Noise2Inpaint: Learning Referenceless Denoising by Inpainting Unrolling

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Abstract. Deep learning based image denoising methods have been recently popular due to their improved performance. Traditionally, these methods are trained in a supervised manner, requiring a set of noisy input and clean target image pairs. More recently, self-supervised approaches have been proposed to learn denoising from noisy images only, without requiring clean ground truth during training. Succinctly, these methods assume that an image pixel is correlated with its neighboring pixels, while the noise is independent. In this work, building on these approaches and recent methods from image reconstruction, we introduce Noise2Inpaint (N2I), a training approach that recasts the denoising problem into a regularized image inpainting framework. This allows us to use an objective function, which can incorporate different statistical properties of the noise as needed. We use algorithm unrolling to unroll an iterative optimization for solving this objective function and train the unrolled network end-to-end. The training is self-supervised without requiring clean target images, where pixels in the noisy image are split into two disjoint sets. One of these is used to impose data fidelity in the unrolled network, while the other one defines the loss. We demonstrate that N2I performs successful denoising on real-world datasets, while preserving better details compared to its self-supervised counterpart Noise2Void.

Keywords: Denoising, Deep Learning, Self-Supervision, Inpainting, Algorithm Unrolling

1 Introduction

Image denoising aims to recover clean images from noisy measurements, since it is not feasible to avoid noise contamination in numerous scenarios due to instrumental imperfection or environmental conditions. The implicit assumption of many denoising approaches is that pixels of the underlying clean images are

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spatially correlated, while the contaminating noise instances are uncorrelated \cite{5,8,10,42}. In recent years, convolutional neural networks (CNNs) have gained immense attention for image denoising \cite{19,21,27,31,39}. In CNN-based denoising, parameters of the convolutional kernels are traditionally tuned to minimize the discrepancy between pairs of noisy and clean target images as measured by a pre-specified loss metric \cite{20,31,39}. The network is consequently expected to generalize to denoise future images with similar statistical properties.

The classical supervised training of CNN-based denoiser requires availability of clean target images pertinent to noisy ones, which may not be readily available in some scenarios \cite{21,19,2}. A number of recent research studies have attempted to address this issue by training CNNs without requiring ground truth. Noise2Noise \cite{21} was the first method that proposed to perform the training on pairs of noisy images rather than noisy and clean images. The main underlying assumption of Noise2Noise is the availability of two noisy instances of the same image with independent noise, which may be difficult to obtain in practice, such as medical imaging applications. To tackle this challenge, a number of other methods such as Noise2Void \cite{19} and Noise2Self \cite{2} have been proposed to utilize self-supervision for CNN-based image denoising. In these methods, CNNs are trained to estimate some retrospectively erased pixels of the noisy images by learning the spatial dependencies from its neighboring pixels, under the assumption of independent noise across pixels. These self-supervised methods train the CNNs by efficiently utilizing the available noisy images only, without requiring clean images, but they assume independent noise.

In this work, we propose a novel self-supervised image denoising approach, called Noise2Inpaint. Noise2Inpaint aims to estimate retrospectively erased pix-
els of the noisy images, similar to Noise2Void and Noise2Self, but recasts this problem as an image inpainting problem with an objective function. Subsequently, an iterative optimization procedure for solving this objective function is unrolled [13], which incorporates a CNN-based regularizer and a linear data fidelity unit in each iteration [11,16,28,38]. This network is then trained end-to-end by exploiting the recently proposed idea of self-supervision by data undersampling for unrolled image reconstruction neural networks [34].

We evaluate Noise2Inpaint for denoising in multiple scenarios, including natural images, fluorescence microscopy images and compare it with Noise2Void, as well as supervised training when target clean images are available.

In summary, our major contributions to image denoising is as follows:

– Introducing a self-supervised learning approach for referenceless denoising by recasting the denoising problem as an inpainting task with an objective function to be minimized in an optimization framework.
– Training an unrolled neural network with several data fidelity and CNN-based regularization units to solve the optimization problem pertinent to the inpainting challenge using self-supervision.
– Providing an objective function that can incorporate different noise statistics, which can be used to generalize the approach to different noise models either during training or testing.

This paper is organized as follows: In Section 2 related works including supervised and existing self-supervised methods are summarized. The Noise2Inpaint method, along with its optimization-based framework for inpainting, is introduced in Section 3. Section 4 describes the experimental protocols and results for denoising on several datasets in this paper. Section 5 concludes this work.

2 Related Work

In this section, we discuss CNN-based denoising algorithms, including three approaches that do not require ground truth clean data for training. We present the main concept of each approach and their corresponding training loss function.

Image denoising focuses on recovering a clean target image, $x$, from a noisy image, $y$. Typically, an additive noise model is assumed [8,10] with

$$y = x + n,$$  \hspace{1cm} (1)

where $n$ denotes the noise which is generally modeled as Gaussian and is independent from $x$ [58]. More complicated statistical models may also be encountered in practical applications [22,23].

2.1 Supervised Training

Deep learning methods for image denoising aim to learn spatial correlations among image pixels in an efficient manner. In the supervised setting, training
dataset consists of pairs of noisy input and clean target signal, \( \{y^i, x^i\}_{i=1}^N \). Supervised training aims to learn a set of network parameters that minimizes the difference between ground truth and network output, by minimizing

\[
\min_{\theta} \sum_{i} \mathcal{L}(f(y^i; \theta), x^i),
\]

where \( f(\cdot; \theta) \) is the output of the CNN with parameters \( \theta \), and \( \mathcal{L}(\cdot, \cdot) \) is a loss function. For the additive Gaussian noise model, mean-square error loss is typically used \([6,12,33,39,41]\).

### 2.2 Noise2Noise Training

Unlike supervised learning, Noise2Noise (N2N) training does not require any clean images \([21]\). N2N performs training by learning a mapping function between pairs of noisy images that have the same underlying clean images but independently drawn noises from the same distribution. The key concept of N2N is that given a set of two such degraded images, \( \{y^i = x^i + n^i, \hat{y}^i = x^i + \hat{n}^i\} \), the expected value of both these noisy images are equivalent to the clean signal. Hence, N2N modifies loss function in Equation (2) into

\[
\min_{\theta} \sum_{i} \mathcal{L}(f(y^i; \theta), \hat{y}^i),
\]

### 2.3 Noise2Void and Noise2Self Training

Noise2Void (N2V) \([19]\) and Noise2Self (N2S) \([2]\) enable training of CNNs without requiring ground truth or pairs of noisy measurements as in N2N \([21]\). Both N2V and N2S use a self-supervised learning approach, where the loss function is defined over a single noisy image with the assumption of correlated underlying image pixels with pixel-wise independent noise.

Let \( M \) be the number of pixels in an image. For ease of notation and without loss of generality, we assume \( M \) is fixed for all images in the database. Let \( V \subset \{1, \ldots, M\} \) be an index set. We will use \( y_V \) to denote the set of pixels specified by the index set \( V \), i.e. \( \{y_i : i \in V\} \). We also define a masking operator \( P_V \), which selects the pixels specified by \( V \). In other words, \( P_V \) is an \( M \times M \) diagonal matrix whose \( k \)th diagonal element is 1 if \( k \in V \) and 0 if \( k \not\in V \).

N2V extracts random patches from the noisy images and the central pixel of each extracted patch is replaced by a neighboring pixel from the patch \([19]\). The loss is performed only on those central pixels that are hidden during the training. For the \( i \)th image in the training database, let \( y_{iU_j}^i \) denote the extracted input patch, \( U_j \), around pixel \( j \) whose pixel value, \( y_j^i \), is replaced with a neighboring pixel. The training is performed by minimizing a loss function of the form

\[
\arg\min_{\theta} \sum_{i} \sum_{j} \mathcal{L}(P_j(f(y_{iU_j}^i; \theta)), y_j^i),
\]
where $P_j$ is defined as the operator that selects only the $j$th pixel of the network output.

N2S is another self-supervised learning approach with the same assumptions as N2V, but with stronger theoretical guarantees [2]. Let $J$ be a partition of the set of pixels of an image, $\{1, \ldots, M\}$. N2S selects a subset $J \in J$ in a special way, such that pixels in $J$ are estimated from the ones in its complement $J^C$, while ensuring these pixels in the subsets are independent [2]. $J$ typically contains non-neighboring pixels with additional constraints. For each such $J$, the network is trained to minimize the difference between original pixels at masked locations and the network output at corresponding locations. Following loss function is minimized during the training

$$\arg \min_\theta \sum_i \sum_{J \in J} \mathcal{L}(P_J f(y_{J^C}; \theta), P_J y),$$

(5)

where $P_J$ is defined as the masking operator specified by the index set $J$ in order to perform the loss.

3 Methods

Our proposed Noise2Inpaint (N2I) method builds on the masking idea from N2V [19] and N2S [2], as well as a recent self-supervision method from image reconstruction that uses an optimization-focused algorithm unrolling for neural networks [34]. In conventional image denoising, a regularized objective function is typically used [8,14]:

$$\arg \min_x \|y - x\|_2^2 + R(x),$$

(6)

where the first term denotes data fidelity term between the desired output and the noisy input, while the second term $R(\cdot)$ is a regularizer. These regularizers can have explicit closed forms [4,9], or the whole objective function can be solved implicitly either with traditional methods [5,8] or using CNNs [12,31,33,39,41].

Here instead of viewing the masking approach in N2V and N2S as estimating a pixel from its neighbors, we recast it as an image inpainting problem [15]. In image inpainting, missing pixels are estimated from available pixels using a regularized objective function. To this end, let $A$ be the masked pixels, and $A^C$ be the pixels that are available at the input of the neural network. The available data is given as

$$y_{A^C} = P_{A^C} x + n_{A^C}$$

(7)

where $P_{A^C}$ is the masking operator as defined in Section 2.3. Note that when $A^C = \{1, \ldots, M\}$, i.e. no pixels are masked, then $P_{A^C} = I$, and Equation (7) reduces to the denoising problem in Equation (1). This problem is also reminiscent of image reconstruction for under-determined inverse problems, where a recent method was developed for self-supervision using unrolled neural networks.
Fig. 2. The self-supervised training in Noise2Inpaint for training the unrolled network to solve equations in (10a) and (10b). Each step in the unrolled network consist of data fidelity (DF) and regularizer unit.

While inpainting seems like a more difficult problem than denoising, this recasting allows us to write an objective function that can be solved using algorithms that enforce data fidelity and regularization. In this work, we will use such an approach to solve the inpainting problem, and devise a self-supervised training approach to adapt it for learning denoising without clean images.

3.1 Algorithm Unrolling for Inpainting

The objective function corresponding to the measurement model in Equation (7) for the inpainting problem is given as

$$\arg \min_x \| y_A - P_A x \|^2 + R(x),$$

(8)

The regularized inpainting problem has been extensively studied using only CNNs [25,35,36]. An alternative approach to solve the regularized inpainting problem is to use algorithm unrolling [13]. In these methods, an iterative optimization algorithm, such as proximal gradient descent or variable splitting [7,32] for solving the objective function in Equation (5) is unrolled for a fixed number of iterations. Each iteration consists of a data fidelity and regularizer term, as shown in Figure 2. The unrolled network is trained end-to-end by minimizing a loss function that characterizes the discrepancy between a reference and network output. Algorithm unrolling has gained significant popularity in many fields such as image reconstruction tasks in MRI or computational tomography due to its improved precision and accuracy [16,17,18,28,29,37].

One approach to solve the objective function in Equation (5) is to use variable splitting (VS) [32]. VS decouples the data fidelity and regularizer term by introducing an auxiliary variable $z$ that is constrained to be equal to $x$. Following variable splitting approach, the objective function in Equation (5) can be rewritten using quadratic relaxation:

$$\arg \min_{x,z} \| y_A - P_A x \|^2 + \mu \| x - z \|^2 + R(z),$$

(9)
where $\mu$ denotes the penalty parameter. The above objective function can be solved by alternating minimization over $x$ and $z$ as

$$x^{(k)} = \arg \min_x \|y_{AC} - P_{AC}x\|^2_2 + \mu \|x - z^{(k-1)}\|^2_2$$ (10a)

$$z^{(k)} = \arg \min_z \mu \|x^{(k)} - z\|^2_2 + R(z)$$ (10b)

In algorithm unrolling, this problem is solved for fixed number of iterations with each iteration including both data fidelity and regularizer. The subproblem in Equation (10b) does not have a closed form solution and it is solved by CNNs. The first term in Equation (10a) corresponds to data fidelity term and it has a closed form solution of

$$x^{(k)} = (P_{AC}^TP_{AC} + \mu I)^{-1}(P_{AC}^T y_{AC} + \mu z^{(k)})$$ (11)

The above expression can be further simplified to

$$x^{(k)}_j = \begin{cases} z^{(k-1)}_j & \text{if } j \in A \\ \frac{1}{1+\mu} y_j + \frac{\mu}{1+\mu} z^{(k-1)}_j & \text{if } j \notin A \end{cases}$$ (12)

where $j$ indicates the pixel location in the image. In other words, at iteration $k$ in the unrolled network, the denoised image is comprised of network output at missing locations and a weighted average for the non-missing locations.

### 3.2 Noise2Inpaint Self-Supervised Training

In Noise2Inpaint, for the $i$th training image, we split the set of all pixels, $\{1, \ldots, M\}$, into two disjoint sets as

$$\{1, \ldots, M\} = \Theta^i \cup A^i \quad \text{with} \quad \Theta^i = (A^i)^C$$ (13)

where we have used $\Theta^i$ to denote the complement of the masking set $A^i$ for ease of notation. Extending on the idea of self-supervision by data undersampling from image reconstruction [34], we propose to use the pixels in $\Theta^i$, i.e. $y^i_{\Theta^i}$, in the data fidelity units of the unrolled network as described in Equation (10a). The remaining pixels in $A^i$ are used to define the loss, similar to N2V and N2S.

Furthermore instead of selecting a single $A^i$ (and a corresponding $\Theta^i$) for each training image, we propose to repeatedly partition all the pixels into smaller subsets. To this end, let

$$\{1, \ldots, M\} = \bigsqcup_{l=1}^L A^i_l$$ (14)

where $\bigsqcup$ denotes a union of disjoint sets, and $L$ denotes the number of subsets in the partition. In this study, we promote a uniform random selection of $A^i_l$, as random selection of masks in inpainting have shown to be beneficial [11]. Furthermore, we also fix the cardinality of $A^i_l$ to be constant, as described in Section 4, although more general implementations are possible.
With this partitioning, we model the loss function for the Noise2Inpaint denoising as

\[
\min_\theta \sum_i \sum_l L\left(P_{\Lambda l}(g_{\text{unroll}}(y_{\Theta l}, P_{\Theta l}; \theta)), y_{\Lambda l}'\right),
\]

where \(g_{\text{unroll}}(y_{\Theta l}, P_{\Theta l}; \theta)\) denotes the output of the unrolled network for inpainting described by Equations (10a)-(10b), with \(y_{\Theta l}\) and \(P_{\Theta l}\) denoting the inputs used at the data fidelity units of the unrolled network. \(\theta\) includes the parameters of the CNN that implements the regularization unit of Equation (10b), as well as the learnable quadratic penalty parameter \(\mu\) used in Equation (10b). As before, \(L(\cdot, \cdot)\) denotes the loss function for training, which is the mean square loss for additive Gaussian noise.

We note a few important points about the objective function in Equation (15): First, the loss is defined between noisy pixels not used in the training and the network output at corresponding unseen locations, which is reminiscent of N2V and N2S. Second, contrary to N2V and N2S, because an inpainting framework is used, the neural network used is an unrolled network, which has a well-defined separation between linear data consistency and regularization. Third, the data fidelity unit is the only unit that uses the available points, \(y_{\Theta l}\) and its corresponding masking function \(P_{\Theta l}\), whereas these only come into play implicitly in the CNN-based regularization units.

4 Experiments

In this section, we evaluate Noise2Inpaint using natural images and microscopy data. We compare our results with supervised learning that uses ground truth as reference (when applicable), and a self-supervised technique, Noise2Void.

The regularized inpainting algorithm presented in Equations (10a) and (10b) was unrolled for 5 iterations. The same U-Net architecture used in the Noise2Void [19] was also used in both supervised training and regularization units in the unrolled network of Noise2Inpaint approach for fair comparisons.

Fig. 3. Performance of Noise2Inpaint for varying value of \(\rho = |\Lambda|/|\Omega|\) on BSD68 dataset. Noise2Inpaint performance visibly and quantitatively improves as \(\rho\) decreases.
4.1 Noise2Inpaint Loss Mask Selection

Noise2Inpaint requires splitting the $M$ pixels in an image into two complementary disjoint sets, $\{\Theta_i\}_{l=1}^L$ and $\{A_i\}_{l=1}^L$, as described earlier, one of which is used in the data fidelity units, and the other is utilized for defining training loss. In this study, each $\{A_i\}_{l=1}^L$ are chosen uniformly randomly while enforcing disjointness among the $L$ subsets such that Equation (14) is satisfied. Furthermore, each $A_i$ is chosen to have the same cardinality, the effect of which was studied further. In particular, we let $\rho = |A_i|/M$ and vary $\rho$ among $\{0.05, 0.1, 0.2, 0.5\}$, where $|\cdot|$ defines the cardinality of the index set.

Figure 3 shows the results on one representative test image for different values of $\rho$, reporting the PSNR. Both qualitative and quantitative results show that the denoising performance degrades as $\rho$ increases. $\rho = 0.05$ shows best performance and this ratio was used for remainder of the study.

4.2 Denoising of Natural Images

Natural images were used to evaluate Noise2Inpaint performance, using the BSD dataset [24]. 400 gray scale BSD images of size $180 \times 180$ were used for training all methods [21,40]. Testing was performed on BSD68 dataset. For training and testing, noisy images were generated by adding white Gaussian noise with standard deviation of $\sigma = 25$. We tested the results on BSD68 gray scale images.

Figure 4 shows example results on BSD68 data. The average PSNR values over the test dataset are reported on a plot in the Figure 7. Noise2Inpaint outperforms Noise2Void both visually and quantitatively, while performing similarly with supervised approach. In order to show the merit of Noise2Inpaint over Noise2Void, we have shown failure case presented in Noise2Void. Figure 5 shows that Noise2Inpaint retained the bright isolated pixel that is not retained in Noise2Void. Moreover, Noise2Inpaint preserves most of the grainy structure lost in Noise2Void case.

![Image: Examples of denoising results for BSD68 dataset]

**Fig. 4.** Example results on BSD68 dataset for different denoising techniques. Noise2Inpaint outperforms Noise2Void in terms of denoising and retaining details. It performs similarly with the supervised training.
Fig. 5. A failure case shown in Noise2Void study. Bright isolated pixel in zoom area, marked with red arrow, is lost during the denoising of Noise2Void. Our method Noise2Inpaint retained the bright pixel while performing a superior denoising compared to Noise2Void. Noise2Inpaint preserves significantly more amount of grainy structure existent in the image compared to Noise2Void. Moreover, it can be clearly seen from zoomed area, Noise2Void suffers from patchy artifacts.

4.3 Denoising of Fluorescence Microscopy Data

Noise2Inpaint was also evaluated on a noisy dataset without clean target images, using fluorescence microscopy data [19]. In this dataset, supervised training cannot be performed. We used the same datasets from Cell Tracking challenge [30] as Noise2Void, namely Fluo-C2DL-MSC and Fluo-N2DH-GOWT1, and compared results with Noise2Void. Figure 6 shows that Noise2Inpaint and Noise2Void successfully remove noise, with slightly visually sharper images using Noise2Inpaint.

Fig. 6. Representative results from fluorescence microscopy datasets Fluo-C2DL-MSC and Fluo-N2DH-GOWT1. Noise2Inpaint and Noise2Void successfully suppress noise, with the Noise2Inpaint image reducing blurring further.
4.4 Generalization Performance for Different Noise Levels

The generalization performance of Noise2Inpaint across different noise levels was evaluated on the BSD68 dataset. Noise with standard deviation ranging from 15 to 50 were added to the BSD68 dataset. Denoising of these images were tested on the network trained with noisy images with standard deviation of 25. The results in Figure 7 shows that Noise2Inpaint has better generalization compared to Noise2Void and supervised training approaches. The reason for the poor generalization of the supervised approach has been reported as a bias...
towards the training data noise level, which precludes its discovery when noise level considerably changes [3].

4.5 Performance for Structured Noise

One of the drawbacks of the Noise2Void and other referenceless denoising learning approaches is the difficulty with structured noise as it violates their main requirement of having independent noise. However, structured noise is a commonly encountered noise type especially for biomedical imaging applications [26]. However, because our method has a well-defined objective function, where the noise statistics can be incorporated into the data fidelity term of Equation (8), our approach can handle structured noise both in training or testing. To illustrate this point, spatially correlated noise was added to the images. Figure 8 shows that our method Noise2Inpaint with a modified data fidelity term incorporate the statistical noise model successfully and removes the structured noise, whereas Noise2Void and supervised approaches fails to remove the correlated noise. This example highlights how Noise2Inpaint can be adapted to different noise statistical models in a straightforward way. However, Noise2Void is prone to fail as the core assumption for independent noise is violated, while supervised training again suffers from generalization [3], as discussed in Section 4.4.

5 Conclusions

In this paper, we proposed Noise2Inpaint algorithm, which enables learning a denoising method from single noisy measurements. In particular, we used an unrolled neural network to solve an objective function for the inpainting problem, which included both data fidelity and regularization. The self-supervised end-to-end training of this network was performed by splitting noisy image pixels into two disjoint sets, where one set was utilized in the data fidelity units of the unrolled network, while the other was used to define the loss. The experiments on different datasets showed that our method outperforms another self-supervised approach Noise2Void, while performing similarly to the supervised approach (when target clean data is available).

Rather than taking a direct denoising approach of using CNNs as most of the existent works, we introduced algorithm unrolling for solving a related but seemingly more difficult problem of inpainting. However, using inpainting, allowed the recasting of this method using a regularized optimization framework. Our unrolling approach has shown superior performance compared to Noise2Void in terms of capturing details besides successful denoising performance.

Furthermore, the objective function used for inpainting is able to incorporate different noise statistics either in training and testing. This was shown with colored noise during testing, but its application to non-Gaussian statistics is especially important for applications like microscopy or MRI, where acquisition of clean target is often challenging and noisy data may be corrupted with non-Gaussian or colored noise.
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