 annotated real-world hazy images of the RESIDE RTTS set [50] as the training and/or validation sets (the split is up to the participants). Five categories of objects (car, bus, bicycle, motorcycle, pedestrian) are labeled with tight bounding boxes. We provide another 4,807 unannotated real-world hazy images collected from the same traffic camera sources, for the possible usage of semi-supervised training too.

The participants can optionally use pre-trained models (*e.g.*, on ImageNet or COCO), or external data. But if any pre-trained model, self-synthesized or self-collected data are used, that must be explicitly mentioned in their submissions, and the participants must ensure all their used data to be public available at the time of challenge submission, for reproducibility purposes.

There will be a held-out test set of 2,987 real-world hazy images, collected from the same sources, with the same classes of object annotated. Fig. 1 shows the basic statistics of the RTTS set and the hold set. The hold out test set has a similar distribution of number of bounding boxes per image, bounding box size and relative scale of bounding boxes to input images compared to the RTTS set, but has relatively large image size. Samples from RTTS set and held-out set can be found in Fig. 2 and Fig. 3.

#### 3.2. (Semi-)Supervised Face Detection in the Low Light Condition

In Sub-challenge 2.2, we use our self-curated DARK FACE dataset. It is composed of 10,000 images (6,000 for training and validation, and 4,000 for testing) taken in under-exposure condition where human faces are annotated.
Figure 1. Sub-challenge 2.1: Basic statistics on the training/validation set (the top row) and the held out test set (the bottom row). The first column shows the image size distribution (number of pixels per image), the second column the bounding box count distribution (number of bounding boxes per image), the third column the bounding box size distribution (number of pixels per bounding box), and the last column the ratios of bounding box size compared to frame size.

Figure 2. Sub-challenge 2.1: Examples of images in training/validation set (i.e., RESIDE RTTS [50]).

by human with bounding boxes; and 9,000 images taken with the same equipment in the similar environment without human annotations. Additionally, we provided a unique set of 789 paired low-light / normal-light images captured in controllable real lighting conditions (but unnecessarily containing faces), which can be optionally used as parts of the training data.

The training and evaluation set includes 43,849 annotated faces and the held-out test set includes 32,571 annotated faces. Table 3 presents a summary of the dataset and Fig. 4 presents example images.

Collection and annotation. This collection consists of images recorded from Digital Single Lens Reflexes, specifically Sony α6000 and α7 E-mount camera with different capturing parameters on several busy streets around Beijing, where faces of various scales and poses are captured. The images in this collection are open source content tagged with a Creative Commons license. The resolution of these images is 1080 × 720 (down-sampled from 6K × 4K). Af-
Figure 4. Sub-challenge 2.2: Examples of images in DARK FACE collections.

Figure 5. Sub-challenge 2.2: DARK FACE has a high degree of variability in scale, pose, occlusion, appearance and illumination.

Table 3. Sub-challenge 2.2: Comparison of low-light image understanding datasets.

| Dataset | Training #Image | Training #Face | Testing #Image | Testing #Face |
|---------|-----------------|----------------|---------------|---------------|
| ExDark  | 400             | -              | 209           | -             |
| UFDD    | -               | -              | 612           | -             |
| DarkFace| 6,000           | 43,849         | 4,000         | 32,571        |

After filtering out those without sufficient information (lacking faces, too dark to see anything, etc.), we select 10,000 images for human annotation. The bounding boxes is labeled for all the recognizable faces in our collection. We make the bounding tightly around the forehead, chin, and cheek, using the LabelImg Toolbox\(^1\). If a face is occluded, we only label the exposed skin region. If most of a face is occluded, we ignore it. For this collection, we observed commonly seen degradations in addition to under exposure, such as intensive noise. Each annotated image contains 1-34 human faces. The face number and resolution range distribution are displayed in Figure 6. Each annotated image contains 1-34 human faces. The face resolutions in these images range from 1 \(\times\) 2 to 335 \(\times\) 296. The resolution of most faces in our dataset is below 300 pixel\(^2\) and the face number mostly falls into the range [1, 20].

Table 4. Sub-challenge 2.3: Object statistics in the held-out test set.

| Categories | Car | Person | Bus | Bicycle | Motorcycle |
|------------|-----|--------|-----|---------|------------|
| test set   | 7332| 1135   | 613 | 268     | 968        |

3.3. Zero-Shot Object Detection with Raindrop Occlusions

In Sub-challenge 2.3, we release 1,010 pairs of realistic raindrop images and corresponding clean ground-truths, collected through the physical simulation process described in [85], as the training and/or validation sets. Our held-out test set contains 2,495 real rainy images from high-resolution driving videos. As shown in Figure 7, all images are contaminated by raindrops on camera lens. They were captured in diverse real traffic locations and scenes during
multiple drives. We labeled bounding boxes for selected traffic objects: car, person, bus, bicycle, and motorcycle, that commonly appear on the roads of all images. Most images are of $1920 \times 990$ resolution, with a few exceptions of $4023 \times 73024$ resolution.

The participants can optionally use pre-trained models (e.g., using ImageNet or COCO) or external data. But if any pre-trained model, self-synthesized or self-collected data are used, that must be explicitly mentioned in their submissions, and the participants must ensure their used data to be public available at the time of challenge submission, for reproducibility purposes.

4. Baseline Results and Analysis

For all three sub-challenges, we report results by cascading off-the-shelf enhancement methods and popular pre-trained detectors. There has been no joint training performed, hence the baseline numbers are in no way very competitive. We expect to see much performance boosts over the baselines from the competition participants.

4.1. Sub-challenge 2.1 Baseline Results

4.1.1 Baseline Composition

We test three state-of-the-art object detectors: (1) Mask R-CNN[33]; (2) RetinaNet[61]; and (3) YOLO-V3[86]; (4) Feature Pyramid Network (FPN)[60].

We also try three state-of-the-art dehazing approaches: (a) AOD-Net[48]; (b) Multi-Scale Convolutional Neural Network (MSCNN)[89]; (c) Densely Connected Pyramid Dehazing Network (DCPDN)[124]. All dehazing models adopt officially released versions.

4.1.2 Results and Analysis

Fig. 8 shows the object detection performance on the original hazy images of RESIDE RTTS set using Mask R-CNN. The detectrons is pretrained on Microsoft COCO, a large-scale object detection, segmentation, and captioning dataset. A more detailed detection performance on the five objects categories can be found in Table 5.

Results show that without preprocessing or dehazing, the object detectors pretrained on clean images fail to predict a large amount of objects in the hazy image. The overall detection performance has a mAP of only 41.83% using Mask R-CNN and 42.54% using YOLO-V3. Among all the five object categories, person has the highest detection AP, while bus has the lowest AP.

We also compare the validation and test set performance in Table 5. One possible reason for the performance gap between validation and test sets is that the bounding box size of the latter is smaller compared to the former, as showed in Fig.1 as well as visualized in Fig. 9.

Effect of Dehazing. We further evaluate the current state-of-the-art dehaze approaches on hazy dataset, with pre-trained detectors subsequently applied without tuning or adaptation. Fig. 9 shows two examples that dehazing algorithms can improve not only the visual quality of the images but also the detection accuracies. More detection results are included in Table 5. Detection mAPs of dehazed images using DCPDN and MSCNN approaches are 1% higher on average compared to on hazy images.
Table 5. Detection results (mAP) on the RTTS (train/validation dataset) and held-out test sets.

| mAP   | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|-------|--------|--------------|------------|--------------|
| hazy | 55.85  | 54.93        | 56.70      | 58.07        |
|       | 41.19  | 37.61        | 42.68      | 42.77        |
|       | 39.61  | 37.80        | 36.96      | 38.16        |
|       | 27.37  | 23.31        | 39.84      | 34.29        |
|       | 16.88  | 15.70        | 16.34      | 18.34        |
| mAP   | 36.18  | 33.87        | 36.37      | 37.27        |

| validation | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|------------|--------|--------------|------------|--------------|
| RetinaNet  | 67.52  | 66.71        | 67.18      | 69.23        |
|            | 48.93  | 47.76        | 52.37      | 51.93        |
|            | 40.81  | 39.66        | 40.40      | 40.42        |
|            | 33.78  | 26.71        | 34.58      | 31.38        |
|            | 18.11  | 16.91        | 18.25      | 18.42        |
| mAP        | 41.83  | 39.55        | 42.56      | 42.28        |

| Mask R-CNN | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|------------|--------|--------------|------------|--------------|
| 60.81      | 60.21  | 60.42        | 61.56      | 49.75        |
| 47.84      | 47.32  | 48.17        | 42.01      | 37.01        |
| 41.03      | 37.55  | 38.17        | 41.11      | 37.01        |
|            | 23.71  | 20.91        | 23.35      | 23.15        |
| mAP        | 42.54  | 41.64        | 42.06      | 43.52        |

| YOLO-V3    | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|------------|--------|--------------|------------|--------------|
| 51.85      | 52.35  | 51.04        | 54.50      | 38.88        |
| 37.48      | 36.05  | 37.19        | 38.88      | 37.01        |
| 35.31      | 35.93  | 32.57        | 37.01      | 37.01        |
|            | 23.65  | 21.07        | 22.97      | 23.86        |
| mAP        | 42.54  | 41.64        | 42.06      | 43.52        |

| FPN        | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|------------|--------|--------------|------------|--------------|
| RetinaNet  | 17.64  | 18.23        | 16.65      | 19.34        |
|            | 31.41  | 29.30        | 33.31      | 32.97        |
|            | 0.42   | 0.84         | 0.38       | 0.75         |
|            | 1.69   | 1.37         | 1.93       | 2.03         |
|            | 12.77  | 13.68        | 12.07      | 15.82        |
| mAP        | 12.79  | 12.69        | 12.87      | 15.82        |

| Mask R-CNN | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|------------|--------|--------------|------------|--------------|
| 25.60      | 26.63  | 24.59        | 27.94      | 19.34        |
| 39.31      | 39.71  | 39.12        | 42.57      | 42.57        |
| 0.64       | 0.52   | 0.22         | 0.37       | 0.37         |
| 3.37       | 2.81   | 2.83         | 2.99       | 2.99         |
|            | 15.66  | 15.41        | 16.69      | 16.55        |
| mAP        | 16.92  | 17.02        | 17.42      | 18.09        |

| YOLO-V3    | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|------------|--------|--------------|------------|--------------|
| 20.64      | 21.41  | 21.42        | 22.11      | 35.93        |
| 34.68      | 33.90  | 34.52        | 35.93      | 35.93        |
| 0.50       | 0.38   | 0.98         | 0.57       | 0.57         |
| 4.26       | 4.10   | 4.72         | 5.27       | 5.27         |
|            | 13.55  | 14.35        | 13.75      | 15.04        |
| mAP        | 14.69  | 14.83        | 15.08      | 15.78        |

| FPN        | Person | AOD-Net [48] | DCPDN [89] | MSCNN [124] |
|------------|--------|--------------|------------|--------------|
| 12.65      | 12.57  | 11.13        | 14.19      | 32.68        |
| 30.54      | 31.24  | 27.81        | 32.68      | 32.68        |
| 1.91       | 0.39   | 1.12         | 0.97       | 0.97         |
| 2.25       | 1.7    | 1.96         | 1.89       | 1.89         |
|            | 6.08   | 7.93         | 7.39       | 8.31         |
| mAP        | 10.69  | 10.77        | 9.88       | 11.61        |

* RetinaNet, Mask R-CNN and YOLO-V3 are pretrained on Microsoft COCO dataset.

FPN using ResNet-101 backbone is pretrained on the PASCAL Visual Object Classes (VOC) dataset.
Eventually, the choice of pre-trained detectors seem to also matter here: Mask R-CNN outperforms the other two detectors on both validation and test sets, and both before and after apply dehazing.

4.2. Sub-challenge 2.2 Baseline Results

4.2.1 Baseline Composition

We test five state-of-the-art deep face detectors: (1) Dual Shot Face Detector (DSFD) [52]; (2) Pyramid-box [100]; (3) Single Shot Scale-Invariant Face Detector (S3FD) [129]; (4) Single Stage Headless Face Detector (SSH) [79]; (5) Faster RCNN [37].

We also include seven state-of-the-art algorithms for light/contrast enhancement: (a) Bio-Inspired Multi-Exposure Fusion (BIMEF) [21]; (b) Dong [18]; (c) Low-light Image Enhancement (LIME) [32]; (d) MF [24]; (e) Multi-Scale Retinex (MSR) [39]; (f) Joint Enhancement and Denoising (JED) [93]; (g) RetinexNet [113].

4.2.2 Results and Analysis

Fig. 12 (a) depicts the precision-recall curves of the original face detection methods, without enhancement. The baseline methods are trained on WIDER FACE, a large dataset with large scale variations in diversified factors and conditions. The results demonstrate that without proper pre-processing or adaptation, the state-of-the-art methods cannot achieve desirable detection rates on DARK FACE. Result examples are illustrated in Fig. 10. The evidences may imply that previous face datasets, though covering variations in poses, appearances, scale, et al., are still insufficient to capture the facial features in the highly under-exposure condition.

Effect of Enhancement

We next use the enhancement algorithms to pre-process the annotated dataset and then apply the above two pre-trained face detection methods to the processed data. While the visual quality of the enhanced images is better, as expected, the detectors do perform better. As shown in Fig. 12 (b) and (c), in most instances, the precision of the detectors notably increased compared to that of the data without enhancement. Except for JED, various existing enhancement methods seem to result in similar improvements here. JED leads to a performance drop. Despite being encouraging to see, the overall performance of the detectors still drops a lot compared to normal-light datasets. The simple cascade of low light enhancement and face detectors leave much improvement room open.

Effect of Face Scale and Light Condition

We analyze the performance of the face detectors on subsets of different levels of difficulty. We define difficulty of the sets based on two criteria: face scale and facial light condition. Face scale is divided into three levels based on the average size of the bounding boxes in an image: small face (<100 pixel²), medium face (100-300 pixel²), large face (>300 pixel²). Facial illumination is also divided into three levels based on

9https://github.com/TencentYouTuResearch/FaceDetection-DSFD
10https://github.com/EricZgw/PyramidBox
11https://github.com/sfzhang15/SFD

12https://github.com/mahyarnajibi/SSH.git
13https://github.com/playerkk/face-py-faster-rcnn
14https://github.com/baidut/BIMEF
15https://sites.google.com/view/xjguo/lime
16https://github.com/tonghelen/JED-Method
17https://github.com/weichen582/RetinexNet
the average pixel value of the bounding boxes: low illumination, medium illumination, high illumination. We present the results in Fig. 13 and 14. Clearly, the performance degrades for small faces and those with low illumination. DSFD achieves the best performance, with average precision rates greater than 45, while lower than 55. The results suggest that current face detectors are limited when face scale and light condition change.

4.3. Sub-challenge 2.3 Baseline Results

4.3.1 Baseline Composition

We use four state-of-the-art object detection models: (1) Faster R-CNN (FRCNN) [88]; (2) YOLO-V3 [86]; (3) SSD-512 [70]; and (4) RetinaNet [61].

We employ five state-of-the-art deep learning-based deraining algorithms: (a) JOint Rain DEtection and Removal 18 (JORDER) [119]; (b) Deep Detail Network 19 (DDN) [23]; (c) Conditional Generative Adversarial Network 20 (CGAN) [126]; (d) Density-aware Image Deraining method using a Multistream Dense Network 21 (DID-MDN) [125]; and (e) DeRaindrop 22 [85]. For fair comparisons, we re-trained all deraining algorithms using the same provided training set.

Results and Analysis Table 6 shows mAP results comparisons for different deraining algorithms using different detection models on the held-out test set. Unfortunately, we find that almost all existing deraining algorithms deteriorate the objects detection performance compared to directly using the rainy images for YOLO-V3, SSD-512, and RetinaNet (The only exception is the detection results by FRCNN). This could be due to those deraining algorithms were not trained towards the end goal of object detection, they are unnecessary to help this goal, and the deraining process itself might have lost discriminative, semantically meaningful true information, and thus hamper the detection performance. In addition, Table 6 shows that YOLO-V3 achieves the best detection performance, independently of deraining algorithms applied. We attribute this to the small objects in relative long distance from the camera in the test set since YOLO-V3 is known to improve small object detection based on multi-scale prediction structure.

References

[1] M. Abdullah-Al-Wadud, M. H. Kabir, M. A. A. Dewan, and O. Chae. A dynamic histogram equalization for image contrast enhancement. IEEE Transactions on Consumer Electronics, 53(2):593–600, May 2007.

[2] C. O. Ancuti, C. Ancuti, R. Timofte, and C. De Vleeschouwer. I-HAZE: a dehazing benchmark with real hazy and haze-free indoor images. arXiv e-prints, page arXiv:1804.05091, April 2018.

[3] C. O. Ancuti, C. Ancuti, R. Timofte, and C. De Vleeschouwer. O-HAZE: a dehazing benchmark with real hazy and haze-free outdoor images. arXiv e-prints, page arXiv:1804.05101, April 2018.

[4] P. C. Barnum, S. Narasimhan, and T. Kanade. Analysis of rain and snow in frequency space. Int’l Journal of Computer Vision, 86(2-3):256–274, 2010.

[5] D. Berman, T. Treibitz, and S. Avidan. Non-local image dehazing. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, pages 1674–1682, June 2016.

[6] M. Bevilacqua, A. Roumy, C. Guillelmet, and M. line Alberi Morel. Low-complexity single-image super-resolution based on nonnegative neighbor embedding. In Proc. of the British Machine Vision Conf., pages 135.1–135.10. BMVA Press, 2012.

[7] J. Bossu, N. Hauti`ere, and J.-P. Tarel. Rain or snow detection in image sequences through use of a histogram of

---

Figure 10. Sample face detection results of pretrained baseline on the original images of the proposed DARK FACE dataset.

Figure 11. Sample face detection results of pretrained baseline on the enhanced images of the proposed DARK FACE dataset.
Table 6. Detection results (mAP) on the held-out test set.

| Model          | FRCNN [88] | JORDER [119] | DDN [23] | CGAN [126] | DID-MDN [125] | DeRaindrop [85] |
|----------------|------------|---------------|----------|------------|---------------|-----------------|
| Rainy          | 16.52      | 16.97         | 18.36    | **23.42**  | 16.11         | 15.58           |
| YOLO-V3 [86]   | **27.84**  | 26.72         | 26.20    | 23.75      | 24.62         | 24.96           |
| SSD-512 [70]   | 17.71      | 17.06         | 16.93    | 16.71      | 16.70         | 16.69           |
| RetinaNet [61] | **23.92**  | 21.71         | 21.60    | 19.28      | 20.08         | 19.73           |

Figure 12. Evaluation results of pretrained baseline on original and enhanced images of the proposed DARK FACE dataset.

Figure 13. Comparison of detection accuracies for different face scales for DARK FACE.

Figure 14. Comparison of detection accuracies for different face brightness for DARK FACE.
orientation of streaks. *International journal of computer vision*, 93(3):348–367, 2011.

[8] N. Brewer and N. Liu. Using the shape characteristics of rain to identify and remove rain from video. In *Joint IAPR International Workshops on SPR and SSPR*, pages 451–458, 2008.

[9] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao. Dehazenet: An end-to-end system for single image haze removal. *IEEE Trans. on Image Processing*, 25(11):5187–5198, November 2016.

[10] J. Cai, S. Gu, and L. Zhang. Learning a deep single image contrast enhancer from multi-exposure images. *IEEE Trans. on Image Processing*, 27(4):2049–2062, April 2018.

[11] Y. Chang, L. Yan, and S. Zhong. Transformed low-rank model for line pattern noise removal. In *Proc. IEEE Int’l Conf. Computer Vision*, Oct 2017.

[12] C. Chen, Q. Chen, J. Xu, and V. Koltun. Learning to see in the dark. In *Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition*, pages 3291–3300, June 2018.

[13] J. Chen and L. P. Chau. A rain pixel recovery algorithm for videos with highly dynamic scenes. *IEEE Trans. on Image Processing*, 23(3):1097–1104, March 2014.

[14] J. Chen, C.-H. Tan, J. Hou, L.-P. Chau, and H. Li. Robust video content alignment and compensation for rain removal in a cnn framework. In *Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition*, June 2018.

[15] Y.-L. Chen and C.-T. Hsu. A generalized low-rank appearance model for spatio-temporally correlated rain streaks. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1968–1975, 2013.

[16] B. Cheng, Z. Wang, Z. Zhang, Z. Li, D. Liu, J. Yang, S. Huang, and T. S. Huang. Robust emotion recognition from low quality and low bit rate video: A deep learning approach. In *2017 Seventh International Conference on Affective Computing and Intelligent Interaction (ACII)*, pages 65–70. IEEE, 2017.

[17] C. Dong, Y. Deng, C. C. Loy, and X. Tang. Compression artifacts reduction by a deep convolutional network. In *Proc. IEEE Int’l Conf. Computer Vision*, pages 576–584, Dec 2015.

[18] X. Dong, G. Wang, Y. Pang, W. Li, J. Wen, W. Meng, and Y. Lu. Fast efficient algorithm for enhancement of low lighting video. In *Proc. IEEE Int’l Conf. Multimedia and Expo*, pages 1–6. IEEE, 2011.

[19] A. Dutta, R. Veldhuis, and L. Spreeuwers. The impact of image quality on the performance of face recognition. In *Symposium on Information Theory in the Benelux and Joint WIC/IEEE Symposium on Information Theory and Signal Processing in the Benelux*, pages 141–148, Netherland, 5 2012. Werkgemeenschap voor Informatie- en Communicatiethoorie (WIC).

[20] R. Fattal. Single image dehazing. *ACM Trans. Graph.*, 27(3):72:1–72:9, August 2008.

[21] R. Fergus, B. Singh, A. Hertzmann, S. T. Roweis, and W. T. Freeman. Removing camera shake from a single photograph. In *ACM Trans. Graphics*, pages 787–794, 2006.

[22] X. Fu, J. Huang, X. Ding, Y. Liao, and J. Paisley. Clearing the skies: A deep network architecture for single-image rain removal. *IEEE Trans. on Image Processing*, 26(6):2944–2956, June 2017.

[23] X. Fu, J. Huang, D. Zeng, Y. Huang, X. Ding, and J. Paisley. Removing rain from single images via a deep detail network. In *Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition*, July 2017.

[24] X. Fu, D. Zeng, Y. Huang, Y. Liao, X. Ding, and J. Paisley. A fusion-based enhancing method for weakly illuminated images. *Signal Processing*, 129:82 – 96, 2016.

[25] X. Fu, D. Zeng, Y. Huang, X. P. Zhang, and X. Ding. A weighted variational model for simultaneous reflectance and illumination estimation. In *Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition*, pages 2782–2790, June 2016.

[26] A. Fujimoto, T. Ogawa, K. Yamamoto, Y. Matsui, T. Yamashita, and K. Aizawa. Manga109 dataset and creation of metadata. In *Proc. of Int’l Workshop on coMics ANalysis, Processing and Understanding*, pages 1–5, 2016.

[27] K. Garg and S. K. Nayar. Detection and removal of rain from videos. In *Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition*, volume 1, pages I–528, 2004.

[28] K. Garg and S. K. Nayar. When does a camera see rain? In *Proc. IEEE Int’l Conf. Computer Vision*, volume 2, pages 1067–1074, 2005.

[29] K. Garg and S. K. Nayar. Photorealistic rendering of rain streaks. In *ACM Trans. Graphics*, volume 25, pages 996–1002, 2006.

[30] K. Garg and S. K. Nayar. Vision and rain. *Int’l Journal of Computer Vision*, 75(1):3–27, 2007.

[31] M. Grgic, K. Delac, and S. Grgic. Scface — surveillance cameras face database. *Multimedia Tools Appl.*, 51(3):863–879, February 2011.

[32] X. Guo, Y. Li, and H. Ling. Lime: Low-light image enhancement via illumination map estimation. *IEEE Trans. on Image Processing*, 26(2):982–993, Feb 2017.

[33] K. He, G. Gkioxari, P. Dollár, and R. Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017.

[34] K. He, J. Sun, and X. Tang. Single image haze removal using dark channel prior. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 33(12):2341–2353, Dec 2011.

[35] P. H. Hennings-Yeomans, S. Baker, and B. V. K. V. Kumar. Simultaneous super-resolution and feature extraction for recognition of low-resolution faces. In *Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition*, pages 1–8, June 2008.

[36] J. Huang, A. Singh, and N. Ahuja. Single image super-resolution from transformed self-exemplars. In *Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition*, pages 5197–5206, June 2015.

[37] H. Jiang and E. G. Learned-Miller. Face detection with the faster r-cnn. *IEEE Int’l Conf. on Automatic Face and Gesture Recognition*, pages 650–657, 2017.

[38] T.-X. Jiang, T.-Z. Huang, X.-L. Zhao, L.-J. Deng, and Y. Wang. A novel tensor-based video rain streaks removal
approach via utilizing discriminatively intrinsic priors. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, July 2017.

[39] D. J. Jobson, Z. Rahman, and G. A. Woodell. A multiscale retinex for bridging the gap between color images and the human observation of scenes. IEEE Trans. on Image Processing, 6(7):965–976, July 1997.

[40] D. J. Jobson, Z. Rahman, and G. A. Woodell. Properties and performance of a center/surround retinex. IEEE Trans. on Image Processing, 6(3):451–462, Mar 1997.

[41] L. W. Kang, C. W. Lin, and Y. H. Fu. Automatic single-image-based rain streaks removal via image decomposition. IEEE Trans. on Image Processing, 21(4):1742–1755, April 2012.

[42] S. Karahan, M. Kilinc Yildirim, K. Kirtac, F. S. Rende, G. Butun, and H. K. Ekenel. How image degradations affect deep cnn-based face recognition? In Int’l Conf. of the Biometrics Special Interest Group, pages 1–5, Sep. 2016.

[43] J. H. Kim, C. Lee, J. Y. Sim, and C. S. Kim. Single-image deraining using an adaptive nonlocal means filter. In Proc. IEEE Int’l Conf. Image Processing, pages 914–917, Sept 2013.

[44] J. H. Kim, J. Y. Sim, and C. S. Kim. Video deraining and desnowing using temporal correlation and low-rank matrix completion. IEEE Trans. on Image Processing, 24(9):2658–2670, Sept 2015.

[45] L. Kratz and K. Nishino. Factorizing scene albedo and depth from a single fogy image. In Proc. IEEE Int’l Conf. Computer Vision, pages 1701–1708, Sep. 2009.

[46] E. H. Land. The retinex theory of color vision. Sci. Amer., pages 108–128, 1977.

[47] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng. An all-in-one network for dehazing and beyond. arXiv preprint arXiv:1707.06543, 2017.

[48] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng. Aod-net: All-in-one dehazing network. In Proc. IEEE Int’l Conf. Computer Vision, pages 4780–4788, Oct 2017.

[49] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng. End-to-end united video dehazing and detectionc. Feb. 2018.

[50] B. Li, W. Ren, D. Fu, D. Tao, D. Feng, W. Zeng, and Z. Wang. Benchmarking single-image dehazing and beyond. IEEE Trans. on Image Processing, 28(1):492–505, 2019.

[51] H. Li, Z. Lu, Z. Wang, Q. Ling, and W. Li. Detection of blotch and scratch in video based on video decomposition. IEEE Transactions on Circuits and Systems for Video Technology, 23(11):1887–1900, 2013.

[52] J. Li, Y. Wang, C. Wang, Y. Tai, J. Qian, J. Yang, C. Wang, J. Li, and F. Huang. Dsfd: Dual shot face detector. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, 2019.

[53] L. Li, R. Wang, W. Wang, and W. Gao. A low-light image enhancement method for both denoising and contrast enlarging. In Proc. IEEE Int’l Conf. Image Processing, pages 3730–3734, Sept 2015.

[54] M. Li, J. Liu, W. Yang, X. Sun, and Z. Guo. Structure-revealing low-light image enhancement via robust retinex model. IEEE Trans. on Image Processing, 27(6):2828–2841, June 2018.

[55] M. Li, Q. Xie, Q. Zhao, W. Wei, S. Gu, J. Tao, and D. Meng. Video rain streak removal by multiscale convolutional sparse coding. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, June 2018.

[56] S. Li, I. B. Araujo, W. Ren, Z. Wang, E. K. Tokuda, R. H. Junior, R. Cesar-Junior, J. Zhang, X. Guo, and X. Cao. Single image deraining: A comprehensive benchmark analysis. arXiv preprint arXiv:1903.08558, 2019.

[57] Y. Li, R. T. Tan, and M. S. Brown. Nighttime haze removal with glow and multiple light colors. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, pages 226–234, Dec 2015.

[58] Y. Li, R. T. Tan, X. Guo, J. Lu, and M. S. Brown. Rain streak removal using layer priors. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, pages 2736–2744, 2016.

[59] Y. li Tian. Evaluation of face resolution for expression analysis. In Proc. of Int’l Conf. on Computer Vision and Pattern Recognition Workshop, pages 82–82, June 2004.

[60] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie. Feature pyramid networks for object detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2117–2125, 2017.

[61] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár. Focal loss for dense object detection. IEEE transactions on pattern analysis and machine intelligence, 2018.

[62] D. Liu, B. Cheng, Z. Wang, H. Zhang, and T. S. Huang. Enhance visual recognition under adverse conditions via deep networks. arXiv preprint arXiv:1712.07732, 2017.

[63] D. Liu, Z. Wang, Y. Fan, X. Liu, Z. Wang, S. Chang, and T. Huang. Robust video super-resolution with learned temporal dynamics. In Proceedings of the IEEE International Conference on Computer Vision, pages 2507–2515, 2017.

[64] D. Liu, Z. Wang, Y. Fan, X. Liu, Z. Wang, S. Chang, X. Wang, and T. S. Huang. Learning temporal dynamics for video super-resolution: A deep learning approach. IEEE Transactions on Image Processing, 27(7):3432–3445, 2018.

[65] D. Liu, B. Wen, J. Jiao, X. Liu, Z. Wang, and T. S. Huang. Connecting image denoising and high-level vision tasks via deep learning. arXiv preprint arXiv:1809.01826, 2018.

[66] D. Liu, B. Wen, X. Liu, Z. Wang, and T. S. Huang. When image denoising meets high-level vision tasks: A deep learning approach. arXiv preprint arXiv:1706.04284, 2017.

[67] J. Liu, S. Yang, Y. Fang, and Z. Guo. Structure-guided image inpainting using homography transformation. IEEE Transactions on Multimedia, 20(12):3252–3265, 2018.

[68] J. Liu, W. Yang, S. Yang, and Z. Guo. Erase or fill? deep joint recurrent rain removal and reconstruction in videos. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, June 2018.

[69] P. Liu, J. Xu, J. Liu, and X. Tang. Pixel based temporal analysis using chromatic property for removing rain from videos. In Computer and Information Science, 2009.

[70] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg. Ssd: Single shot multibox detector.
In European conference on computer vision, pages 21–37, 2016.

[71] Y. Liu, G. Zhao, B. Gong, Y. Li, R. Raj, N. Goel, S. Kesav, S. Gottumukkala, Z. Wang, W. Ren, et al. Improved techniques for learning to dehaze and beyond: A collective study. arXiv preprint arXiv:1807.00202, 2018.

[72] Y. P. Loh and C. S. Chan. Getting to know low-light images with the exclusively dark dataset. Computer Vision and Image Understanding, 178:30–42, 2019.

[73] K. G. Lore, A. Akintayo, and S. Sarkar. Linet: A deep autoencoder approach to natural low-light image enhancement. Pattern Recognition, 61:650 – 662, 2017.

[74] Y. Luo, Y. Xu, and H. Ji. Removing rain from a single image via discriminative sparse coding. In Proc. IEEE Int'l Conf. Computer Vision, pages 3397–3405, 2015.

[75] D. Martin, C. Fowlkes, D. Tal, and J. Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In Proc. IEEE Int'l Conf. Computer Vision, volume 2, pages 416–423, July 2001.

[76] M. Mueller, N. Smith, and B. Ghanem. A benchmark and simulator for uav tracking, 2016.

[77] H. Nada, V. A. Sindagi, H. Zhang, and V. M. Patel. Pushing the Limits of Unconstrained Face Detection: a Challenge Dataset and Baseline Results. arXiv e-prints, page arXiv:1804.10275, Apr 2018.

[78] D. Nair, P. A. Kumar, and P. Sankaran. An effective surround filter for image dehazing. In Proc. of Int’l Conf. on Interdisciplinary Advances in Applied Computing, ICON-IAC ’14, pages 20:1–20:6, New York, NY, USA, 2014. ACM.

[79] M. Najibi, P. Samangouei, R. Chellappa, and L. S. Davis. Ssh: Single stage headless face detector. In Proc. IEEE Int’l Conf. Computer Vision, pages 4885–4894, Oct 2017.

[80] K. Nishino, L. Kratz, and S. Lombardi. Bayesian defogging. Int’l Journal of Computer Vision, 98(3):263–278, July 2012.

[81] S. Oh, A. Hoogs, A. Perera, N. Cuntoor, C. Chen, J. T. Lee, S. Mukherjee, J. K. Aggarwal, H. Lee, L. Davis, E. Swears, X. Wang, Q. Ji, K. Reddy, M. Shah, C. Vondrick, H. Pirsiavash, D. Ramanan, J. Yuen, A. Torralba, B. Song, A. Feng, A. Roy-Chowdhury, and M. Desai. A large-scale benchmark dataset for event recognition in surveillance video. In CVPR 2011, pages 3153–3160, June 2011.

[82] S. M. Pizer, R. E. Johnston, J. P. Erickson, B. C. Yankaskas, and K. E. Muller. Contrast-limited adaptive histogram equalization: speed and effectiveness. In Proceedings of Conference on Visualization in Biomedical Computing, pages 337–345, May 1990.

[83] T. Pltz and S. Roth. Benchmarking denoising algorithms with real photographs. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, pages 2750–2759, July 2017.

[84] R. Prabhuj, X. Yu, Z. Wang, D. Liu, and A. Jiang. U-finger: Multi-scale dilated convolutional network for fingerprint image denoising and inpainting. arXiv preprint arXiv:1807.10993, 2018.

[85] R. Qian, R. T. Tan, W. Yang, J. Su, and J. Liu. Attentive generative adversarial network for raindrop removal from a single image. In IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[86] J. Redmon and A. Farhadi. Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767, 2018.

[87] J. Ren, J. Liu, and Z. Guo. Context-aware sparse decomposition for image denoising and super-resolution. IEEE Transactions on Image Processing, 22(4):1456–1469, 2013.

[88] S. Ren, K. He, R. Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems, pages 91–99, 2015.

[89] W. Ren, S. Liu, H. Zhang, J. Pan, X. Cao, and M.-H. Yang. Single image dehazing via multi-scale convolutional neural networks. In European Conference on Computer Vision, 2016.

[90] W. Ren, J. Pan, X. Cao, and M.-H. Yang. Video deblurring via semantic segmentation and pixel-wise non-linear kernel. In Proceedings of the IEEE International Conference on Computer Vision, pages 1077–1085, 2017.

[91] W. Ren, J. Tian, Z. Han, A. Chan, and Y. Tang. Video denoising and deraining based on matrix decomposition. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, July 2017.

[92] W. Ren, J. Zhang, X. Xu, L. Ma, X. Cao, G. Meng, and W. Liu. Deep video dehazing with semantic segmentation. IEEE Trans. on Image Processing, 28(4):1895–1908, April 2019.

[93] X. Ren, M. Li, W.-H. Cheng, and J. Liu. Joint enhancement and denoising method via sequential decomposition. May 2018.

[94] V. Santhaseelan and V. K. Asari. Utilizing local phase information to remove rain from video. Int’l Journal of Computer Vision, 112(1):71–89, March 2015.

[95] C. Shan, S. Gong, and P. McOwan. Recognizing facial expressions at low resolution. In Proc. of IEEE Conf. on Advanced Video and Signal Based Surveillance, pages 330–335, Sep. 2005.

[96] J. Shao, C. C. Loy, and X. Wang. Scene-independent group profiling in crowd. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, pages 2227–2234, June 2014.

[97] H. R. Sheikh, M. F. Sabir, and A. C. Bovik. A statistical evaluation of recent full reference image quality assessment algorithms. IEEE Trans. on Image Processing, 15(11):3440–3451, Nov 2006.

[98] L. Shen, Z. Yue, F. Feng, Q. Chen, S. Liu, and J. Ma. MSR-net:Low-light Image Enhancement Using Deep Convolutional Network. ArXiv e-prints, November 2017.

[99] L. Stasiak, A. Pacut, and R. Vincente-Garcia. Face tracking simulator for uav tracking, 2016.

[100] X. Tang, D. K. Du, Z. He, and J. Liu. Pyramidbox: A context-assisted single shot face detector. In Proc. IEEE European Conf. Computer Vision, September 2018.
[101] R. Timofte, E. Agustsson, L. Van Gool, M.-H. Yang, and L. Zhang. Ntire 2017 challenge on single image super-resolution: Methods and results. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pages 114–125, 2017.

[102] A. Torralba, R. Fergus, and W. T. Freeman. 80 million tiny images: A large data set for nonparametric object and scene recognition. IEEE Trans. on Pattern Analysis and Machine Intelligence, 30(11):1958–1970, November 2008.

[103] A. K. Tripathi and S. Mukhopadhyay. A probabilistic approach for detection and removal of rain from videos. IETE Journal of Research, 57(1):82–91, 2011.

[104] A. K. Tripathi and S. Mukhopadhyay. Video post processing: low-latency spatiotemporal approach for detection and removal of rain. IET Image Processing, 6(2):181–196, March 2012.

[105] V. Vaˇsek, V. Franc, and M. Urban. License plate recognition and super-resolution from low-resolution videos by convolutional neural networks. In Proc. of British Machine Vision Conference, September 2018.

[106] R. G. VidalMata, S. Banerjee, B. RichardWebster, M. Albright, P. Davalos, S. McCluskey, B. Miller, A. Tambo, S. Ghosh, S. Nagesh, et al. Bridging the gap between computational photography and visual recognition. arXiv preprint arXiv:1901.09482, 2019.

[107] S. Wang, J. Zheng, H. M. Hu, and B. Li. Naturalness preserved enhancement algorithm for non-uniform illumination images. IEEE Trans. on Image Processing, 22(9):3538–3548, Sept 2013.

[108] Z. Wang, S. Chang, Y. Yang, D. Liu, and T. S. Huang. Studying very low resolution recognition using deep networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4792–4800, 2016.

[109] Z. Wang, H. Li, Q. Ling, and W. Li. Robust temporal-spatial decomposition and its applications in video processing. IEEE Transactions on Circuits and Systems for Video Technology, 23(3):387–400, 2013.

[110] Z. Wang, D. Liu, S. Chang, Q. Ling, Y. Yang, and T. S. Huang. D3: Deep dual-domain based fast restoration of jpeg-compressed images. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2764–2772, 2016.

[111] Z. Wang, Y. Yang, Z. Wang, S. Chang, W. Han, J. Yang, and T. Huang. Self-tuned deep super resolution. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pages 1–8, 2015.

[112] Z. Wang, Y. Yang, Z. Wang, S. Chang, J. Yang, and T. S. Huang. Learning super-resolution jointly from external and internal examples. IEEE Transactions on Image Processing, 24(11):4359–4371, 2015.

[113] C. Wei, W. Wang, W. Yang, and J. Liu. Deep retina decomposition for low-light enhancement. In British Machine Vision Conference, page 155. BMVA Press, 2018.

[114] W. Wei, L. Yi, Q. Xie, Q. Zhao, D. Meng, and Z. Xu. Should we encode rain streaks in video as deterministic or stochastic? In Proc. IEEE Int’l Conf. Computer Vision, Oct 2017.

[115] J. Xu, H. Li, Z. Liang, D. Zhang, and L. Zhang. Real-world Noisy Image Denoising: A New Benchmark. arXiv e-prints, page arXiv:1804.02603, Apr 2018.

[116] Y. Yan, W. Ren, Y. Guo, R. Wang, and X. Cao. Image de-blurring via extreme channels prior. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4003–4011, 2017.

[117] J. Yang, X. Jiang, C. Pan, and C.-L. Liu. Enhancement of low light level images with coupled dictionary learning. In Proc. IEEE Int’l Conf. Pattern Recognition, pages 751–756, Dec 2016.

[118] J. Yang, J. Wright, T. S. Huang, and Y. Ma. Image super-resolution via sparse representation. IEEE Trans. on Image Processing, 19(11):2861–2873, Nov 2010.

[119] W. Yang, R. T. Tan, J. Feng, J. Liu, Z. Guo, and S. Yan. Deep joint rain detection and removal from a single image. In IEEE Conference on Computer Vision and Pattern Recognition, 2017.

[120] B. Z. Yao, X. Yang, and S.-C. Zhu. Introduction to a large-scale general purpose ground truth database: Methodology, annotation tool and benchmarks. In EMMCVPR, 2007.

[121] Z. Yang, G. Li, and W. Gao. A Bio-Inspired Multi-Exposure Fusion Framework for Low-light Image Enhancement. ArXiv e-prints, November 2017.

[122] Z. Yu, H. Li, Z. Wang, Z. Hu, and C. W. Chen. Multi-level video frame interpolation: Exploiting the interaction among different levels. IEEE Transactions on Circuits and Systems for Video Technology, 23(7):1235–1248, 2013.

[123] R. Zeyde, M. Elad, and M. Protter. On single image scale-up using sparse-representations. In Proc. of the Int’l Conf. on Curves and Surfaces, pages 711–730, Berlin, Heidelberg, 2012. Springer-Verlag.

[124] H. Zhang and V. M. Patel. Densely connected pyramid dehazing network. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3194–3203, 2018.

[125] H. Zhang and V. M. Patel. Density-aware single image de-raining using a multi-stream dense network. In IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[126] H. Zhang, V. Sindagi, and V. M. Patel. Image de-raining using a conditional generative adversarial network. arXiv preprint arXiv:1701.05957, 2017.

[127] H. Zhang, J. Yang, Y. Zhang, N. M. Nasrabadi, and T. S. Huang. Close the loop: Joint blind image restoration and recognition with sparse representation prior. In 2011 International Conference on Computer Vision, pages 770–777. IEEE, 2011.

[128] J. Zhang, Y. Cao, S. Fang, Y. Kang, and C. W. Chen. Fast haze removal for nighttime image using maximum reflectance prior. In Proc. IEEE Int’l Conf. Computer Vision and Pattern Recognition, pages 7016–7024, July 2017.

[129] S. Zhang, X. Zhu, Z. Lei, H. Shi, X. Wang, and S. Z. Li. S3fd: Single shot scale-invariant face detector. In Proc. IEEE Int’l Conf. Computer Vision, pages 192–201, Oct 2017.

[130] X. Zhang, H. Li, Y. Qi, W. K. Leow, and T. K. Ng. Rain removal in video by combining temporal and chromatic prop-
erties. In Proc. IEEE Int’l Conf. Multimedia and Expo, pages 461–464, 2006.

[131] X. Zhang, P. Shen, L. Luo, L. Zhang, and J. Song. Enhancement and noise reduction of very low light level images. In Proc. IEEE Int’l Conf. Pattern Recognition, pages 2034–2037, Nov 2012.

[132] Y. Zhang, L. Ding, and G. Sharma. Hazerd: an outdoor scene dataset and benchmark for single image dehazing. In Proc. IEEE Int’l Conf. Image Processing, pages 3205–3209, 2017.

[133] J. Zhou and F. Zhou. Single image dehazing motivated by retinex theory. In Proc. of Int’l Symposium on Instrumentation and Measurement, Sensor Network and Automation, pages 243–247, Dec 2013.

[134] P. Zhu, L. Wen, D. Du, X. Bian, H. Ling, Q. Hu, Q. Nie, H. Cheng, C. Liu, X. Liu, et al. Visdrone-det2018: The vision meets drone object detection in image challenge results. In Proceedings of the European Conference on Computer Vision (ECCV), pages 0–0, 2018.

[135] Q. Zhu, J. Mai, and L. Shao. A fast single image haze removal algorithm using color attenuation prior. IEEE Trans. on Image Processing, 24(11):3522–3533, Nov 2015.

[136] X. Zhu, C. C. Loy, and S. Gong. Video synopsis by heterogeneous multi-source correlation. In Proc. IEEE Int’l Conf. Computer Vision, pages 81–88, Dec 2013.

[137] W. W. Zou and P. C. Yuen. Very low resolution face recognition problem. IEEE Trans. on Image Processing, 21(1):327–340, Jan 2012.