Segmentation-Aware Image Denoising without Knowing True Segmentation

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Abstract—Several recent works discussed application-driven image restoration neural networks, which are capable of not only removing noise in images but also preserving their semantic-aware details, making them suitable for various high-level computer vision tasks as the pre-processing step. However, such approaches require extra annotations for their high-level vision tasks, in order to train the joint pipeline using hybrid losses. The availability of those annotations is yet often limited to a few image sets, potentially restricting the general applicability of these methods to denoising more unseen and unannotated images. Motivated by that, we propose a segmentation-aware image denoising model dubbed U-SAID, based on a novel unsupervised approach with a pixel-wise uncertainty loss. U-SAID does not need any ground-truth segmentation map, and thus can be applied to any image dataset. It generates denoised images with comparable or even better quality, and the denoised results show stronger robustness for subsequent semantic segmentation tasks, when compared to either its supervised counterpart or classical “application-agnostic” denoisers. Moreover, we demonstrate the superior generalizability of U-SAID in three-folds, by plugging its “universal” denoiser without fine-tuning: (1) denoising unseen types of images; (2) denoising as pre-processing for segmenting unseen noisy images; and (3) denoising for unseen high-level tasks. Extensive experiments demonstrate the effectiveness, robustness and generalizability of the proposed U-SAID over various popular image sets.

I. INTRODUCTION

IMAGE denoising aims to recover the underlying clean image signal from its noisy measurement. It has been traditionally treated as an independent signal recovery problem, focusing on either single-level fidelity (e.g., PSNR) or human perception quality of the recovery results. However, once high-level vision tasks are conducted on noisy images and such a separate image denoising step is typically applied as preprocessing, it will become suboptimal because of its unawareness of semantic information. A series of recent works [29], [5], [20], [12], [28], [27] discussed application-driven image restoration models that are capable of simultaneously removing noise and preserving semantic-aware details for certain high-level vision tasks. Those models achieve visually promising denoising results with richer details, in addition to better utility when supplied for high-level task pre-processing.

However, a common drawback of them is their demand for extra annotations for the high-level vision tasks, in order to train the joint pipeline with hybrid low-level and high-level supervisions. On one hand, such annotations (e.g., object bounding boxes, semantic segmentation maps) are often highly non-trivial to obtain for real images, therefore limiting current works to synthesizing noise on existing annotated clean datasets, to demonstrate the effectiveness of their methods. On the other hand, training with only one annotated dataset runs the risk of overly tying the resulting denoiser with the semantic information of this specific dataset, which causes a lack of universality and may show various artifacts due to overfitting, when applied to denoising other substantially different images.

This paper attempts to break the above hurdles of existing application-driven image restoration models. We propose a novel unsupervised segmentation-aware image denoising (U-SAID) model, that enforces segmentation awareness and discriminative ability of denoisers, without actually needing any segmentation groundtruth during training. It is implemented by creating a novel loss term, that penalizes the pixel-wise uncertainty of the denoised outputs for segmentation. Our contributions are in two-folds:

- On the low-level vision side, to the best of our knowledge, U-SAID is the first unsupervised (or “self-supervised”) application-driven image restoration model. In contrast to the existing peer work [29], U-SAID can be trained on any image dataset, without needing ground-truth (GT) segmentation maps. That greatly extends the applicability of U-SAID as a more “universal” denoiser, that can be applied to denoise images with few semantic annotations while being substantially different from natural images in existing segmentation datasets. Compared to standard “application-agnostic” denoisers such as [52], U-SAID is observed to provide better visual details, that are also more favored under perception-driven metrics [33].
- On the high-level vision side, the U-SAID denoising network is shown to be robust and “universal” enough, when applied to denoising different noisy datasets, as well as when used towards boosting the segmentation task performance on unseen noisy datasets, thanks to its less semantic association with any dataset annotation. Furthermore, U-SAID trained with segmentation awareness generalizes well to unseen high-level vision tasks, and can be plugged into without fine-tuning, which reduces the training effort when applied to various high-level tasks.

Extensive experiments on various popular image sets
demonstrating the outstanding effectiveness, robustness, and universality of the proposed approach. We advocate that our methodology is (almost) a free lunch for image denoising, and has a plug-and-play nature to be incorporated with existing deep denoising models.

II. RELATED WORK

Image denoising has been studied with intensive efforts for decades. Earliest methods refer to various image filters [41]. Later on, many model-based method with various priors have been introduced to this topic, in either spatial or transform domain, or their hybrid, such as spatial smoothness [38], non-local patch similarity [7], sparsity [11], [31], [47] and low-rankness [13]. More recently, a number of deep learning models have demonstrated superior performance for image denoising [3, 32, 52]. Despite their encouraging process, most existing denoising algorithms reconstruct images by minimizing the mean square error (MSE), which is well-known to be mis-aligned with human perception quality and often tends to over-smooth textures [17]. Moreover, while image denoising algorithms are often needed as the pre-processing step for the acquired noisy visual data before subsequent high-level visual analytics, their impact on the semantic visual information was much less explored.

Lately, a handful of works are devoted to closing the gap between the low-level (e.g., image denoising, as a representative) and high-level computer vision tasks. Such marriage leads to, not only better utility performance for high-level target tasks, but also the denoising outputs with richer visual details after receiving the extra semantic guidance from the high-level tasks, the latter being first revealed in [19], [46], [29] presented a systematical study on the mutual influence between the low-level and high-level vision networks. The authors cascaded a fixed pre-trained semantic segmentation network after a denoising network, and tuned the entire pipeline with a joint loss function of MSE and segmentation loss. In that way, the authors showed the denoised images to have sharper edges and clearer textual details, as well as higher segmentation and classification accuracies when feeding such denoised images for those tasks. A similar effort was described in [12], where a segmentation-aware deep fusion network was proposed to utilize the segmentation labels in MRI datasets to aid MRI compressive sensing recovery. [20] considered a joint pipeline of image dehazing and object detection. [39] proposed to incorporate global semantic priors (e.g., eyes and mouths) as an input to deblur the highly structured face images. This field is now rapidly growing, with a few benchmarks launched recently [21], [45], [22], [50].

Following [29], [12], we also adopt segmentation as our high-level task, because it can supply pixel-wise feedbacks and is thus considered to be more helpful for dense regression tasks. As pointed out by [15], the availability of segmentation information can compromise the over-smoothening effects of CNNs across regions and increases their spatial precision. However, we would like to emphasize (again) that while [29], [15], [12] all exploit GT segmentation maps as extra strong supervision information during training, we have only a weaker form of feedbacks available from the segmentation task, due to the absence of its GT as extra information. Straightforwardly, our methodology is applicable when cascaded with other high-level tasks as well.

Our work is also broadly related to training deep network with noisy or uncertain annotations [44], [40]. Especially for the segmentation task, existing supervised models require manually labeled segmentations for training. But pixel-based labeling for high-resolution images is often time-consuming and error-prone, causing incorrect pixel-wise annotations. Existing works often consider them as label noise [37]. For example, [23] proposed a noise-tolerant deep model for histopathological image segmentation, using the label-flip noise models proposed in [40]. However, those algorithms still need to be given segmentation maps (though inaccurate), and often demand more statistical estimations of the label noise.

III. THE PROPOSED MODEL: U-SAID

Our proposed unsupervised segmentation-aware image denoising (U-SAID) network follows the same cascade idea of the segmentation-guided denoising framework proposed by [29]. We replace their self-designed U-Net denoiser with the classical deep denoiser DnCNN [52], using the 20-layer blind color image denoising model referred to as CDnCNN-B [3] since we favor more robustness to varying noise labels. Note that the choice of denoiser network should not affect much our obtained conclusions. Its loss $L_{MSE}$ is the reconstruction MSE between the denoised output and the clean image.

The critical difference between U-SAID and existing works lies in the high-level component of the cascade. Unlike [29], [12] that placed a pre-trained and fixed segmentation network with true segmentation labels given for training, we design a new unsupervised segmentation awareness (USA) module, that requires no segmentation labels to train with. The network architecture is illustrated in Figure 1.

A. Design of USA Module

The USA module is composed of a feature embedding sub-network for transforming the input (denoised image) to the feature space, followed by an unsupervised segmentation sub-network that calculates the pixel-wise uncertainty of semantic segmentation.

For the feature embedding sub-network, we used a Feature Pyramid Network (FPN) [24], with a ResNet-101 backbone as the feature encoder. We used ImageNet-pretrained weights [7] for the backbone, and keep all default architecture details of FPN/ResNet-101 unchanged. During training, the ResNet-101 backbone is frozen as a fixed feature extractor, and the top-down feature pyramid part of FPN started with random Gaussian initializations and also kepted fixed. It is very important to notice that we have not used any image segmentation dataset to pre-train the feature embedding sub-network.

For the unsupervised segmentation sub-network, we assume the input image resolution to be $M \times N$ and contain

https://github.com/cszn/DnCNN
https://github.com/pytorch/vision/blob/master/torchvision/models/resnet.py
at most $K$ different semantic classes. After FPN, we obtain 512 channels of feature maps $\in \mathbb{R}^{M \times N}$. We then apply $K$ $3 \times 3$ convolutions to re-organize the output feature maps into $K$ channels, eventually leading to a (resized) $K$-class segmentation map.

Since the image segmentation task can be casted as pixel-wise classification, classical segmentation networks will adopt pixel-wise softmax loss function to generate a $K$-class probability vector $p_{i,j}$, for the $(i,j)$-th $\mathbb{R}^K$ vector ($i,j$ range from 1 to $M,N$, respectively), choosing the highest probability class and producing the final segmentation map $\in \mathbb{R}^{M \times N}$. However, since we have no GT pixel labels in the unsupervised case, we instead minimize the average entropy function of all predicted class vectors $p_{i,j}$, denoted as $L_{USA}$, to encourage confident predictions at all pixels:

$$L_{USA} = \frac{1}{MN} \sum_{1 \leq i \leq M, 1 \leq j \leq N} -p_{i,j} \log p_{i,j}$$

All layer-wise weights in the unsupervised segmentation sub-network are random Gaussian initialized, and the ResNet-101 backbone uses the pre-trained ImageNet weights. Similar to [29], [12], we use a fixed high-level network, but we do not include the perceptual loss in training the network.

**B. Training Strategy**

We train the cascade of denoising network and USA module in an end-to-end manner, while fixing the weights in the feature embedding sub-network of the latter. The overall loss for U-SAID is: $L_{MSE} + \gamma L_{USA}$, with the default $\gamma = 1$ unless otherwise specified. The training dataset for U-SAID could be any image set and is unnecessary to have segmentation annotations, overcoming the limitations in [29], [12]. That said, we need an estimate of segmentation class numbers $K$ to construct $L_{USA}$: an ablation study of estimated $K$ will follow.

We use the Adam solver to train both the denoiser part and the USA module. The batch size is 16. The input patches are set to be $48 \times 48$ pixels (patches are randomly sampled from images with a stride of 1). The initial learning rate is set as 1e-3 for all learnable parts of U-SAID, using a multi-step learning decay strategy, i.e. dividing the learning rate by 10 at epoch 10, 40 and 80, respectively. The training is terminated after 100 epochs.

**C. Why It Works?**

A noteworthy feature of U-SAID is frozen high-level network, together with the denoiser. Without strong label supervision, one may wonder why it can regularize the denoiser training effectively, since it is high level features include the random initialization keep fixed, and the ResNet-101 ImageNet features can still be regressed into some unknown map, that is only required to be low-entropy pixel-wise. In fact, if the network itself holds large enough capacity, one may expect to be able to find parameters that can fit with any given pixel-wise map (low-entropy or not), that conveys little semantical information (e.g., random maps).

That might have reminded the *deep image prior* proposed in [43]: the authors first trained a convolutional network from random scratch, to regress from a random vector to a given corrupted image, and then used the trained network as a regularization. Since no aspect of the network is pre-trained from data, such deep image prior is effectively handcrafted and was shown to work well for various image restoration tasks. The authors attributed the success to the convolutional architecture itself, that appeared to possess high noise impedance. In our case, the ImageNet features are thought as highly relevant to image semantics. Therefore, we make the similar hypothesis with the authors of [43]: although the parametrization may regress to any random unstructured label map, it does so very reluctantly.

![Fig. 1: The architecture of the proposed U-SAID network](image-url)
To verify our hypothesis, we conduct a simple proof-of-concept experiment inspired by [51]. In the USA module, we replace $L_{USA}$ with a standard pixel-wise softmax loss, having ResNet-101 fixed with ImageNet weights and other parts initialized randomly. We then use PASCAL VOC 2012 training set to train this modified USA module, in a supervised way, but with three different choices for the supervision: 1) the GT segmentation maps; 2) evenly cutting each GT map into 4 sub-images, and randomly permuting their locations; 3) randomly permuting all pixel locations in each GT map. Notice that if we compute $L_{USA}$ values for the three target maps, they should be the same.

We show in Figure 2 the value of training loss, as a function of the gradient descent iterations for three supervisions. Apparently, the network can converge much faster to GT maps; the more GT maps were permuted, the more convergence “inertia” we observe. In other words, the network descends much more quickly towards semantically meaningful maps, and resists “bad” solutions with fewer semantics, although their entropies might have been the same.

IV. EXPERIMENTS

A. Denoising Study on PASCAL-VOC

The U-SAID denoiser takes RGB images as input and outputs the reconstructed images. We choose the PASCAL VOC 2012 training set, and add i.i.d. Gaussian noise with zero mean and standard deviation $\sigma$ to synthesize the noisy input images during training. The testing set is generated similarly by adding noise on the PASCAL VOC 2012 validation set. Since we used CDnCNN-B as the backbone denoiser, we focus on the challenging blind denoising scenario, by setting the Gaussian noise standard deviations $\sigma$ to uniformly range between $[0, 55]$ for the training set, creating a “one-for-all” denoiser that can be simply evaluated at different testing sets with various $\sigma$s. The PASCAL VOC 2012 sets have 20 classes of interested objects, plus a background class, leading to $K = 21$ unless otherwise specified.

We compare U-SAID with the original CDnCNN-B (retrained on our training set) [52], which requires no segmentation information at all. We further create another denoiser following the same idea of [29]: cascading CDnCNN-B with the supervised segmentation network (i.e., replacing $L_{USA}$ with a standard pixel-wise softmax loss), with all other training protocols and initialization the same as U-SAID. We call it supervised segmentation-aware image denoising (S-SAID), and train it with the hybrid MSE-segmentation loss (the two losses are weighted equally), using the ground-truth segmentation maps available on the PASCAL training set. Note that S-SAID is the only method that exploits “true” segmentation information, making it a natural baseline for U-SAID to show the effect of such extra information. We do not include other denoising methods such as [7], [3], [13] because: 1) their average performance was shown to be worse than CDnCNN; and 2) most of them are not designed for the blind denoising scenario, thus hard to make fair comparisons. We have exhaustively tuned the hyper-parameters (learning rates, etc.) for CDnCNN-B and S-SAID, to ensure the optimal performance of either baseline.

The typical metric used for image denoising is PSNR, which has been shown to correlate poorly with human assessment of visual quality [13]. On the other hand, in the metric of PSNR, a model trained by minimizing MSE on the image domain should always outperform a model trained by minimizing a hybrid weighted loss. Therefore, we emphasize that the goal of our following experiments is not to pursue the highest PSNR, but to quantitatively demonstrate the different behaviors between models with and without segmentation awareness.

Table II reports the denoising performance in terms of PSNR, SSIM and Naturalness Image Quality Evaluator (NIQE) [33]. The last one is a well-known no-reference image quality score to indicate the perceived “naturalness” of an image: a smaller score indicates better perceptual quality. Our observations from Table II are summarized as below:

- Since CDnCNN-B is optimized towards the MSE loss, it is not surprising that it consistently achieves the best PSNR results among all. However, U-SAID is able to achieve only marginally inferior PSNR/SSIMs to CDnCNN-B, which usually surpass S-SAID.
- The two methods with segmentation awareness (U-SAID and S-SAID) are significantly more favored by NIQE.
showing a large margin over CDnCNN-B (e.g., nearly 0.4 at $\sigma = 25$). That testifies the benefits of considering high-level tasks for denoising.

- While not exploiting the true segmentation maps during training as S-SAID did, the performance of U-SAID is almost as competitive as S-SAID under the NIQE metric. In other words, we did not lose much without using the true segmentation as supervision.

| $K$   | 10  | 15  | 20  | 21 (default) | 22  | 25  | 40  |
|-------|-----|-----|-----|-------------|-----|-----|-----|
| NIQE  | 3.9878 | 3.8329 | 4.0783 | 3.8975 | 3.8455 | 4.1139 | 3.9746 |
| PSNR  | 31.00 | 31.06 | 30.99 | 31.13 | 31.01 | 30.99 | 30.98 |

**TABLE II:** Ablation study of varying $K$ in U-SAID training.

a) Ablation Study on “Unsupervised Segmentation”: In training U-SAID above, we have used the “true” class number $K = 21$. It is then to our curiosity that: is this ground-truth value really best for training denoisers? Or, if the class number information cannot be accurately inferred when tackling general images, how much the denoising performance might be affected?

We hereby present an ablation study, by training several U-SAID models with different $K$ values (all else remain unchanged), and compare their denoising performance on the testing set, as displayed in Table II. It is encouraging to observe that, the U-SAID denoising performance (PSNR and SSIM) consistently increase as $K$ grows from smaller values (10, 15) towards the true value (21), and then gradually decreases as $K$ get further larger. The NIQE values show the similar first-go-up-then-down trend, except the peak slightly shifted to 15. That acts as a side evidence that rather than learning a semantically blind discriminator, the USA module indeed picks up the semantic class information and benefits from the correct $K$ estimate. On the other hand, the variations of denoising performance w.r.t $K$ are mild and smooth, showing certain robustness to inaccurate $K$’s too.

b) More Comparison to Relevant Methods: To solidify our results, we include more off-the-shelf denoising methods for comparison. We performed these experiments on Kodak dataset with three test sigmas 15, 25 and 35. A detailed comparison for each method we use is shown in Table III. However, all methods we mentioned previously, i.e. CDnCNN-B, S-SAID and U-SAID, are blind to the noise level, the competing methods are non-blind. Therefore, we created two settings to simulate blind denoising:

- Applying the median sigma as denoising input ($\sigma = 25$);
- Assuming the oracle sigma is known in denoising

The second setting is apparently unfair to our blind model. Even so, we demonstrate the results in [IV] from which U-SAID constantly yields the best performance.

**TABLE III:** Comparison of different methods. The three categories (columns) verify if the methods i) are using deep learning, ii) are semantic-aware denoising methods, and iii) require extra segmentation annotation.

| Methods          | Deep Learning | Semantic -Aware | Segmentation Annotation |
|------------------|---------------|-----------------|-------------------------|
| U-SAID           | ✓             | ✓               | ✓                       |
| S-SAID           | ✓             | ✓               | ✓                       |
| CDnCNN-B         | ✓             | ✓               | ✓                       |
| MLP [3]          | ✓             | ✓               | ✓                       |
| MC-WNNM [49]     |               |                 |                         |
| CBM3D [8]        |               |                 |                         |

**TABLE IV:** The average Image denoising performance comparison in NIQE/PSNR on the Kodak dataset, with noise $\sigma = 15, 25, 35$, respectively.

U-SAID), We then apply a FPN pre-trained on the clean PASCAL-VOC 2012 training set, on the denoised testing sets, and evaluate the segmentation performance in terms of mean intersection-over-union (mIOU).

As compared in Table III when we apply the CDnCNN-B denoiser without considering high-level semantics, it easily fails to achieve high segmentation accuracy due to the artifacts introduced during denoising (even though those artifacts might not be reflected by PSNR or SSIM). With their segmentation awareness, both S-SAID and U-SAID have led to remarkably higher mIOUs. Most impressively, U-SAID is comparable to S-SAID, provided that the former has never seen true segmentation information on this dataset (training set), while the latter does. Figure [V] has visually confirmed the impact of denoisers on the segmentation performance.

C. Generalizability Study: Data, Semantics, and Task

In this section, we define and compare three aspects of general usability, which were often overlooked in previous research of learning-based denoisers:

- **Data Generalizability**: whether a denoiser trained on one dataset can be applicable to restoring another.
- **Semantic Generalizability**: whether a denoiser trained on one dataset can be effective in preserving semantics, as the preprocessing step for applying semantic segmentation over another noisy dataset (with unseen classes).
- **Task Generalizability**: whether a denoiser trained with segmentation awareness can also be effective as preprocessing for other high-level tasks over noisy images.
Fig. 3: Visualized semantic segmentation examples from Pascal VOC 2012 validation set. The first row is added with noise of $\sigma = 15$, the second row $\sigma = 25$ and the third row $\sigma = 35$. Columns (a) - (b) are the ground truth images and true segmentation maps; (c) - (e) are the results by applying the pre-trained segmentation model on the denoised images using (c) C-DnCNN-B; (d) S-SAID; and (e) U-SAID.

Table V: Segmentation results (mIoU) after denoising noisy image inputs, averaged over Pascal VOC 2012 validation dataset.

|    | noisy | CDnCNN-B | S-SAID | U-SAID |
|----|-------|----------|--------|--------|
| $\sigma=15$ | 0.4227 | 0.4238 | 0.4349 | 0.4336 |
| $\sigma=25$ | 0.4007 | 0.4003 | 0.4084 | 0.4047 |
| $\sigma=35$ | 0.3667 | 0.3724 | 0.3802 | 0.3785 |

Throughout the whole section below, all three denoisers used are the same models trained on PASCAL-VOC 2012 above. **There is no re-training involved.**

Our hypothesis is that since U-SAID is not trained with any annotation on the original training set, it may less likely overfit the training set’s semantics than U-SAID, while still preserving discriminative features, and hence could generalize better to various unseen data, semantics and tasks.

a) Denoising Unseen Datasets: We evaluate the denoising performance over the widely used Kodak dataset consisting of 24 color images. Table VI reports the quantitative results, which show strong consistency across all three noise levels: CDnCNN-B achieves the highest PSNR and SSIM values, while S-SAID performs the best in terms of NIQE. Interestingly, U-SAID seems to be the “balanced” solution in terms of data generalizability: it tends to obtain very close PSNR and SSIM values compared to CDnCNN-B, while producing comparable or even better NIQE values to S-SAID (especially at smaller $\sigma$). We further observe that U-SAID is usually able to preserve sharper edges and textures than CDnCNN-B, sometimes even better than S-SAID. Figure 4 displays a group of examples, where U-SAID finds clear advantages in preserving local fine details on the sail. Please refering more visualizations to [5]

b) Denoising for Unseen Dataset Segmentation: We choose two recently released real-world datasets, whose class categories are substantially different from PASCAL VOC: i) The ISIC 2018 dataset [6] We choose the validation set of Task 1: Lesion Segmentation, whose goal is to predict lesion segmentation boundaries from dermoscopic lesion images; ii) The DeepGlobe dataset[5] We choose the validation set of Track 3: Land Cover Classification, whose goal is to predict a pixel-level mask of land cover types (urban, agriculture, rangeland, forest, water, barren, and unknow) from satellite images.

We add $\sigma = 25$ noise to both validation sets, to create unseen testing sets for the trained denoisers. For either denoised validation set, we apply a pyramid scene parsing network (PSPNet) [53], that is pre-trained on the original clean training dataset.

Table VI: The average Image denoising performance comparison on the Kodak dataset, with noise $\sigma = 15, 25, 35$, respectively.

|    | CDnCNN-B | S-SAID | U-SAID |
|----|----------|--------|--------|
| $\sigma=15$ | PSNR 34.75 | SSIM 0.9242 | NIQE 2.7570 | 34.57 | 0.9217 | 2.6288 | 34.62 | 0.9222 | 2.5690 |
| $\sigma=25$ | PSNR 32.27 | SSIM 0.8812 | NIQE 2.8493 | 32.17 | 0.8770 | 2.6006 | 32.17 | 0.8790 | 2.6355 |
| $\sigma=35$ | PSNR 30.69 | SSIM 0.8418 | NIQE 2.9753 | 30.50 | 0.8366 | 2.5619 | 30.50 | 0.8395 | 2.6687 |
Table VII: Segmentation results (mIoU) after denoising noisy image inputs, on ISIC 2018 and DeepGlobe validation sets, respectively.

|                  | ISIC 2018 | CDnCNN-B | S-SAID  | U-SAID  |
|------------------|-----------|----------|---------|---------|
| ISIC 2018        | 0.8095    | 0.8084   | 0.8076  | 0.8061  |
| DeepGlobe        | 0.4260    | 0.4198   | 0.4260  | 0.4260  |

Table VIII: Classification results after denoising noisy image inputs ($\sigma = 25$) from CIFAR-100.

|                  | ISIC 2018 | CDnCNN-B | S-SAID  | U-SAID  |
|------------------|-----------|----------|---------|---------|
| PSNR             | 20.17     | 29.13    | 28.98   | 28.98   |
| SSIM             | 0.6556    | 0.9232   | 0.9203  | 0.9219  |
| Top-1 Acc        | 11.99     | 56.86    | 57.87   | 58.16   |
| Top-5 Acc        | 29.83     | 82.64    | 83.65   | 83.70   |

While also listing PSNR and SSIM, we primarily focus on comparing their utility metrics (i.e., accuracy and mAP).

For classification, we choose the challenging CIFAR-100 dataset and add $\sigma = 25$ noise to its validation set. We then pass it through three denoisers, followed by a ResNet-110 classification model, pre-trained on the clean CIFAR-100 training set. As seen from Table VIII, while U-SAID is second best in terms of both PSNR and SSIM (marginally inferior to CDnCNN-B), it demonstrates a notable boost in terms of both top-1 and top-5 accuracies, with a good margin compared to CDnCNN-B and S-SAID. While S-SAID also outperforms CDnCNN-B in improving classification, U-SAID proves to have even better generalizability here.

For detection, we choose the MS COCO benchmark [26], and add $\sigma = 15, 25, 35$ noise to its validation set. We evaluate three denoisers in the same way as for the classification experiment, using a pre-trained YOLOv3 detection model [30]. Table IX shows consistent observations as above: U-SAID always leads to the largest improvements in the detection mean average precision (mAP), and hence has the best task generalizability among all. Another interesting observation is...
Fig. 5: More denoised visualizations from Kodak data set by CDnCNN, S-SAID and U-SAID under three different noise level (lower NIQE indicates better visual quality).
that S-SAID is not as competitive as CDnCNN-B for the detection task, which we leave for future work to explore.

Both experiments show that the high-level semantics of different tasks are highly transferable for U-SAID, in terms of low-level vision tasks, as in line with [29].

### D. Statistical Significance Study of U-SAID’s Improvement

|                  | CDnCNN-B | S-SAID | U-SAID |
|------------------|----------|--------|--------|
| mIOU             | 39.46%   | 40.19% | 40.35% |
| mAP              | 3.30E-6  | 3.98E-6| 3.15E-6|
| NIQE             | 2.87     | 2.90   | 2.62   |
| Variance         | 1.74E-4  | 1.78E-4| 6.00E-4|
| Cross-set Kodak Denoising |             |        |        |
| mAP              | 0.45     | 0.52   | 0.53   |
| Cross-task CIFAR-100 classification |             |        |        |
| top-1 Accuracy   | 56.89%   | 57.82% | 58.47% |
| top-1 Variance   | 0.03     | 0.06   | 0.02   |
| top-5 Accuracy   | 82.89%   | 83.57% | 83.91% |
| top-5 Variance   | 0.02     | 0.05   | 0.06   |

**TABLE IX:** Detection results after denoising noisy MS COCO images.

In CIFAR-100 experiment, for top-1 accuracy, U-SAID yields mean accuracy of 58.47%, which is significantly higher than DnCNN, which has mean = 56.89%, with p-value = 3.6147E-14. U-SAID has also higher accuracy than S-SAID (mean = 57.82%) with p-value = 1.3486E-6. Similarly for top-5, U-SAID’s performance (83.91%) is statistically significant better than DnCNN (82.89%), and S-SAID (83.57%), with p-values of 1.3982E-9 and 4.3994E-3, respectively.

V. CONCLUSION

This paper proposes a segmentation-aware image denoising model that requires no ground-truth segmentation map for training. The proposed U-SAID model leads to comparable performance with its supervised counterpart, in terms of both low-level (denoising) and high-level (segmentation) vision metrics, when trained on and applied to the same noisy dataset (without utilizing extra segmentation information as the latter has to). Furthermore, U-SAID shows remarkable generalizability to unseen data, semantics, and high-level tasks, all of which endorse it to be a highly robust, effective and general-purpose denoising option.

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