LFRanker: An Iterative Method for Identifying Top-Performing Loss Functions in SEM Image Denoising

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***Abstract*—This work focuses on identifying the best performing loss functions for denoising scanning electron microscopy (SEM) images. Recent studies on the impact and effect of loss functions in image denoising are multiplying, particularly in the fields of low-light and microscopic imaging. Most studies have focused on hybrid loss functions, which are a mixture of multiple loss functions, and have shown their significance. However, manual experiments with different loss functions to build a hybrid function are generally very time-consuming. Thus, we propose a framework named LFRanker (Loss Function Ranker) that automatically and iteratively experiments loss function from a given set. LFRanker automatically calculates combinations using set theory from a given set of loss functions. The findings indicated significant variations across the different assessment criteria (such as PSNR, SSIM and keypoints preservation). In this work, we focus on SEM image denoising, which may be subject to reconstruction in the next step. Thus, it is necessary to preserve the maximum keypoints for point-cloud reconstruction during denoising, along with high quality. Based on these criteria, we found a hybrid loss function, combining L_{MSE}, L_{MAE}, L_{PER} and L_{SIM} performs best. Finally, LFRanker demonstrates the ability to automate manual experimental efforts in identifying appropriate loss functions for denoising.**

***Index Terms*—Scanning Electron Microscopy (SEM), SEM image denoising, Loss functions, Deep learning, Image processing.**

I. Introduction

Noise has traditionally been a major challenge for scanning electron microscopy (SEM) because of its presence at multiple stages of the signal formation process. Identifying the sources and characteristics of noise in the SEM detector signal is complex because they arise from multiple stages, each contributing to its own unique noise component [2]. These noises in SEM images are uncertain and tend to change type depending on several factors, especially environmental configurations such as dwell time [3]. Dwell time, sometimes known as scanning speeds of SEM, is defined as the time during which the electric beam remains focused on each pixel of the surface of nano-micro objects objects (i.e. in materials science) during acquisition [3]. Removal of those noises from SEM images has become crucial for various industrial applications in many areas, including material science. In recent years, various convolutional neural network (CNN) based solutions have been proposed for image denoising. But very few deal with SEM image denoising. Furthermore, studies have shown that the contrast and fidelity of denoised microscopic images critically depend on the CNN architecture and the chosen loss function [4].

An essential point when designing a CNN-based image denoiser is the availability of data and, more specifically, of clean image samples in a supervised context. However, acquiring a suitable dataset (containing pairs of clean/noisy images) in practice from SEM is difficult, thus preparing a synthetic dataset using appropriate noise model and identifying an effective denoising network is crucial. The acquisition of clean images depends on slow SEM scanning speeds that can destroy samples [3], [6]. However, there is a SEM dataset [7] with a random mix of clean and blurred/noisy images used for classification, but no clean/noisy pair. This dataset is partially used to prepare a set of synthetic noisy/clean pairs.

On the other side, noises in SEM images are not always Gaussian, but can be Poisson or Gamma [3], [8]. Furthermore, in a previous work [9], we showed that a model trained with a series of noise models, including Poisson and Speckle, outperformed both state-of-the-art and benchmark studies for SEM images. Indeed, in [9], we found that SCUNet [10], which is a hybrid convolutional neural networks (CNNs)-Transformer network, outperformed in terms of visual results but in some cases causes oversmoothing in SEM images. Thus, we conducted few experiments for determining the best combination of noise models to built dataset synthesizing and found that a mixture of Poisson and Speckle outperformed in SEM image denoising. The comparative analysis of SEM image denoisers also highlighted that loss functions have significant impact on denoising performance [9]. This observation is not specific to SEM image denoising, since loss functions guide the training of any neural network [5].

Although most research on image denoising typically fo-

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cuses on network architecture, there is an increasing interest on loss functions in many works, for example [5], [11]–[13] and many more. However, a major problem is that everyone is proposing its own assumptions, experiments, and loss functions, while the superiority of loss functions may differ depending on the chosen network architecture or the dataset used for training. Thus, it is important to automatically identify the best performing loss functions, whether traditional (for example MSE or MAE) or hybrid (i.e. a combination of MSE and MAE) for specific image data samples to reduce manual evaluation for any loss functions, whether individual or the result of a combination.

To solve this issue, we propose a novel iterative method based on training/validating a network with different loss functions and then testing each of its trained instance with real noisy image samples, in order to rank the loss functions and determine the top performer based on qualitative metrics PSNR and SSIM, keypoints preservation and manual visual assessments. The proposed approach starts with a set of loss functions from which the method will automatically calculate combinations by following the power set theory [14] except empty set. For example, if there is a n number of elements in a set then the total number of combinations will be 2^n and without empty set it will be $2^n - 1$. Each loss function issued from the power set is then evaluated using SEM image samples collected considering different dwell times (or scanning speeds). We found that, based on noise level, simple loss functions sometimes outperformed and other times hybrid loss functions. These results led us to claim that the proposed technique is able to successfully identify the top performing loss functions for different samples of SEM images and cope with changes accordingly. The major contribution of this proposal is therefore to automate the identification of effective losses from a set of loss functions. This process minimizes the list of manual experiments for each loss function. Additionally, it automatically experiments the traditional loss functions individually at the same time hybrid loss functions sequentially.

The rest of the paper is organized as follows. Section II discusses background work found in the literature. The proposed methodology is described in Section III, while Section IV represents and discusses the experiments, results, and comparative findings. Finally, Section V concludes the paper with possible future directions.

II. Background

The impact of various loss functions are manually assessed in [4] for microscopy images and in particular for biological cells. The authors have found that the combination of Fast Fourier Transform (FFT) and pixel wise loss, as well as the loss in the frequency domain with feature based loss, not only outperforms, but also preserved the cell structures in the denoising output. In a similar study [13], performed on positron emission tomography (PET) images, the authors claimed that L1 norm loss function derived from histogram count provides high performance in supervised denoising, whereas in self-supervised techniques mean squared error (MSE) helps to preserve local features.

Wavelet-Based loss function has been proposed in a recent work [11] for protecting denoising output from blurring of contours and local high-frequency details. According to the authors of [15], L1 norm loss function with the combination of perceptual loss can produce visually pleasant, a combination inspired by [15] who showed that a combination of L1 and Multi-Scale Structural Similarity Index Measure (SSIM) can improve the output performance. Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Squared Logarithmic Error (MSLE), Huber, Peak Signal-to-Noise ratio (PSRN) and Structural Similarity Index Measure (SSIM) were manually experimented in one study [5] for medical image applications.

In [16], four loss functions, namely pixel-wise L2, pixel-wise L1, structural dissimilarity (DSSIM), and perceptual loss were individually experimented, revealing that that perceptual loss outperforms int the context of Magnetic resonance imaging (MRI). However, they did not investigate their combination, because a set of four loss functions can make $2^n - 1 = 2^4 - 1 = 15$ combinations. Doing many experiments manually is quite expensive and time-consuming. It is therefore important to automate the process and obtain optimized results for specific data samples. The combination of several loss functions was studied for adversarial based denoising in [17], resulting in a combination of three loss functions: MSE, perceptual loss, and adversarial loss, to preserve details in denoised images.

The aforementioned works show an increasing interest on hybrid loss functions, as well as exploration of loss functions, in the training of denoisers in different domain. However, a manual process may make the process complex when someone intends to have experiments with a set of loss functions. It is not only important to study loss functions individually, but also to perform automated combinations of them with experiments, in order to determine the best performing individual function or combination in a specific domain. Thus, this work propose a novel automated approach, called Loss Function Ranker (LFRanker), which solves the challenges of manual calculations and experiments. Additionally, it enables the ranking mechanism to identify top performing loss functions, either individual or hybrid (combinations), from a given set. The proposed method is experimented and evaluated with SEM images. The SEM image samples to be tested are collected from different dwell times (or scan speeds) to have varieties of noises.

Almost all of the previous studies used PSNR and SSIM as qualitative metrics to evaluate their respective proposals. However, we have shown in [9] that for SEM images, these two measures are not sufficient for evaluation. Thus, in this study, AKAZE [18] local features keypoints detection and a manual check of the visual quality of the denoised images are both carried out for each of the losses studied for training.

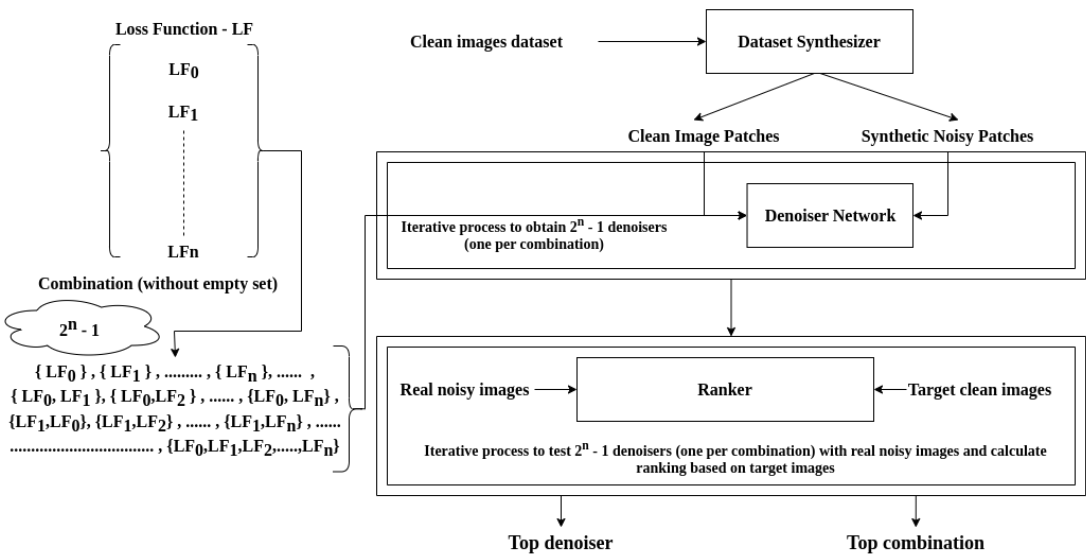

Figure 1. The proposed Loss Function Ranker - LFRanker approach

III. Proposed Method

The proposed LFRanker approach is described in Fig. III. As can be seen, the framework starts with the building of a dataset using clean SEM images from [7]. There are 500 clean images selected based on high resolution, which we made available at [19]. In the dataset, the samples are collected from multiple sources including biological cells, tips, particles, porous sponge, powder, fibres, nanowires. These different categories of samples will give diversity to the denoiser network. From the clean samples only, pairs of clean/noisy image patches are created to train the denoising network. In the next step, the loss functions combination generation ($2^n - 1$ times) is completed, after which a denoising network is trained for each of the generated loss functions. Finally, a ranker performs evaluation of the $2^n - 1$ trained denoisers (one per loss function) on real noisy images. The denoised output is compared with real target clean images by ranker itself, initially in terms of PNSR and SSIM.

It is important to mention that we have collected samples of different dwell time, or scanning speeds, as reported in Table I. Normally, we have selected scanning speed 2, 3, and 5 as noisy samples, whereas scanning speed 8 is the clean target. Per scanning speed, we collected at least one sample from Zeiss Auriga SEM at FEMTO-ST lab to perform the real application assessment of our proposal.

Table I
Example of Zeiss Auriga SEM configurations

Scan Speed	*Dwell time*
8	10 microseconds
5	2 microseconds
3	510 nanoseconds
2	280 nanoseconds

All the experiments are completed on a GPU server from Mésocentre de calcul de Franche-Comté. Additionally, PyTorch python framework and Numpy, Pillow python packages are basically used for the implementation. We performed the training process on a selection of mixed Poisson and Speckle noises. As stated before, there are different opinions on the type of noise, but we found in our experiments that the combination of these two noise models performed the best in our case. The detailed process of the method will be discussed step by step in the following subsections with possible implementation details.

A. Dataset Synthesis

Initially, NFRanker synthesized the dataset by loading clean images and creating multiple patches from the original images. Indeed, we divided the images into multiple patches to increase the number of size in training samples. Subsequently, an artificial mixture of Poisson and Speckle noises was added to the clean patches, thereby generating a dataset of clean/noisy pairs. As we used the mixture of Poisson and Speckle noises, we formulated our synthetic noise function as in Equation 1.

$$NM = clamp((\alpha \times P_n + \beta \times S_p), 0, 1) \tag{1}$$

where:

- NM is the noise model,
- α and β are the weights of the two noise models and in our case we use unweighted or same weight for both such as $\alpha = \beta = 1$,
- P_n is Poisson noise and S_p is Speckle noise,
- $clamp(p, x, y)$ clamps the values of p to be within the range $[x, y]$.

B. Denoising Network

In this step, we used the best-performing denoiser we identified for denoising SEM images in a previous work [9].

From this denoiser, named SCUNet [10], we have taken the architecture as it is, but we updated the loss functions in the training process as follows.

At initial stage, we take a set of four noise models, which includes MSE, MAE, $SSIM$ and $VGG19$ perceptual loss function. We can denote our set as in Equation 2.

$$LF = \{L_{\text{MAE}}, L_{\text{MSE}}, L_{\text{SIM}}, L_{\text{PER}}\} \tag{2}$$

where:

- LF is the set of selected Loss Functions
- L_{MAE} is the Mean Absolute Error loss,
- L_{MSE} means the Mean Squared Error loss,
- L_{SIM} represents Structural Similarity Index Measure (SSIM) loss,
- L_{PER} denotes the Perceptual loss function.

Combining the four individual loss functions in our set produces a number of subsets that can be calculated using power set formula (in our case except empty or null set). We therefore have a total of $|P\{LF\}|$ = 2^n - 1 where n = 4, which results in (2^4 - 1) = (16 - 1) = 15 initial subsets:

$P(LF) = \{L_{\text{MAE}}\}, \{L_{\text{MSE}}\}, \{L_{\text{SIM}}\}, \{L_{\text{PER}}\}, \{L_{\text{MAE}}, L_{\text{MSE}}\}, \{L_{\text{MAE}}, L_{\text{SIM}}\}, \{L_{\text{MSE}}, L_{\text{SIM}}\}, \{L_{\text{SIM}}, L_{\text{PER}}\}, \{L_{\text{MSE}}, L_{\text{PER}}\}, \{L_{\text{MAE}}, L_{\text{PER}}\}, \{L_{\text{MAE}}, L_{\text{MSE}}, L_{\text{SIM}}\}, \{L_{\text{MAE}}, L_{\text{MSE}}, L_{\text{PER}}\}, \{L_{\text{MAE}}, L_{\text{SIM}}, L_{\text{PER}}\}, \{L_{\text{MSE}}, L_{\text{SIM}}, L_{\text{PER}}\}, \{L_{\text{MAE}}, L_{\text{MSE}}, L_{\text{SIM}}, L_{\text{PER}}\}$

A SCUNet model is trained for each subset of $P(LF)$, each time using as loss function the weighted combination defined by the subset. The obtained trained models are stored for further treatment by the ranker in the next step.

C. Ranker

Pairs of clean/noisy patches are used to perform denoising with the different trained instances of the SCUNet model and calculate for each the average PSNR and SSIM values. These values are then used to rank the denoisers and determine the best performer, which has been trained by the best combination of weighted loss functions.

IV. Results and Discussion

LFRanker is initially evaluated with real noisy SEM images collected from electron microscope at FEMTO-ST lab according to different scan speeds denoted as $spd2$, $spd3$, and $spd5$ for scan speeds 2, 3, and 5, respectively.

The average values obtained for PNSR and SSIM are presented in Table II. According to these results, the winning combinations are L_{MAE} and L_{SIM} if we consider SSIM as the main metric, but for PSNR the top performer is the combination of L_{PER} and L_{SIM}. Let us now explore the individual results of the different scanning speeds, which are reported in Table III. We can see that the results confirm the previous observation. The combination of L_{PER} and L_{SIM} performs best, with a balance between PSNR and SSIM.

However, we found in a previous work [9] that PNSR and SSIM results are not enough to evaluate the denoising of SEM images. To improve the assessment, we decided to extend it to include a visual check of the quality of the denoised images, as well as the preservation of keypoints identified with AKAZE keypoint detection. Thus, Table IV shows the keypoints preserved with a good match using the threshold value of 0.50 in the brute force analyzer with hamming distance as the measure. The threshold is used to eliminate non-unique matches and identify good matches. The 0.50 threshold helps us to identify the best matches in this distance.

Table II

Average results found for each combination (best in **bold**)

Loss Functions	***PSNR/SSIM (Avg.)***
L_{MAE}	18.1732 / 0.3255
L_{MAE} + L_{PER}	18.2821 / 0.2958
L_{MAE} + L_{PER} + L_{SIM}	18.3876 / 0.3122
L_{MAE} + L_{SIM}	18.1361 / **0.3290**
L_{MSE}	18.1342 / 0.3206
L_{MSE} + L_{MAE}	18.1463 / 0.3226
L_{MSE} + L_{MAE} + L_{PER}	18.3407 / 0.2885
L_{MSE} + L_{MAE} + L_{PER} + L_{SIM}	18.2490 / 0.3126
L_{MSE} + L_{MAE} + L_{SIM}	18.1798 / 0.3264
L_{MSE} + L_{PER}	18.2045 / 0.2878
L_{MSE} + L_{PER} + L_{SIM}	18.4269 / 0.3171
L_{MSE} + L_{SIM}	18.0450 / 0.3154
L_{PER}	17.6269 / 0.2553
L_{PER} + L_{SIM}	**18.4566** / 0.3233
L_{SIM}	7.7816 / 0.0091

Table IV reports the number of well-matched keypoints for scan speeds 2, 3 and 5. We can see that, as expected, the fastest the scan speed (or the lower the dwell time) the lower the number of well-preserved keypoints. We also note that for a given scan speed, the numbers obtained for the different loss functions are very different. These results suggest the use of a hybrid loss (a combination) for very noisy images collected with $spd2$, whereas $spd3$ and $spd5$,support a traditional loss function. The combination of L_{MSE}, L_{MAE}, L_{PER} and L_{SIM} performs best at the fastest scan speed.

Table V summarizes the most significant results. Clearly, the best loss function will vary according to the measure used to assess the quality of the denoised image. Thus, if we target evaluation with PSNR, the combination of L_{PER} and L_{SIM} is the top performer, while for SSIM, it is the combination of L_{MAE} and L_{SIM}. As SEM images can be used for 3D reconstruction similar to [21], the keypoints of denoised SEM images are crucial. So, if the aim is to denoise SEM images for reconstruction, in the case of denoising very noisy images it may be necessary to use a hybrid loss function, whereas an individual loss function is sufficient for apparently less noisy images.

Finally, we focus on the visual quality of the denoised images. In Fig. 2, denoised images at scan speeds $spd2$, $spd3$, and $spd5$ are visualized alongside noisy and clean images. It is evident that the hybrid loss function L_{MSE} + L_{MAE} + L_{PER} + L_{SIM}, which yields the largest number of keypoints for scan speed $spd2$, produces, after training, a denoising network that generates denoised images of high visual quality. However, over-smoothing issues were observed at some scan speeds,

Table III
AVERAGE RESULTS OBTAINED FOR EACH COMBINATION FOR SCAN SPEEDS 2, 3, AND 5 (BEST IN **BOLD**)

Loss Functions	***PSNR/SSIM - spd2***	***PSNR/SSIM - spd3***	***PSNR/SSIM - spd5***
L_{MAE}	17.7675 / 0.2990	18.0906 / 0.3267	18.6615 / 0.3507
L_{MAE} + L_{PER}	17.8475 / 0.2574	18.2228 / 0.2997	18.7759 / 0.3303
L_{MAE} + L_{PER} + L_{SIM}	17.9282 / 0.2720	18.3281 / 0.3180	18.9064 / 0.3464
L_{MAE} + L_{SIM}	17.6593 / **0.3016**	18.0889 / **0.3304**	18.6602 / **0.3549**
L_{MSE}	17.7289 / 0.2921	18.0601 / 0.3223	18.6135 / 0.3475
L_{MSE} + L_{MAE}	17.7203 / 0.2941	18.0759 / 0.3247	18.6428 / 0.3491
L_{MSE} + L_{MAE} + L_{PER}	17.8737 / 0.2328	18.2689 / 0.2979	18.8796 / 0.3347
L_{MSE} + L_{MAE} + L_{PER} + L_{SIM}	17.7809 / 0.2741	18.1874 / 0.3185	18.7787 / 0.3453
L_{MSE} + L_{MAE} + L_{SIM}	17.7099 / 0.2973	18.1059 / 0.3283	18.7236 / 0.3536
L_{MSE} + L_{PER}	17.8041 / 0.2344	18.1456 / 0.2979	18.6637 / 0.3310
L_{MSE} + L_{PER} + L_{SIM}	17.9813 / 0.2865	18.3566 / 0.3194	18.9430 / 0.3455
L_{MSE} + L_{SIM}	17.4581 / 0.2775	17.9875 / 0.3194	18.6894 / 0.3494
L_{PER}	17.1542 / 0.1943	17.6407 / 0.2680	18.0858 / 0.3035
L_{PER} + L_{SIM}	**18.0182** / 0.2940	**18.3759** / 0.3248	**18.9757** / 0.3510
L_{SIM}	7.8181 / 0.0092	7.7855 / 0.0087	7.7410 / 0.0094

Table IV
NUMBER OF WELL-MATCHED KEYPOINTS WITH AKAZE FOR EACH COMBINATION FOR SCAN SPEEDS 2, 3 AND 5 (BEST IN **BOLD**)

Loss Functions	***Keypoints - spd2***	***Keypoints - spd3***	***Keypoints - spd5***
L_{MAE}	479	607	731
L_{MAE} + L_{PER}	426	549	668
L_{MAE} + L_{PER} + L_{SIM}	462	578	690
L_{MAE} + L_{SIM}	478	582	685
L_{MSE}	483	**648**	**783**
L_{MSE} + L_{MAE}	**497**	615	776
L_{MSE} + L_{MAE} + L_{PER}	441	565	725
L_{MSE} + L_{MAE} + L_{PER} + L_{SIM}	**498**	571	676
L_{MSE} + L_{MAE} + L_{SIM}	478	578	693
L_{MSE} + L_{PER}	464	580	703
L_{MSE} + L_{PER} + L_{SIM}	418	546	665
L_{MSE} + L_{SIM}	482	624	734
L_{PER}	457	571	740
L_{PER} + L_{SIM}	429	503	619
L_{SIM}	0	0	0

Table V
SUMMARY OF RESULTS OBTAINED ONLY WITH THE BEST-PERFORMING COMBINATIONS FOR THE DIFFERENT SCAN SPEEDS ($spd2$ - $spd3$ - $spd5$) (BEST IN **BOLD**)

Loss Functions	***PSNR***	***SSIM***	***Keypoints***
L_{MAE} + L_{SIM}	(17.6593 - 18.0889 - 18.6602)	**(0.3016 - 0.3304 - 0.3549)**	(478 - 582 - 685)
L_{MSE}	(17.7289 - 18.0601 - 18.6135)	(0.2921 - 0.3223 - 0.3475)	(483 - **648** - **783**)
L_{MSE} + L_{MAE}	(17.7203 - 18.0759 - 18.6428)	(0.2941 - 0.3247 - 0.3491)	(**497 - 615 - 776**)
L_{MSE} + L_{MAE} + L_{PER} + L_{SIM}	(17.7809 - 18.1874 - 18.7787)	(0.2741 - 0.3185 - 0.3453)	(**498** - 571 - 676)
L_{PER} + L_{SIM}	**(18.0182 - 18.3759 - 18.9757)**	(0.2940 - 0.3248 - 0.3510)	(429 - 503 - 619)

which may be addressed in future work through hyperparameter optimization or the utilization of alternative denoising networks. In summary, for highly noisy image denoising, the hybrid loss function outperformed the others. These results were obtained from the validation of the method on SEM noisy images; thus, it would be valuable to cross-validate the proposed framework with other domains in future research.

V. CONCLUSION

We have proposed and tested a new method, called LFRanker, to automate the selection of the best loss function for denoising SEM images. First, given a set of basic loss functions (MSE, MAE, and so on), each of their possible combinations is used to train the SCUNet deep learning model, using clean and noisy synthesized image pairs as input. Second, the obtained trained models are automatically ranked according to qualitative measures in order to identify the top-performing loss function for SEM image denoising. Thus, our contribution eliminates the challenges of manual experiments to individually assess the various loss functions. Depending on the qualitative measure chosen, the ranking obtained is different. In this work, we targeted the reconstruction capability after denoising. Thus, we focused on keypoint detection and visualization evaluation, which led us to conclude that highly

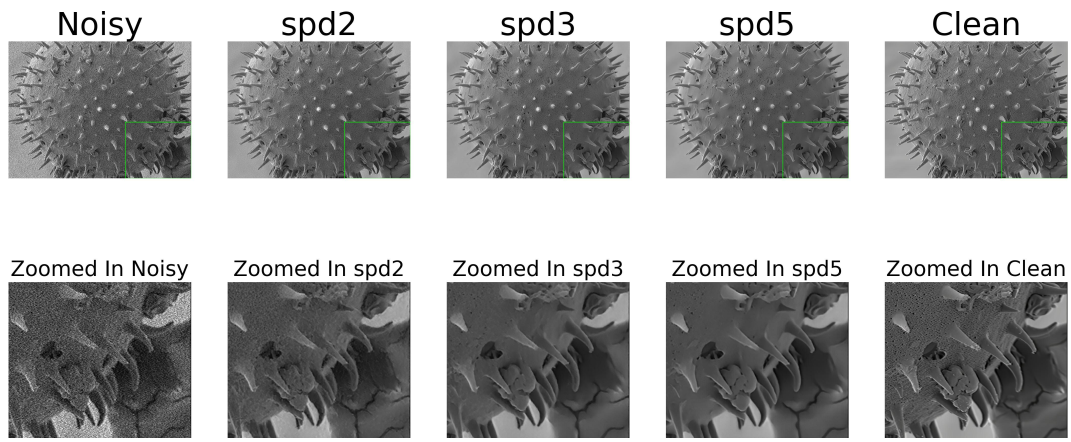

Figure 2. Visual results for hybrid loss function L_{MSE} + L_{MAE} + L_{PER} + L_{SIM} (spd2 preserves more keypoints (Table IV) and visually more closer to clean and others may have over-smoothing issue)

noisy images require a hybrid loss function to improve quality without losing the detailed feature keypoints in the denoised images.

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