Restoring from Restored: Video Restoration with Pseudo Clean Video

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Abstract. In this paper, we propose a self-supervised video denoising method called “restore-from-restored” that fine-tunes a baseline network by using a pseudo clean video at the test phase. The pseudo clean video can be obtained by applying an input noisy video to the pre-trained baseline network. By adopting a fully convolutional network (FCN) as the baseline, we can restore videos without accurate optical flow and registration due to its translation-invariant property unlike many conventional video restoration methods. Moreover, the proposed method can take advantage of the existence of many similar patches across consecutive frames (i.e., patch-recurrence), which can boost performance of the baseline network by a large margin. We analyze the restoration performance of the FCN fine-tuned with the proposed self-supervision-based training algorithm, and demonstrate that FCN can utilize recurring patches without the need for registration among adjacent frames. The proposed method can be applied to any FCN-based denoising models. In our experiments, we apply the proposed method to the state-of-the-art denoisers, and our results indicate a considerable improvement in task performance.

Keywords: Video restoration, Fine-tuning, Pseudo label, Self-supervised learning

1 Introduction

Video restoration is one of the oldest research fields of video processing, which aims to recover the high-quality video frames from the low-quality video. This degradation operation can be formulated with a degradation function \( H \) as

\[
Y = H(X^{GT}),
\]

(1)

where \( Y \) and \( X^{GT} \) are an observed input and a desired clean images. In the case of denoising, \( H(X^{GT}) \) add a random noise to the function input image as

\[
H(X^{GT}) = X^{GT} + n,
\]

(2)
where \( n \) denotes the noise (e.g., Additive White Gaussian Noise).

Estimating \( X^{GT} \) from \( Y \) with the known degradation model \( H \) is a well-known inverse problem. In order to solve this problem, various types of approaches have been introduced including prior model, likelihood model, optimization and deep learning.

One of common natural image properties used for image restoration is patch-recurrence that similar patches are existing across different image scales. In particular, it has been adopted a lot in single image super-resolution (SR) methods [10,12,13]. In a video, not only similar but exactly the same patches can exist in different multiple video frames. Although these patches can be deformed by camera and/or object motion, patch-recurrence among video frames is much richer than that of a single image. In order to fine-tune a denoising network at the test-time, the ground-truth labels for the degraded input video are required, which is difficult to obtain, and rich patch-recurrence information can greatly help to fine-tune the video restoration network during the test phase.

Recently, Lehtinen et al. [21] proposed a single image denoising method (noise-to-noise) which allows training without ground-truth clean images. Ehret et al. [8] proposed a frame-to-frame training technique which extends the noise-to-noise training algorithm for video restoration. Specifically, frame-to-frame training can perform fine-tuning without using the ground-truth clean video by aligning noisy patches among multiple frames using optical flow. However, estimating accurate optical flow under large displacements, occlusion, and severe degradation is a very difficult and challenging task. Thus, in this work, we propose a new training (fine-tuning) algorithm “restore-from-restored” that allows to fine-tune the pre-trained network without using the ground-truth clean video and accurate optical flow for registration.

Specifically, the proposed method updates the convolutional network parameter using pseudo clean images which are network outputs of the pre-trained baseline network from noisy input images. Our restore-from-restored algorithm is simple, yet effective for denoising video frames, and works particularly well with the existence of large number of recurring patches. That is, we generate pairs of training images to fine-tune the network, which are composed of the pseudo clean video and its noisy version. In this way, similar patches in different images are automatically paired with different pseudo patches, and thus an optimal latent patch becomes an average version of these pseudo clean patches.

In practice, pixel locations of the same patches in different video frames are different due to motions, but with the aid of translation-invariant property of a fully convolutional network (FCN), our algorithm can update the FCN parameter without using optical flow to align the translated patches.

The proposed restore-from-restored training algorithm can be applied to solve various video restoration problems where \( H \) is known. In this work, we demonstrate the superiority of the proposed algorithm by applying to state-of-the-art video denoising methods. The contributions of this paper are summarized as follows:
– We propose a novel self-supervised training to fine-tune the fully pre-trained network using the pseudo clean video.
– We explain why and how the proposed training scheme works with patch-recurrence property and FCN-based restoration networks.
– The proposed method can be easily employed with the state-of-the-art FCN-based denoiser, and yields state-of-the-art denoising results.

2 Related Works

In this section, we provide a brief overview of recent works that are related to the proposed restoration algorithm, in terms of training with and without using the ground-truth clean data.

Training with ground-truth clean data. When a set of high-quality images is available, we can generate synthetic damaged images using a known degradation function $H$, and train deep neural networks with these images and restore them to their original high-quality state. This paradigm is called “damage and restore”, which is a type of self-supervised learning that most image restoration methods follow.

In the case of image denoising, Xie et al. [30] applied deep neural networks to model the mapping of clean images from noisy images. They created pairs of noisy and clean images by using a predefined degradation function. Similarly, the authors of in [7] and [5] used deep CNN to train pairs of clean and synthetically degraded images for SR and De-JPEG, respectively. Numerous studies on denoising [31,32,33,35,20,22,34,11,2], SR [15] and De-JPEG [23] have since been conducted. As the inputs and outputs of networks for image restoration share almost the same information, especially in terms of the low-frequency components, several studies adopted residual learning scheme [31,35,15]. Residual learning not only allows a network to be very deep but also extends the receptive field. To incorporate long-range dependencies among pixels, several studies utilized non-local networks [34,22]. Recent efforts have attempted to deal with unknown degradation function in real photographs (blind restoration). Guo et al. [11] proposed a two-stage method that consists of noise estimation and non-blind denoising steps. Gao and Grauman [9] proposed an on-demand learning method to handle multiple corruption levels for each restoration task including denoising, inpainting, and deblurring. These research trends have also been applied to video restoration problems. For instance, Davy et al. [6] not only incorporated non-local information with a non-local patch search module, but also adapted residual learning scheme for video denoising. Additional issues in video restoration include utilizing information from multiple frames [29] and making temporally consistent results [19]. Regardless of the techniques they used (e.g., residual learning, non-local network, and model-blind approaches), these studies required to generate synthetic images for network training. The results of these studies are difficult to apply to datasets in which clean images can be rarely obtained, such as medical imaging datasets. In addition, they cannot fine-tune the networks to fit the input during the test phase.
Training without ground-truth clean data. Several attempts have been made recently to learn restoration networks without using ground-truth clean data. Lehtinen et al. [21] trained a network with pairs of noisy patches under the assumption that the average of many corrupted pixels is close to clean data. Then, Krull et al. [18] made a network predict only the center pixel from surrounding pixels of the input patch, and Baston and Royer [3] introduced a self-supervised denoising method without relying on the clean data. As these methods allow networks to learn without clean data, pre-trained networks can be fine-tuned given specific input images or videos in the test phase. In fact, the work in [28] presented a method for training SR networks using test input images. This method can utilize the power of deep learning and the information from input images at test time. Ehret et al. [8] introduced a frame-to-frame training method to learn video restoration networks without clean images by extending the strategy proposed in [21] to videos. For a certain patch, their method searches corresponding patches from adjacent frames by using optical flow, and then warp the images to create pairs of aligned noisy images for network learning. Frame-to-frame training enables the exploitation of patch-recurrence properties within video clip inputs by fine-tuning the pre-trained video restoration networks using real inputs. This approach can further enhance the performance of existing pre-trained networks because networks can be optimized without the ground-truth targets.

However, one disadvantage of this method [8] is that accurate optical flow is required to acquire training sets, which is difficult to estimate under large displacements, occlusions and serious damages. In this paper, we overcome the limitations of [8] by using a new training scheme called “restore-from-restored”. Technically, pseudo clean images are generated from a pre-trained video restoration network (FCN), and then used as targets of the network for fine-tuning during the test phase. It makes a synergy effect with the patch-recurrence property that appears repeatedly among consecutive video frames. In the following sections, we provide detailed analysis on the proposed method, and show how the proposed method can boost the performance of the fully pre-trained FCN-based denoisers with the aid of patch-recurrence property.

To the best of our knowledge, the proposed method is the first attempt to boost the performance of the pre-trained convolutional video restoration networks without using accurate registration or non-local module operation while using patch-recurrence property in the test-phase.

3 Self-supervised Training for Video Restoration

Patch-recurrence across different scales of natural images is rich [28,26] and becomes more redundant when neighboring video frames are available [27]. To utilize this space-time information among given video frames for video restoration, conventional methods require accurate correspondences between adjacent frames, and thus calculate optical flows to warp and align neighboring frames to reference frames [4,25,17]. However, estimating accurate optical flows between
frames with large motion and/or severe degradation such as noise and blur, is difficult.

In this work, we present a novel, yet simple and straightforward training (test-time fine-tuning) algorithm that can be applied to video denoising. Notably, our fine-tuning algorithm is based on self-supervision and does not require ground-truth clean images. Moreover, any convolutional video restoration networks, including state-of-the-art methods can be easily fine-tuned using our self-supervised training algorithm without changing their network original architectures. The proposed algorithm allows restoration networks to exploit patch-recurrence without accurate optical flow estimation and warping steps while improving performance by a large margin. In our experiments, we demonstrate that state-of-the-art video restoration network for video denoising task can be easily fine-tuned and improved at test-time.

3.1 Restoration from restored video

In this section, we explain how we can fine-tune and improve the performance of pre-trained video restoration networks using only degraded video frames available at test-time.

In general, a conventional video restoration network is trained with labeled ground-truth clean images and learns a mapping function \( f_\theta \) from a corrupted input frame \( Y \) to a clean target frame \( X^{GT} \), where \( \theta \) denotes the function parameters. Specifically, we can train the network parameter \( \theta \) by minimizing the loss function \( L \) between the network output and the target as

\[
\text{Loss}(\theta) = L(f_\theta(Y), X^{GT}).
\]  

(3)

For the loss function, \( L_1 \) and \( L_2 \) losses are the best choices in many restoration tasks \([3, 21]\). Although image restoration networks trained by optimizing the loss in \([3]\) can produce highly satisfactory results, these networks can be further upgraded by fully utilizing neighboring video frames with redundant space-time information (e.g., patch-recurrence) \([17, 6]\). However, optical flow estimation networks or non-local operation modules used to extract temporal information are expensive and require additional resources \([16, 25, 22, 34]\).

Therefore, we develop a relatively simple and effective fine-tuning algorithm that can exploit the patch-recurrence in spatio-temporal space without flow estimation or non-local operation. To do so, we simply use rendered video frames \( \{f_{\theta_0}(Y_1), ..., f_{\theta_0}(Y_T)\} \) predicted by a fully pre-trained network parameter \( \theta_0 \) from the given corrupted input video. Although these restored images are not the ground-truth clean images and may include remaining artifacts, they can be used as pseudo targets to fine-tune the network parameter.

That is, we can synthesize corrupted images \( \{H(f_{\theta_0}(Y_1)), ..., H(f_{\theta_0}(Y_T))\} \) with the known degradation model \( H \). For example, the degradation model \( H \) adds random noise for our denoising task, and becomes a super-resolution kernel (e.g., bicubic down-scaler) in a super-resolution task. Then, we can fine-tune the
network by minimizing the proposed loss as follows:

\[
\text{Loss}(\theta) = \sum_{t=1}^{T} L(f_{\theta_0}(Y_t), f_\theta(H(f_{\theta_0}(Y_t))).
\]  

(4)

Note that ground-truth frames are not used during our fine-tuning process. Nevertheless, we can update the parameter \( \theta \) by minimizing the proposed loss with initially restored frames and synthetically degraded frames. Therefore, we call this process “restore-from-restored” training. We repeat our restore-from-restored training algorithm several times to fine-tune the network parameter \( \theta \) progressively, and achieve considerable improvement over the initially given pre-trained network (i.e., baseline model).

3.2 Frame-to-frame vs. restore-from-restoration

The notion of our restore-from-restoration algorithm is based on recent noise-to-noise training mechanisms.

Lehtinen et al. [21] demonstrated that image restoration networks can be trained without ground-truth clean data for certain types of noise (e.g., zero-mean noise such as Gaussian noise and Bernoulli noise) and introduced the noise-to-noise training technique. Krull et al. [18] and Batson et al. [3] pointed out that restoration networks can be even learned with self-supervision available from a single test image.

Recently, Ehret et al. [8] proposed the frame-to-frame training algorithm that extends the noise-to-noise training mechanism to handle video frames with self-supervision. In [8], two aligned input noisy frames were paired for training, and the network was fine-tuned by minimizing the loss as:

\[
\text{Loss}(\theta) = \sum_{t=1}^{T} L(f_\theta(Y_t), Y_{t-1}^w),
\]  

(5)

where \( Y_{t-1}^w \) denotes the warped version of \( Y_{t-1} \) and aligned to \( Y_t \) using a pre-computed optical flow. Thus, optical flow is necessary to make pairs of training images in frame-to-frame training. However, accurately estimating optical flow under serious noise and large displacement is difficult. By contrast, our restore-from-restored loss in \([4]\) does not need warping and alignment procedures.

Assume that we have a fully pre-trained network \( f_{\theta_0} \), and the degradation function (model) \( H \) where \( H(x) = x + n \), Noise \( n \) is a zero-mean Gaussian random noise whose standard deviation is \( \sigma \). Moreover, a set of perfectly aligned images \( \{Y_0, Y_1, ..., Y_T\} \) (e.g., burst mode images from a camera on a tripod) is given, and these images are corrupted by random noise \( n \). Note that the variance of the noise added into the input video frames is \( \sigma^2 \).

Then, we can obtain a latent frame \( \frac{1}{T} \sum_{t=1}^{T} Y_t \) from an optimal parameter obtained by fine-tuning \( \theta_0 \) using the L2 version of the frame-to-frame training loss in \([5]\). The noise variance of the latent frame is reduced to \( \frac{1}{T} \sigma^2 \) (refer to the appendix in \([21]\) for details).
On the other hand, if \( \mathbb{E}[f_{\theta_0}(Y)|Y] = \mathbb{E}[X^{GT}|Y] \), then the latent frame rendered from an optimal parameter obtained by minimizing the L2 version of our loss in (4) becomes \( \frac{1}{T} \sum_{t=1}^{T} f_{\theta_0}(Y_t) \), and its variance is reduced to \( \frac{1}{T} \sigma_{\theta_0}^2 \), where \( \sigma_{\theta_0} \) denotes the average standard deviation of the residual noise in initially restored frames \( \{f_{\theta_0}(Y_1),...,f_{\theta_0}(Y_T)\} \). In general, as \( f_{\theta_0} \) is a fully pre-trained network, the standard deviation of the residual noise \( \sigma_{\theta_0} \) is much lower than the original noise level \( \sigma \) (i.e., \( \sigma_{\theta_0} < \sigma \)). Therefore, the variance of the latent frame from our restore-from-restored algorithm is much lower than the variance from the frame-to-frame training. That is, our algorithm can further reduce the noise in the aligned images than the frame-to-frame method.

When input video frames are not aligned and 2D translational motion exists between frames, the frame-to-frame algorithm requires the calculation of optical flows for registration, whereas our proposed training algorithm does not need to consider registration as in (4). Indeed, if \( f_{\theta_0} \) is an FCN, our method can maintain the performance without accurate registration due to the translation-invariant nature of FCN. Therefore, our restore-from-restored approach can exploit space-time recurring patches across the same and/or different scales of video frames even with the existence of severe degradation and large translational motion. Note that in real scenarios, motion between adjacent frames is near-linear [16]; thus, our algorithm can be employed in practice. In addition, our proposed algorithm can be easily adopted in state-of-the-art convolutional networks without modification of their original architectures to improve performance.

Specifically, under an assumption that the remaining noise in the restored frames is also zero-mean random noise, a latent clean patch of \( M \) corresponding input noisy patches \( \{y_1,...,y_M\} \) among \( T \) video frames becomes an average version of them (i.e., \( \frac{1}{M} \sum_{m=1}^{M} f_{\theta_0}(y_m) \)). Moreover, the noise variance of that latent patch is \( \frac{1}{M} \sigma_{\theta_0}^2 \). Therefore, our restore-from-restored algorithm show space-time varying denoising quality. For example, patches with more patch-recurrence (e.g., \( M > T \)) can be restored better than patches with less patch-recurrence (e.g., \( M < T \)) in the video frames. In addition, for a unique patch (\( M=1 \)), denoising result by fine-tuning on that patch becomes similar to the results by initial baseline network. Note that the noise variance of the latent patch by the frame-to-frame method is \( \frac{1}{M} \sigma^2 \) which is still larger than the noise variance from our method. Brief summary of the comparison results is given in Table 1.

Similar to self-supervision-based methods [218], our approach can be also integrated with L1 loss without loss of generality, and we believe our algorithm can be easily employed in various video restoration tasks such as denoising, super-resolution, deblurring, and DE-JPEG when the degradation model \( H \) is known. In our experiments, we demonstrate the superiority of the proposed training algorithm in video denoising.

## 4 Proposed Method

By minimizing the proposed loss function in (4), we can restore clean images from degraded ones in offline and online manners as introduced in [8].
Table 1: Statistics of a latent patch $y$ with the existence of $M$ corresponding patches among $T$ video frames. Note that, as $\sigma_{\theta_0} << \sigma$, the noise level of the latent patch by our method is much lower than the results by frame-to-frame [8]. Moreover, the proposed method cannot handle unknown noise, does not require accurate optical flow. Note that our algorithm provides space-time varying denoising results depending on $M$.

**Algorithm 1: Offline (batch) restoration algorithm**

| Input: degraded video frames $\{Y_1, \ldots, Y_T\}$ |
| Output: restored video frames $\{X_1, \ldots, X_T\}$ |
| Require: pre-trained network $f_{\theta_0}$, iteration number $N$, degradation model $H$, learning rate $\alpha$ |

1. $i \leftarrow 0$
2. While $i \leq N$ do
   3. Foreach $t$ do
      4. Restore: $X_t \leftarrow f_{\theta_i}(Y_t)$
   5. $\text{Loss}(\theta) = \sum_{t=1}^{T} L(f_{\theta}(H(X_t)), X_t)$ // calculate the loss
   6. $\theta_{i+1} \leftarrow \theta_i - \alpha \nabla_{\theta_i} \text{Loss}(\theta_i)$ // update the network parameter
   7. $i \leftarrow i + 1$
3. Return: $\{X_1, \ldots, X_T\}$

In the offline video restoration mode, we can take advantage of all given frames at once for fine-tuning (i.e., batch mode), and the frames are restored with a fine-tuned global network parameter. In the online restoration mode, fine-tuning and restoration are carried out in a sequential (frame-by-frame) fashion, thus, each frame is restored with a different network parameter.

The offline video restoration algorithm is elaborated in Algorithm 1. For fine-tuning, we first remove artifacts in the input images $\{Y_1, \ldots, Y_T\}$ using an initially given pre-trained network $f_{\theta_0}$, and obtain improved images $\{X_1, \ldots, X_T\}$. Second, we use pairs of training images $\{(X_1, H(X_1)), \ldots, (X_T, H(X_T))\}$ to fine-tune the network parameter by minimizing the loss function in (4). We repeat this process for several times ($=N$), and update the network parameter progressively.
Algorithm 2: Online restoration algorithm

**Input:** degraded frame $Y_t$ at time-step $t$

**Output:** restored frame $X_t$, fine-tuned network $f_{\theta_t}$

**Require:** fine-tuned network $f_{\theta_{t-1}}$, restored frame at the previous time-step $X_{t-1}$, degradation model $H$, learning rate $\alpha$

1. $Loss(\theta_{t-1}) = L(f_{\theta_{t-1}}(H(X_{t-1})), X_{t-1})$ // calculate the loss
2. $\theta_t \leftarrow \theta_{t-1} - \alpha \nabla_{\theta_{t-1}} Loss(\theta_{t-1})$ // update the network parameter
3. Restore: $X_t \leftarrow f_{\theta_t}(Y_t)$

**Return:** $X_t, f_{\theta_t}$ // Will be reused in the next time step

The online video restoration algorithm is given in Algorithm 2. Unlike that in the offline restoration mode, only previous frames are available in the online restoration mode. Thus, we slightly modify the proposed loss function in (4) so as to take only a single pair of images $(X_{t-1}, H(X_{t-1}))$ obtained at the previous time-step $(t-1)$. In Algorithm 2, parameter $\theta_{t-1}$ denotes the fine-tuned network parameter at the time $(t-1)$. Therefore, the network parameter becomes a time-varying variable in our online restoration mode.

5 Experiments

In our experiments, we apply our offline and online restoration algorithms to conventional denoising networks including a state-of-the-art method for video denoising. Please refer to our supplementary material for more experimental results, and the code will be publicly available upon acceptance.

5.1 Implementation details

For denoising, we use FCN-based DnCNN [31] and VNLnet [6] to demonstrate the performance of the proposed methods. DnCNN is a typical convolutional networks and used as backbone or baseline model in many other works including [18] and [8]. Currently VNLnet is the state-of-the-art video denoising network and shows the best denoising performance. Although VNLnet is integrated with the non-local operation module, we show our algorithm can be also applied to a network with the non-local module and can further improve the network performance.

As the source code of VNLnet is publicly available, we use the officially provided fully pre-trained parameter for VNLnet. However, we pre-train DnCNN on the DIV2K [1] training set (800 images) as the official parameter of DnCNN is not available. During the pre-training period of DnCNN, the input images are corrupted with Gaussian random noise $n$ and the standard deviation of the noise is randomly chosen in the range of 0 to 50. Batch size and patch size used
for training are 32 and 48, respectively. We use L1 loss in (3) and minimize
the loss with Adam optimizer. The learning rate starts from 1e-4 and gradually
decreases by cosine decay, and DnCNN is trained until convergence. During the
fine-tuning period using the proposed offline and online restoration algorithms,
we apply L2 loss in (4) to update parameters of VNLnet and DnCNN as it
slightly outperforms L1 loss empirically in our experiments. We also use Adam
for fine-tuning with a learning rate of 1e-5.

In our all experiments, these fully pre-trained DnCNN and VNLnet are used
as baseline networks. To evaluate the performance of the proposed offline and
online restoration algorithms, we use 7 video sequences from Derf database[4] and
7 video clips used in DAVIS video segmentation challenge [24] as test datasets.
We use 100 consecutive frames from each video clip for evaluation, and measure
the performance in terms of PSNR on RGB color channels. Due to our limited
hardware resources, we use down-scaled images for VNLnet.

**Offline restoration** Using Algorithm 1 we can fine-tune the network param-
eters and restore frames progressively. However, this iterative and alternating
optimization process does not guarantee globally optimal solution, and our net-
work parameter can sometimes produce over-smoothed results when \( N \) is large.

To solve this problem, we use the initially restored frames \( \{f_{\theta_0}(Y_1), ... f_{\theta_0}(Y_T)\} \)
in the later fine-tuning stages as additional targets. Specifically, we add another
term to the loss function in Algorithm 1 which yields the following at the \( n^{th} \)
iteration:

\[
\text{Loss}(\theta) = \sum_{t=1}^{T} L(f_{\theta_t}(Y_t), f_{\theta}(H(f_{\theta_t}(Y_t)))) + \sum_{t=1}^{T} L(f_{\theta_0}(Y_t), f_{\theta}(H(f_{\theta_0}(Y_t)))) \tag{6}
\]

**Online restoration** Using Algorithm 2 we can adapt the network parameter
and the frames in sequential manner. To reduce noise in a given input frame
\( Y_{t+1} \), DnCNN uses only a previously restored frame \( X_t = f_{\theta_t}(Y_t) \) as suggested
in Algorithm 2. However, VNLnet uses additional neighboring frames as input as
they are required in the non-local patch search module (refer to [6] for details).
Note that, for our online restoration algorithm, we use the L2 loss proposed in
Algorithm 2 without modification.

### 5.2 Ablation study

In Figure 1, we show performance improvements by our offline and online restora-
tion algorithms over the fully pre-trained baseline network (DnCNN). For eval-
uation, images from Derf test set is used and they are corrupted by Gaussian
random noise (\( \sigma = 40 \)), and difference of average PSNR values between the de-
noising results by fine-tuning and the baseline (i.e., PSNR gain) is given in the
figure. X- and Y-axes denote frame number and the PSNR gain, respectively.

[4] https://media.xiph.org/video/derf/
Fig. 1: Performance gains from our offline and online restoration algorithms. Baseline network is DnCNN. Difference of PSNR values before and after fine-tuning are measured. Number $i$ in “Offline$_i$” denotes the number of updates ($N$). (a) Denoising results on sequences without shot-changes. (b) Denoising results on sequences with shot-changes.

**Video without shot-change** In Figure 1(a), we see that the performance of the network fine-tuned by our online restoration algorithms goes up gradually as frame number increases since it trains the network in a sequential manner. In contrast, the results by our offline restoration algorithm ($N=10$) are consistently better than the baseline results on every input video frame.

**Video with shot-change** In Figure 1(b), we compare the denoising results by our offline and online restoration algorithms with videos including shot-changes. For this experiment, we generate 100 video frames by concatenating two different sequences (50 images in each sequence), and thus the 50th and 51th frames are totally different in the generated video. As there is no patch-recurrence between the 50th and 51th frames, the performance of our online restoration algorithm drops significantly on the 51th frame. However, the network is quickly restored and starts to show improved results over the baseline after only few updates ($\approx 5$). On the other hand, our offline restoration algorithm shows robustness to shot-changes due to use of large number of training images, and thus produces consistent results over the baseline. Note that, although there is a drop of PSNR with our offline restoration algorithm, the PSNR values around 51th and 100th frames are similar.

5.3 Quantitative denoising results

In Table 2 and Table 3 we report the PSNR values obtained by our restore-from-restored algorithms on Derf and DAVIS testsets. We adopt DnCNN and VNNet as baseline networks and apply Gaussian random noise with different noise levels ($\sigma=15, 25, 40$) to generate input noisy videos. The results show that both online and offline restoration algorithms produce consistently better results.
| Method | $\sigma$ | crowd | park | joy | pedestrian | station | sunflower | touchdown | tractor | Average |
|--------|---------|--------|------|-----|-------------|---------|-----------|-----------|---------|---------|
| DnCNN  | 15      | 31.07  | 30.77| 37.12| 35.42       | 37.41   | 34.35     | 34.01     | 34.30   | 34.66   |
|        | 31.16  | 30.87  | 37.20| 35.54| 37.85       | 34.43   | 34.26     | 34.47     |         |         |
|        | 31.35  | 31.02  | 37.35| 35.76| 38.17       | 34.51   | 34.47     | 34.47     |         |         |
|        | 25      | 28.43  | 28.30| 34.89| 33.22       | 34.92   | 32.23     | 31.56     | 31.93   | 32.28   |
|        | 28.52  | 28.36  | 34.98| 33.35| 35.40       | 32.36   | 31.85     | 32.11     |         |         |
|        | 28.67  | 28.44  | 35.14| 33.49| 35.74       | 32.39   | 32.09     | 32.09     |         |         |
|        | 40      | 26.06  | 26.14| 32.68| 31.19       | 32.49   | 30.49     | 29.31     | 29.76   | 30.42   |
|        | 26.16  | 26.20  | 32.8 | 31.33| 33.03       | 30.60   | 29.62     | 29.96     |         |         |
|        | 26.29  | 26.26  | 32.98| 31.51| 33.40       | 32.66   | 29.87     | 30.09     |         |         |
| VNLnet | 15      | 32.57  | 32.51| 37.85| 37.28       | 38.00   | 37.47     | 33.50     | 35.59   | 36.13   |
|        | 32.77  | 32.85  | 37.9 | 37.44| 38.30       | 37.55   | 33.84     | 35.80     |         |         |
|        | 33.08  | 33.20  | 38.13| 37.67| 38.79       | 37.75   | 34.31     | 36.31     |         |         |
|        | 25      | 29.74  | 29.73| 34.95| 35.12       | 34.65   | 35.02     | 31.09     | 32.90   | 33.68   |
|        | 30.03  | 30.30  | 35.29| 35.30| 35.67       | 35.15   | 31.43     | 33.31     |         |         |
|        | 30.38  | 30.71  | 35.60| 35.50| 36.29       | 35.39   | 31.90     | 33.68     |         |         |
|        | 40      | 26.70  | 26.75| 31.42| 32.72       | 30.10   | 32.12     | 28.41     | 29.74   | 31.33   |
|        | 27.43  | 27.86  | 32.42| 33.12| 32.56       | 32.49   | 28.99     | 30.69     |         |         |
|        | 28.01  | 28.49  | 33.21| 33.37| 33.75       | 32.84   | 29.66     | 31.33     |         |         |

Table 2: Denoising results with DnCNN [31] and VNLnet [6] on the Derf testset with different Gaussian noise levels ($\sigma$=15, 25, 40). For each network architecture and each noise level, the PSNR results of the baseline, online learning (Algorithm 2), and offline learning (Algorithm 1) are listed in each box from top to bottom. The best results among baseline, online learning (Algorithm 2) and offline learning (Algorithm 1) are written in bold letters.

than the baseline models, and in particular, the offline restoration algorithm with 10 updates ($N = 10$) achieves the best performance. Note that we provide comparison results with only DnCNN and VNLnet for lack of space, but the results by pre-trained parameter (officially provided) of VNLnet are currently state-of-the-art.

**Run-time** With our NVIDIA 2080Ti Graphics unit, we report the run time of a single back-propagation step required for our online restoration method. DnCNN takes $\approx 0.9$ second to handle a 960×540 image, and VNLnet takes around $\approx 1.3$ seconds in dealing with 384×216 image.

**Visual results** In Figure 2 we provide qualitative comparison results. The input images are corrupted with high-level Gaussian noise ($\sigma = 40$), and VNLnet is fine-tuned by our offline and online restoration algorithms. Fine-tuned denoiser can produce visually much better results and restores tiny details compared to the fully pre-trained baseline models.
| Method    | σ  | chamaleon | giant-slalom | girl-dog | hoverboard | monkeys-trees | salsa | subway | Average |
|-----------|----|-----------|--------------|----------|------------|---------------|-------|--------|---------|
| DnCNN     | 15 | 35.90     | 39.01        | 33.92    | 39.44      | 30.47         | 31.70 | 38.66  | 35.58   |
|           |    | 36.04     | 39.16        | 34.00    | 39.51      | 30.52         | 31.75 | 38.77  | 35.67   |
|           |    | 36.15     | 39.27        | 34.06    | 39.57      | 30.57         | 31.82 | 38.95  | 35.77   |
|           |    | 33.15     | 36.66        | 31.28    | 37.32      | 27.24         | 28.57 | 36.00  | 32.88   |
|           |    | 33.29     | 36.81        | 31.37    | 37.40      | 27.27         | 28.63 | 36.15  | 32.98   |
|           |    | 33.41     | 36.94        | 31.44    | 37.50      | 27.32         | 28.68 | 36.33  | **33.08** |
|           | 25 | 30.61     | 34.56        | 29.18    | 35.22      | 24.64         | 25.96 | 33.47  | 30.52   |
|           |    | 30.74     | 34.69        | 29.25    | 35.32      | 24.67         | 26.04 | 33.64  | 30.62   |
|           |    | 30.87     | 34.87        | 29.31    | 35.45      | 24.70         | 26.11 | 33.84  | **30.73** |
|           | 40 | 35.29     | 40.94        | 34.75    | 38.38      | 34.69         | 33.74 | 36.65  | 36.34   |
|           |    | 35.37     | 41.03        | 34.84    | 38.39      | 34.81         | 33.89 | 38.05  | 36.62   |
|           |    | 35.51     | 41.18        | 34.90    | 38.44      | 34.93         | 34.09 | 38.91  | **36.85** |
| VNLnet    | 15 | 32.44     | 38.37        | 32.12    | 36.05      | 31.81         | 30.48 | 32.21  | 33.35   |
|           |    | 32.60     | 38.45        | 32.28    | 36.11      | 31.89         | 30.80 | 34.41  | 33.79   |
|           |    | 32.84     | 38.59        | 32.40    | 36.23      | 31.99         | 31.19 | 36.29  | **34.21** |
|           | 25 | 29.45     | 35.94        | 29.36    | 33.50      | 29.13         | 27.14 | 28.06  | 30.36   |
|           |    | 29.88     | 36.08        | 29.83    | 33.74      | 29.23         | 27.95 | 30.95  | 31.09   |
|           |    | 30.38     | 36.32        | 30.27    | 34.14      | 29.29         | 28.65 | 33.86  | **31.84** |

Table 3: Denoising results with DnCNN [31] and VNLnet [6] on the DAVIS testset with different Gaussian noise levels (σ=15, 25, 40). For each network architecture and each noise level, the PSNR results of the baseline, online learning (Algorithm 2), and offline learning (Algorithm 1) are listed in each box from top to bottom. The best results among baseline, online learning (Algorithm 2) and offline learning (Algorithm 1) are written in bold letters.

5.4 Extension to other task

In this section, we apply the proposed restore-from-restored algorithms in the video SR task, and see the applicability of our method to different video restoration tasks. The major difference between denoising and SR tasks is the use of degradation model $H$. In SR, $H$ down-scales a high-resolution image to low-resolution image (e.g., bicubic downsampling).

Implementation details For the SR task, we use a single image SR network IDN [14] as the baseline, and the pre-trained network parameter is publicly available. For fine-tuning with Algorithm 1, we use $N = 10$, learning rate=1e-5, and the L1-based loss function. Degradation model $H$ is a bicubic downsample with the scale factor of 4. To further utilize recurring patches at different image scales across multiple video frames for SR, we generate pairs of training images using image pyramid as suggested in [28,26]. Specifically, both images for a training pair ($X_t, H(X_t)$) in Algorithm 1 are augmented by using resizing where the resizing scale changes from 0.7 to 0.99.

5 https://github.com/Zheng222/IDN-tensorflow
Fig. 2: Visual comparisons. Denoising results by VNNet with our offline and online update procedures. Number $i$ in “Offline$_i$” denotes $N$ in Algorithm [1].

Results We evaluate the performance of the fine-tuned IDN on the Vid4 testset$^6$ and the results are shown in Table 4. We can see slightly improved over the baseline by using our online and offline restoration algorithms. Similar to the denoising results, our offline restoration method also produces better results than online restoration method in the SR task. In this experiment, we demonstrate the applicability of the proposed restore-from-restored algorithm to other tasks.

| Method                  | Calendar | City | Foliage | Walk | Average |
|-------------------------|----------|------|---------|------|---------|
| Bicubic                 | 19.82    | 24.93| 23.42   | 26.03| 23.53   |
| IDN base                | 22.09    | 26.00| 24.59   | 28.46| 25.28   |
| IDN online update       | 22.12    | 26.03| 24.61   | 28.50| 25.32   |
| IDN offline update      | 22.17    | 26.07| 24.63   | 28.53| 25.35   |

Table 4: Evaluation on the Vid4 testset (4X scale). Baseline is IDN [14].

6 Conclusion

In this work, we proposed a new training algorithm for video restoration, which is straightforward and easy to train while producing state-of-the-art denoising
results. Our training approach is based on the self-supervision, and thus allows the network to adapt its pre-trained parameter for the given specific input video without using the ground-truth clean images. As we use the restored version of the input noisy frames using the pre-trained FCN as training targets (pseudo clean images), we call the proposed algorithm “restore-from-restored”. Moreover, with the aid of translation-invariant property of the FCN, we can restore images without using the accurate optical flow and registration. In this paper, we analyze the meaning and effects of the proposed training algorithm with the existence of recurring patches among input video frames. We demonstrate the performance of the proposed algorithm using the state-of-the-art FCN-based denoisers without change of network architecture, and show considerable improvements on various benchmark datasets.
References

1. Agustsson, E., Timofte, R.: Ntire 2017 challenge on single image super-resolution: Dataset and study. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW) (2017)

2. Anwar, S., Barnes, N.: Real image denoising with feature attention. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2019)

3. Batson, J., Royer, L.: Noise2self: Blind denoising by self-supervision. In: International Conference on Machine Learning (ICML) (2019)

4. Caballero, J., Ledig, C., Aitken, A., Acosta, A., Totz, J., Wang, Z., Shi, W.: Real-time video super-resolution with spatio-temporal networks and motion compensation. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017)

5. Chao Dong, Yubin Deng, C.C.L.X.T.: Compression artifacts reduction by a deep convolutional network. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2015)

6. Davy, A., Ehret, T., Morel, J.M., Arias, P., Facciolo, G.: Non-local video denoising by cnn. In: IEEE International Conference on Image Processing (ICIP) (2019)

7. Dong, C., Loy, C.C., He, K., Tang, X.: Learning a deep convolutional network for image super-resolution. In: Proceedings of the European Conference on Computer Vision (ECCV). Springer (2014)

8. Ehret, T., Davy, A., Morel, J.M., Facciolo, G., Arias, P.: Model-blind video denoising via frame-to-frame training. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019)

9. Gao, R., Grauman, K.: On-demand learning for deep image restoration. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2017)

10. Glasner, D., Bagon, S., Irani, M.: Super-resolution from a single image. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2009)

11. Guo, S., Yan, Z., Zhang, K., Zuo, W., Zhang, L.: Toward convolutional blind denoising of real photographs. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2018)

12. Huang, J.B., Singh, A., Ahuja, N.: Single image super-resolution from transformed self-exemplars. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)

13. Huang, J.J., Liu, T., Luigi Dragotti, P., Stathaki, T.: Srhrf+: Self-example enhanced single image super-resolution using hierarchical random forests. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. pp. 71–79 (2017)

14. Hui, Z., Wang, X., Gao, X.: Fast and accurate single image super-resolution via information distillation network. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2018)

15. Kim, J., Lee, J.K., Lee, K.M.: Accurate image super-resolution using very deep convolutional networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016)

16. Kim, T.H., Lee, K.M.: Generalized video deblurring for dynamic scenes. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015)

17. Kim, T.H., Sajjadi, M.S., Hirsch, M., Schölkopf, B.: Spatio-temporal transformer network for video restoration. In: Proceedings of the European Conference on Computer Vision (ECCV) (2018)
18. Krull, A., Buchholz, T.O., Jug, F.: Noise2void-learning denoising from single noisy images. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2019)
19. Lai, W.S., Huang, J.B., Wang, O., Shechtman, E., Yumer, E., Yang, M.H.: Learning blind video temporal consistency. In: Proceedings of the European Conference on Computer Vision (ECCV) (2018)
20. Lefkimmiatis, S.: Non-local color image denoising with convolutional neural networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 5882–5891 (2016)
21. Lehtinen, J., Munkberg, J., Hasselgren, J., Laine, S., Karras, T., Aittala, M., Aila, T.: Noise2Noise: Learning image restoration without clean data. In: International Conference on Machine Learning (ICML). vol. 80 (2018)
22. Liu, D., Wen, B., Fan, Y., Loy, C.C., Huang, T.S.: Non-local recurrent network for image restoration. In: Advances in Neural Information Processing Systems (NIPS). pp. 1680–1689 (2018)
23. Maleki, D., Nadalian, S., Mahdi Derakhshani, M., Amin Sadeghi, M.: Blockcnn: A deep network for artifact removal and image compression. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops (2018)
24. Pont-Tuset, J., Perazzi, F., Caelles, S., Arbelaez, P., Sorkine-Hornung, A., Van Gool, L.: The 2017 davis challenge on video object segmentation. arXiv:1704.00675 (2017)
25. Sajjadi, M.S., Vemulapalli, R., Brown, M.: Frame-recurrent video super-resolution. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. pp. 6626–6634 (2018)
26. Shaham, T.R., Dekel, T., Michaeli, T.: Singan: Learning a generative model from a single natural image. In: Proceedings of the IEEE International Conference on Computer Vision (ICCV) (2019)
27. Shahar, O., Faktor, A., Irani, M.: Space-time super-resolution from a single video. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2011)
28. Shocher, A., Cohen, N., Irani, M.: zero-shot super-resolution using deep internal learning. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2018)
29. Wang, X., Chan, K.C., Yu, K., Dong, C., Loy, C.C.: Edvr: Video restoration with enhanced deformable convolutional networks. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops (2019)
30. Xie, J., Xu, L., Chen, E.: Image denoising and inpainting with deep neural networks. In: Advances in Neural Information Processing Systems (NIPS). pp. 341–349 (2012)
31. Zhang, K., Zuo, W., Chen, Y., Meng, D., Zhang, L.: Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. IEEE Transactions on Image Processing 26, 3142–3155 (2017)
32. Zhang, K., Zuo, W., Gu, S., Zhang, L.: Learning deep cnn denoiser prior for image restoration. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 2808–2817 (2017)
33. Zhang, K., Zuo, W., Zhang, L.: Ffdnet: Toward a fast and flexible solution for cnn based image denoising. IEEE Transactions on Image Processing 27, 4608–4622 (2018)
34. Zhang, Y., Li, K., Li, K., Zhong, B., Fu, Y.: Residual non-local attention networks for image restoration. In: Proceedings of the International Conference on Learning Representations (ICLR) (2019)
35. Zhang, Y., Tian, Y., Kong, Y., Zhong, B., Fu, Y.: Residual dense network for image restoration. CoRR abs/1812.10477 (2018)