Digital Image Restoration summary

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Artificial Intelligence & Information Analysis Lab

Digital Image Restoration

- **Inverse Filters**
- Wiener Filters
- Wavelet Restoration
- Blind Deconvolution
- Color Image Restoration
- Neural Image Restoration
- De-Fogging
- De-Raining

Inverse Filters

In digital image restoration, to remove the blur from a recorded image $\mathrm{g}(\mathrm{n}_1, \mathrm{n}_2)$ using a linear filter. If the point-spread function (PSF) of the linear restoration filter, denoted by $\mathrm{h}(\mathrm{n}_1, \mathrm{n}_2)$, has been designed, the restored image is given by:

$$\hat{f}(n_1, n_2) = h(k_1, k_2) * g(n_1, n_2) = \sum_{k_1=0}^{N-1} \sum_{k_2=0}^{M-1} h(k_1, k_2) g(n_1 - k_1, n_2 - k_2), \qquad (1)$$

or in the spectral domain by:

$$\hat{F}(u, v) = H(u, v) G(u, v), \qquad (2)$$

The objective of this section is to design appropriate restoration filters $h(n_1, n_2)$ or $H(u, v)$ for use in (1).

Inverse Filters

(a)

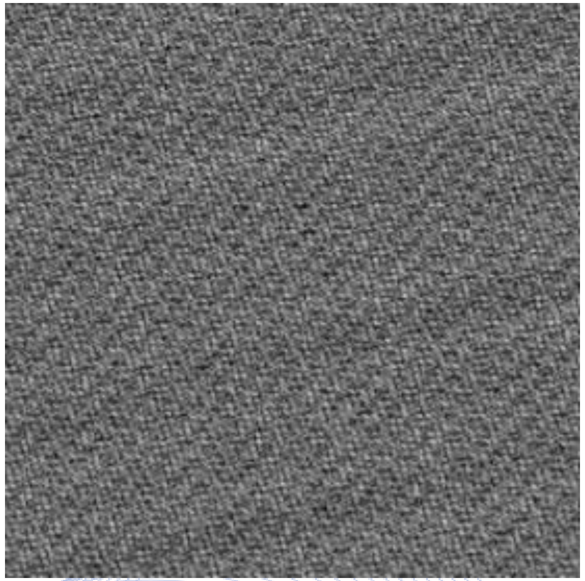
(b)

(c)

a) The original image, b) the image blurred, c) the image after being restored by inverse filtering. (from this project, Rice University, copyright pending)

Inverse Filters

(a)



(b)

a) An image with noise and a blur (R=2.5), b) the image after being restored by inverse filtering, showing how ineffective this method is when used with noise. (from [2], 2009)

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Wiener Filters

To overcome the noise sensitivity of the inverse filter, several restoration filters have been developed that are collectively called least-squares filters. The most-commonly used filter from this collection is the Wiener filter.

The Wiener filter is a linear spatially invariant filter of the form (1), in which the point spread function $h(n_1, n_2)$ is chosen such that it minimizes the mean-squared error between the ideal and the restored image. This criterion attempts to make the difference between the ideal image and the restored one as small as possible.

Wiener Filters

The Wiener filter is the solution to this minimization problem, and we can more easily define it in the spectral domain as:

$$H_{wiener}(u,v) = \frac{D^*(u,v)}{D^*(u,v)D(u,v) + \frac{S_w(u,v)}{S_f(u,v)}}$$

where:

- $D^*(u,v)$: The complex conjugate of $D\,(u,v)$.
- $S_f(u,v)$: The power spectrum of the ideal image.
- $S_w(u,v)$: The power spectrum of the noise.

Wiener Filters

(a) (b) (c) (d)

a) The original image, b) Wiener restoration of image with noise variance equal to 35.0 (ΔSNR=3.7 dB), c) Wiener restoration of image with assumed noise variance equal to 0.35 (ΔSNR=8.8 dB), d) Wiener restoration of image with assumed noise variance equal to 0.0035 (ΔSNR=1.1 dB). (from [2], 2009)

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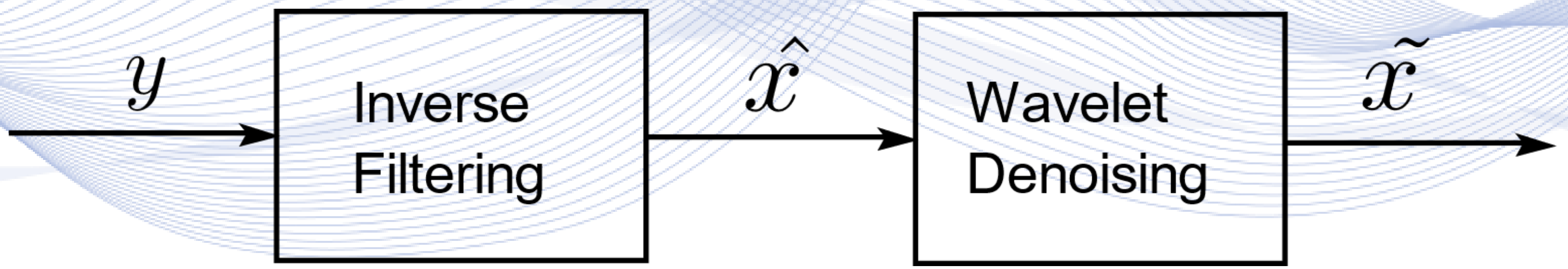
Wavelet Restoration

In image restoration, although the Wiener filtering is the optimal trade-off of inverse filtering and noise smoothing, in the case with singular blurring filter, the Wiener filtering actually amplifies the noise.

This suggests that a denoising step is needed to remove the amplified noise. Wavelet-based denoising schemes provide a natural technique for this purpose. Therefore, the image restoration contains two separate steps, for example a Fourier-domain inverse filtering and wavelet-domain image denoising.



Wavelet Restoration

(a) (b) (c)

a) The original image, b) the blurred image, c) the restored image using the ForWaRD estimate. (from [3], 2004)

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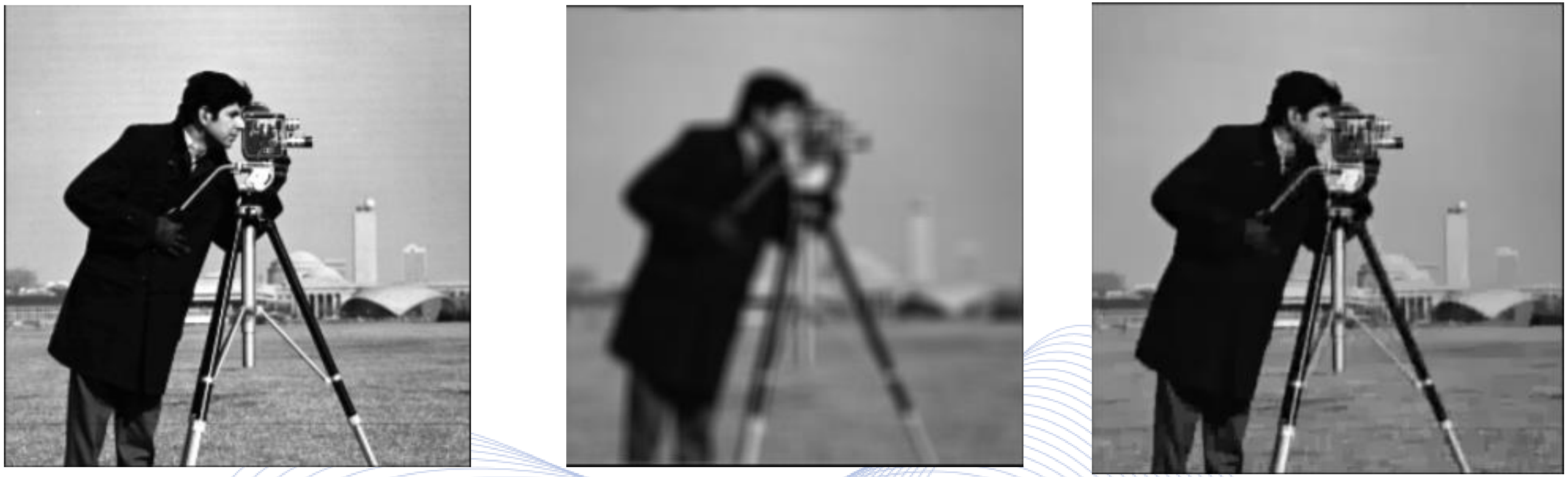
Wavelet Restoration



(a) (b) (c)

a) The original image, b) the blurred image, c) the restored image using the EM algorithm. (from [4], 2003)

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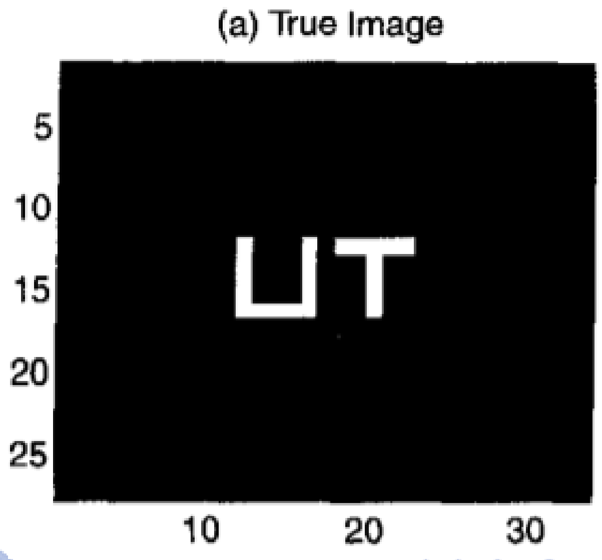
Blind Deconvolution

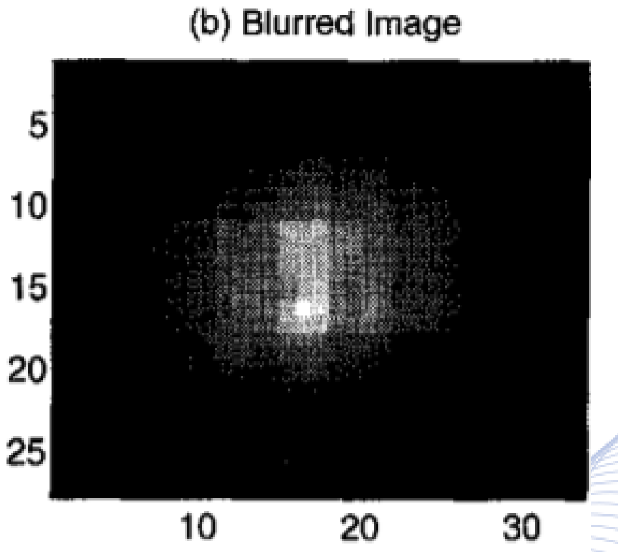
Blind image restoration is the process of estimating both the true image and the blur from the degraded image characteristics, using partial information about the imaging system. Deconvolution is performed in applications like astronomical speckle imaging, remote sensing and medical imaging among others.

In other methods, the blurring function is given and the degradation process is inverted using a certain algorithm. However, in many practical situations, the blur of an image is unknown and little information is known about the original image, therefore blind deconvolution is often used.

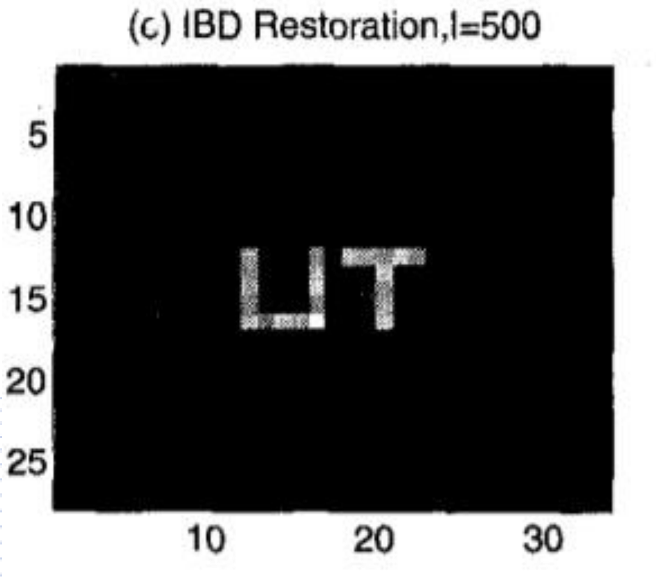
Blind Deconvolution



(a)



(b)



(c)

a) The original image, b) the blurred image, c) the restored image using IDB restoration. (from [5], 1996)

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Color Image Restoration

Because the numerous color channels are related, the problem of color image restoration poses several challenges. Cross-channel correlations should therefore be used in order to achieve optimal restoration outcomes. For colour images, two restoration approaches can be taken:

1) One can extend the equations of the linear spatially invariant restoration filters for greyscale images to incorporate multiple colour components. Because the degradations of the different color components are not independent, it is often the correct approach of modelling the challenge of color image restoration. As a result, a class of algorithms known as "multi-frame filters" is used.

Color Image Restoration

(a) Original

(b) Noisy

(c) Denoised Image

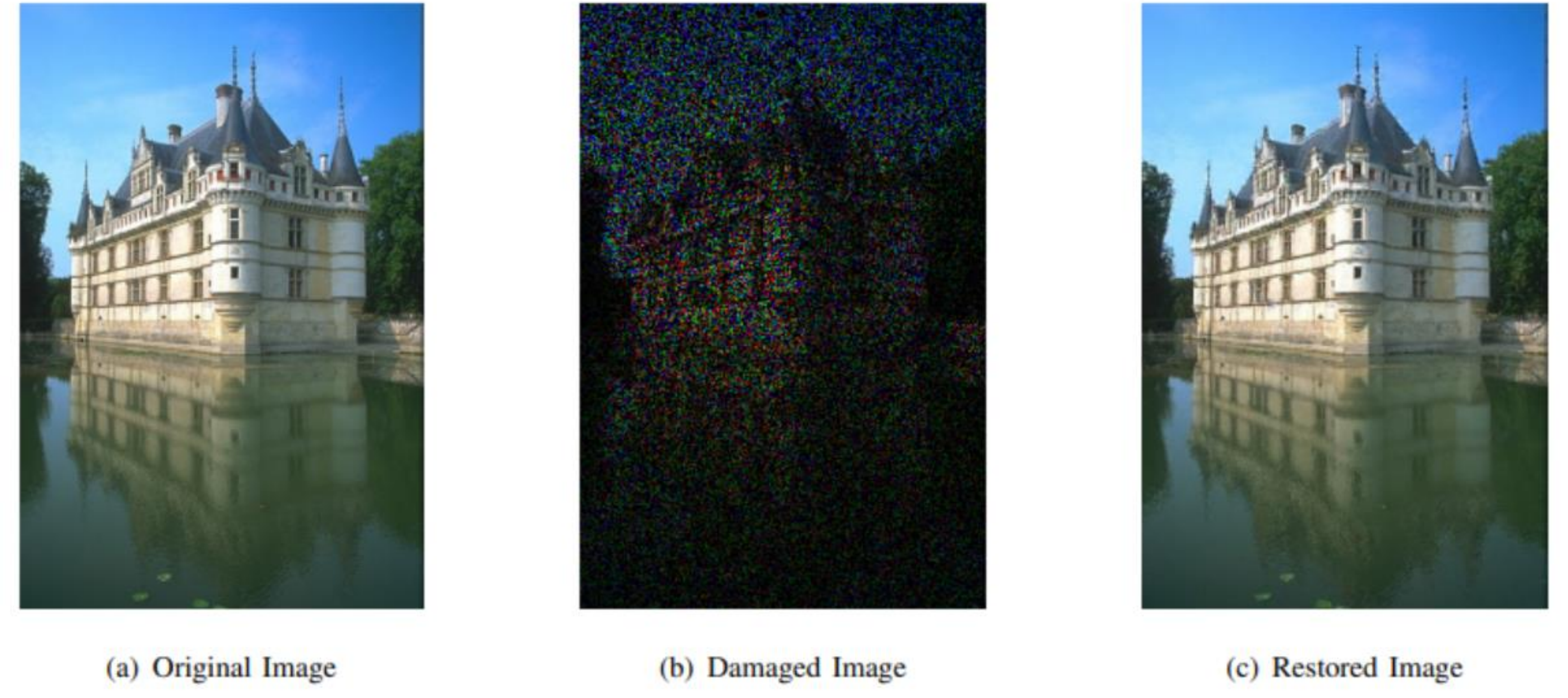
a) The original image, b) White Gaussian noise applied to the image, c) The image denoised using a sparse representation for color image restoration. (from [7], 2008)

Color Image Restoration

Color image inpainting:

Image inpainting is the art of altering an image in an undetectable form, and it frequently refers to the filling-in of holes in the image caused by missing information. Although sparsity is not an efficient model for filling large holes since it leads to a lack of details, it can be used to fill small holes as long as their sizes are smaller than the atoms' size. Iterative and/or multiscale or texture synthesis methods are required for larger holes.

Color Image Restoration



a) The original image, b) the image with 80% data removed, c) the restored image through inpainting. (from [7], 2008)

Color Image Restoration

Color image demosaicing:

Color demosaicing is the process of reconstructing full-resolution images from raw data provided by a standard coloured-filter sensor. Cameras use sensors, each of which is linked to a single pixel and capable of measuring the amount of light energy received in a brief period of time. It extracts the color information of one specific channel when combined with a color filter (R, G, B) so, oftentimes only one color is obtained for each pixel, necessitating interpolation of the missing values.

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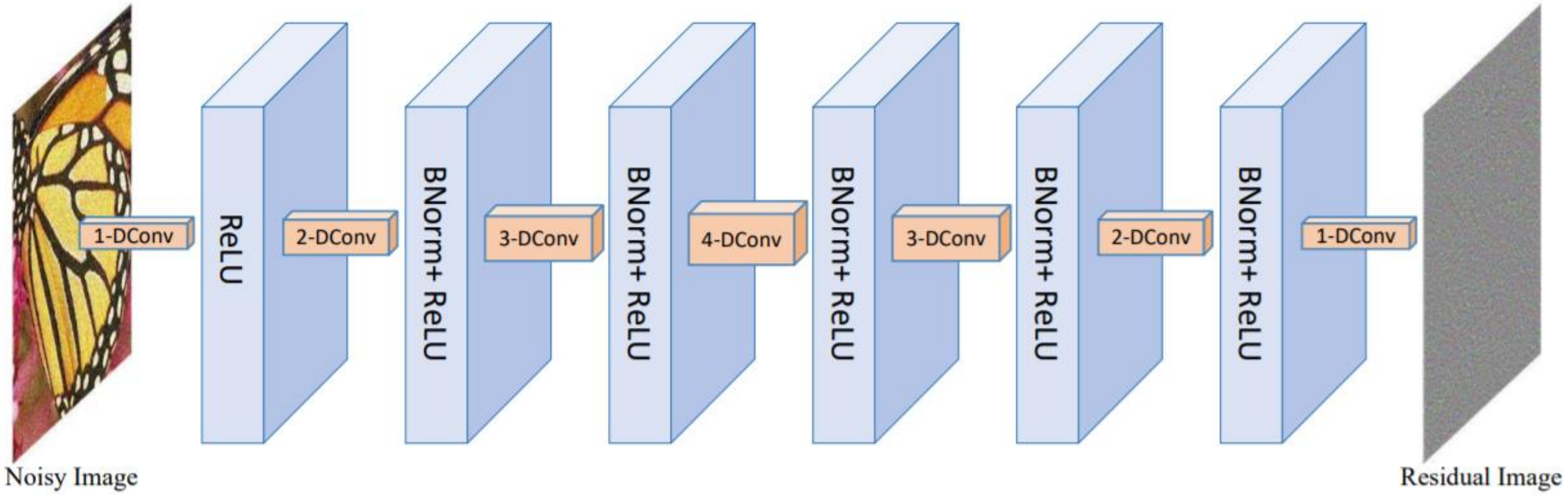
Neural Image Restoration

Because neural networks can successfully adapt to the local nature of the problem, they are well-suited for image restoration. The two most common approaches for handling numerous inverse problems in low-level vision have been discriminative learning techniques and model-based optimization methods.

A set of fast and effective **CNN (convolutional neural network)** denoisers that are integrated into the model-based optimization method to solve inverse problems is a recent method that has proven very effective.

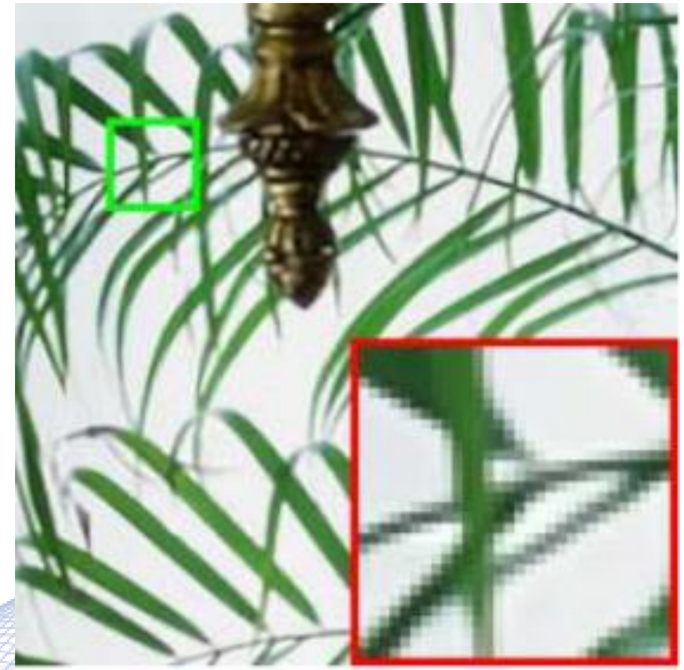
Neural Image Restoration



The architecture of the proposed CNN denoiser consists of seven layers with three different blocks, i.e., "Dilated Convolution+ReLU" block in the first layer, five "Dilated Convolution+Batch Normalization+ReLU" blocks in the middle layers, and "Dilated Convolution" block in the last layer. The dilation factors of (3×3) dilated convolutions from first layer to the last layer are set to 1, 2, 3, 4, 3, 2 and 1, respectively. The number of feature maps in each middle layer is set to 64. (from [8], 2017)

Neural Image Restoration

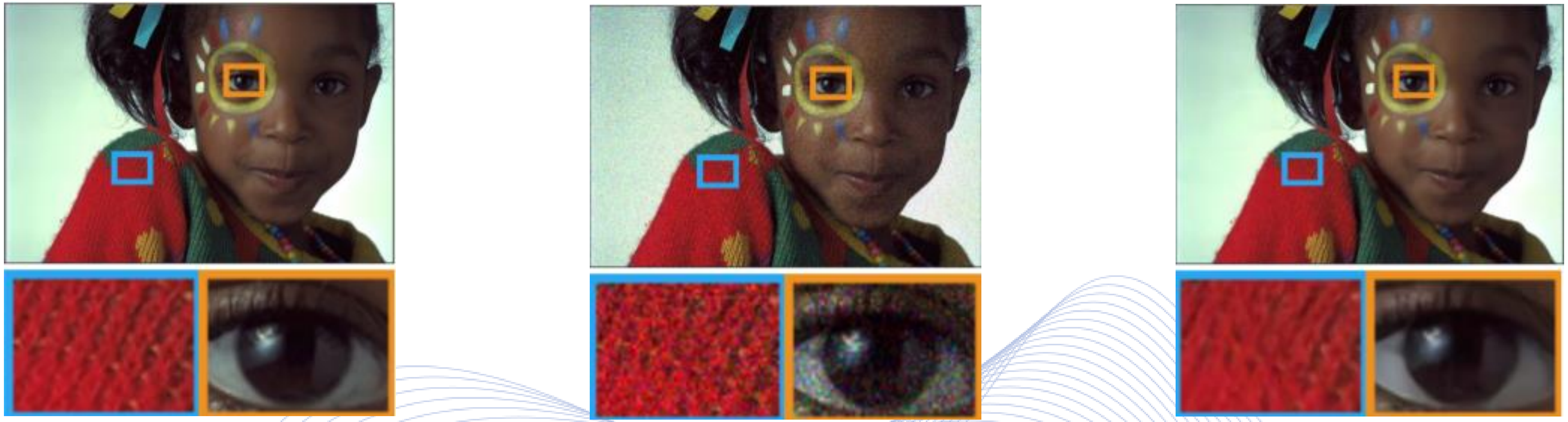
(a)



(b)

a) Blurry and noisy image, b) the restored image through the CNN denoiser. (from [8], 2017)

Neural Image Restoration



(a) (b) (c)

a) The original image, b) the image degraded by Poisson $(\lambda = 30)$ noise, c) the restored using a CNN network trained with noisy data. (from [9], 2018)

Neural Image Restoration

(a) (b) (c)

a) The original image, b) the image degraded by Bernoulli $(p = 0.5)$ noise, c) the restored using a CNN network trained with noisy data. (from [9], 2018)

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De-Fogging

In foggy and hazy weather, there are many atmospheric particles of significant size. Thus, the image acquired by the camera is degraded and usually has low contrast and poor visibility.

The video and image defogging algorithms are widely applied in civil and military fields, such as remote sensing, target detection, and traffic surveillance and refer to algorithms that have the ability to remove fog or haze from an image.

De-Fogging

(a) (b) (c) (d)

a) The original image of an inhomogeneous fog scene, b) the restored image using the Fattal algorithm, c) the original image of a road scene, d) the restored image using the Fattal algorithm. (from [10], 2016)

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De-Raining

Images with rain streaks are often captured by outdoor surveillance equipment, which may significantly degrade the performance of some existing computer vision systems and may also result in a pool visual experience for some multimedia applications.

Modelling it as a signal separation problem, or directly regard it as an image filtering problem and solve by resorting to nonlocal mean smoothing can only cope with rain drops of specific shapes, scales and density, and can easily lead to the destruction of image details which are similar to rain streaks.

De-Raining

(a) (b) (c)

a) The original image showcasing longer rain streaks, b) the de-rained image using the CNN network “DDN” , c) the de-rained image using the NLEDN network. (from [11], 2018)

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Q & A

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