Image filtering by convolution

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ABSTRACT

Image filtering is a common technique used in digital image processing that can be used to take a picture appear differently aesthetically. Noise, also known as distracting visual artifacts, can lower the overall quality of a picture, which is why image improvement techniques are required to fix the problem. It can be utilized in a variety of ways, including smoothing, sharpening, reducing noise, and detecting borders, to name a few. In this piece, we will be using convolutional techniques to correct the images that were messed up. The first thing that needs to be done is a point-by-point multiplication of the frequency domain representation of the picture that's being entered through a black image that has a small white rectangle in the mid of it. This is the first step. Only the lowest harmonics are kept after we apply a filter that gets rid of the higher ones. Because the high frequencies in the input picture are filtered out, the special domain of the image that is produced should look like a blurrier variation of the original picture. Therefore, a greater degree of detail preservation is indicated when the white rectangle W is larger because this indicates that more high-frequency components of I have been preserved.

Keywords: Convolution, Filtering, Noise, Fourier transform, PSNR, SSIM

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1. Introduction

Image processing and reconstruction come first in many kinds of practical vision systems. [1]. The end result is an improvement in image clarity as a whole, along with reliable data that can be used for further visual decision-making. Combining two functions into a single one is the "convolution" mathematical procedure, which has found widespread use in signal processing. Discrete convolution is commonly used in computer graphics and image processing to remove high-frequency noise, sharpen details, identify edges, or modulate the frequency domain of an image [2].

2. Method

2.1. Image convolution

The convolution theorem states that under certain conditions, the Fourier transform of a convolution is equal to the point-wise product of multiple Fourier transforms. Specifically, a point-wise multiplication in the frequency domain is identical to a convolution in the time domain [3]. As shown in the Figure 1, convolution theory can be understood. Given a signal's representation in the frequency domain, the Inverse Fourier Transform (IFT) can be used to determine its representation in the time domain. The Fourier transform (FT) and its counterpart, the inverse Fourier transform (IFT), both determine a signal's frequency domain representation [4].
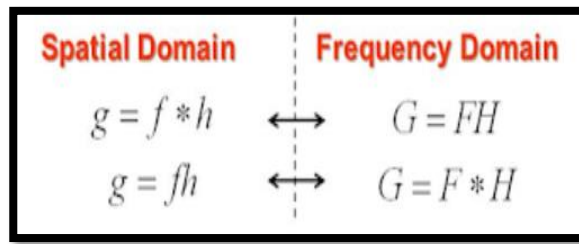
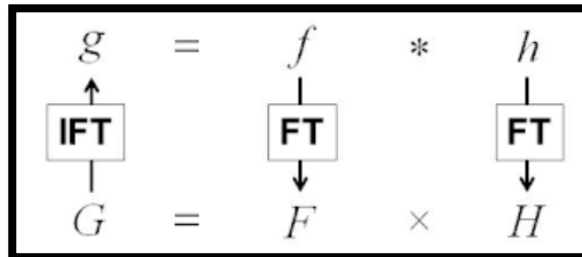Figure 1. Convolution Theorem

Figure 2. FT and IFT

Analyzing signals in two dimensions is also possible with the convolution algorithm [5, 6]. For this reason, it is useful in many different kinds of image analysis and computer vision programs. Images in the special domain (the domain in which we are most accustomed to watching images) and their frequency domain representations are shown side by side in Figure 3 [7].
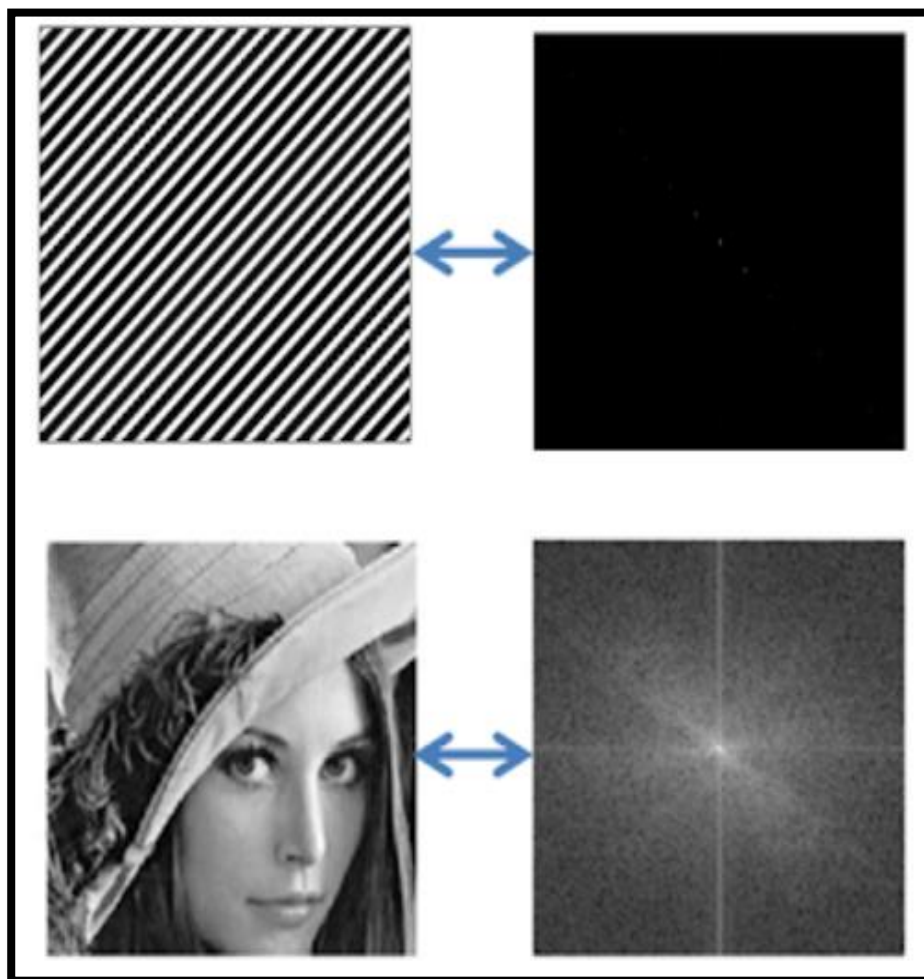

Figure 3. Instances for two descriptions in special and frequency domains

2.2. Filtering

The term "noise" is used in the field of image processing to describe a variation in image intensity that happens at random and appears as grains in the image [8]. The photon nature of light or thermal energy of heat generated inside the image sensors are just two examples of how basic physics can have an impact on the final product. Noise, in its simplest form, is when an image's pixels don't show the exact values that were sent to the computer, but instead show random variations in strength. Restoration of the original signal from a version that has been corrupted by noise is of utmost importance in the process of developing image processing systems. Specifically, the Nyquist-Shannon sampling hypothesis in information theory establishes the mathematical bounds on how much noise can be suppressed. Here is a quick rundown of the various types of noise that can be discovered in digital images [9]:

When it comes to probability density functions, the normal distribution (also known as the Gaussian Distribution) and Gaussian noise are practically interchangeable terms. This phenomenon is also known as electronic noise because it is produced by electrical devices. Communications pathways in telecommunications and computer networks are vulnerable to interference from wideband Gaussian noise. Thermal vibrations of atoms in conductors (thermal noise or Johnson-Nyquist noise) and other warm [9] events are two examples of the natural sources that can produce this type of noise.

In order to create salt and pepper noise, random bright (255 value) and random dark (0 value) pixels are added all over the picture. In order to give the impression of greater randomness throughout the picture, this is done. Basically, it's just a bunch of black and white pixels strewn about in a picture at random [9]. The error originates in the camera's sensing cell.

For speckle noise, Ultrasound medical images frequently exhibit multiplicative noise. This granular noise is a characteristic of both Active Radar and Synthetic Aperture Radar (SAR), and it degrades the image quality of both kinds of radar. It darkens the overall tone of the area [9].

For blurring, to put it simply, an edge is any place in an image where the scene suddenly shifts or breaks. We get a better sense of an image's perceived clarity and detail when we can identify all of the items and their shapes within it. To achieve a smoother transition from one hue to the next, we simply reduce the quantity of material used in the blurring process [10].

For Sharpening, unlike distortion, sharpening is a positive procedure. The edge content of an image is reduced during blurring but raised during enhancement. Finding the edges is the first stage in increasing the image's overall edge content [4]. Roberts Edge Detection and the Sobel Edge Detection method are just two examples of the many operators available for finding edges. Once we've found the edges, we'll incorporate them into a picture, giving it more definition and sharpness [10].

2.3. Proposed algorithm

Let's start by creating a black image (W) of the same dimensions as the initial image (I), except with a white rectangle superimposed on top of it. The first step is to multiply the frequency domain of image I by image W to get the following for image I: One method is to apply the Fourier transform to I and then label the resulting function as F. Multiply F by W by each individual number, and record the product as F W. Third, find R1 by performing the inverse Fourier transform on FW. Applying the inverse procedure to the same image I yields the result of the convolution of the special domain of I and the inverse Fourier transform of W. Ultimately, this will lead to the same result. Start by taking the inverse Fourier transform of W, where M is the resulting matrix. After using the method to find the sum of I and M, we can refer to the resulting number as R2.

3. Result and discussion

First, we execute a point-wise multiplication on the frequency domain representation of the input image by a black image that has a tiny white rectangle in its center. The higher harmonics are discarded while the lower ones are kept. The spatial domain of the output picture should be fuzzier than the input image because high frequencies are suppressed in the process. This is because of the nature of the supplied picture.

As the size of the white rectangle in the middle of W is decreased, a greater number of frequencies will be eliminated, causing the image to blur.

The results of the R1 and R2 tests for the input picture 1 are shown in Figures 4 and 5, respectively. White rectangles in both instances have W dimensions that are 30% of the full picture's W dimensions.
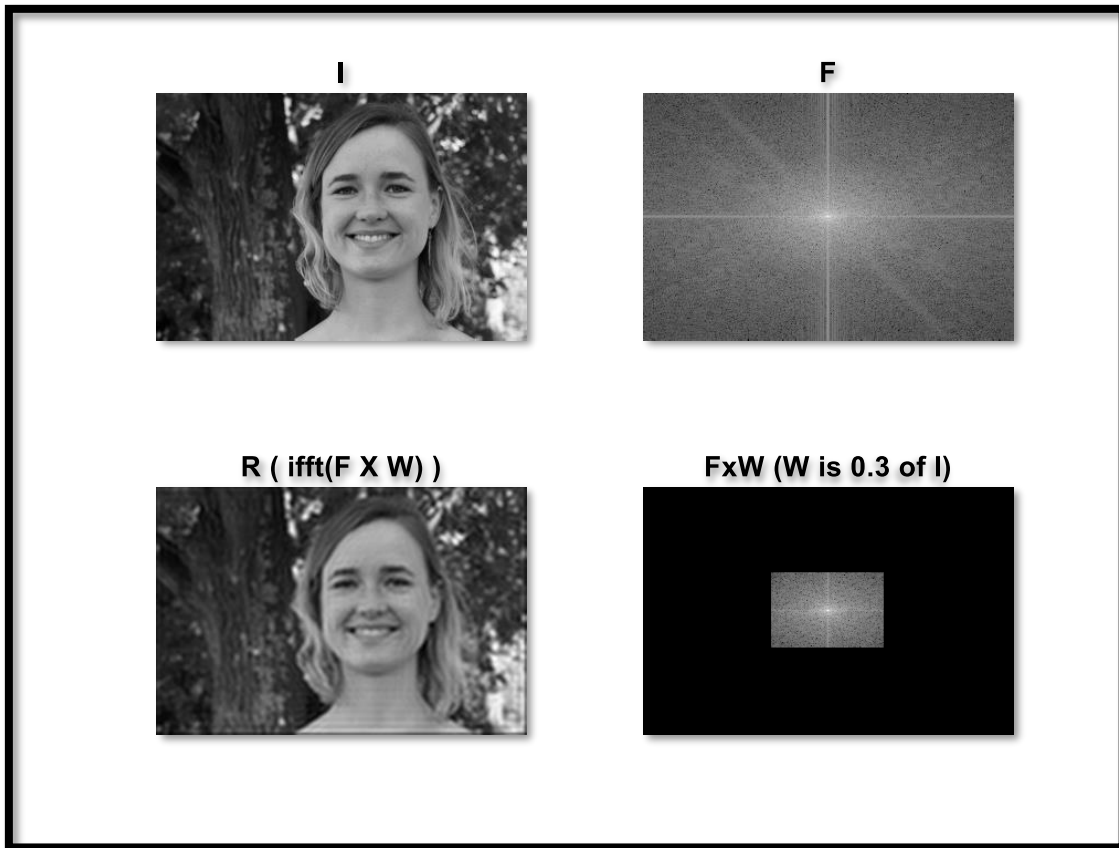
Figure 4. R1 for image1, rectangles of white with 30% of picture sizes
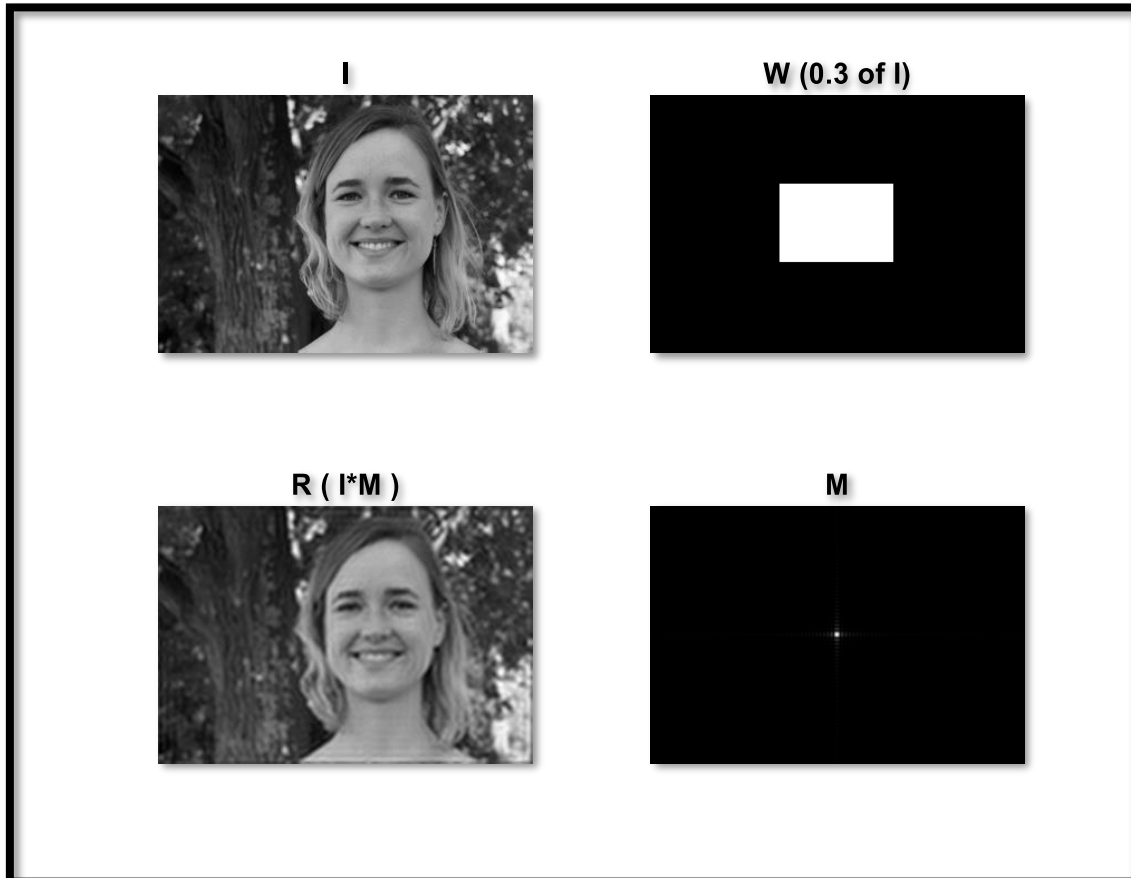

Figure 5. R2 for image1, rectangles of white with 30% of picture sizes

A similar result is obtained if we again visualize R1 and R2 from the same picture, but this time reduce the white rectangle of W so that its dimensions are only 10% of the image's overall dimensions, rather than 30%. As can be seen in figures 6 and 7, the resulting picture deteriorates in clarity as expected. The amount of information retained in regions R1 and R2 grows in tandem with the area of the white rectangle W. When the white parallelogram W is made larger, more of the high-frequency components of I are kept. Figures 8–13 demonstrate that the quality of the resulting image improves as W is scaled up to 50%, 70%, and 90%.
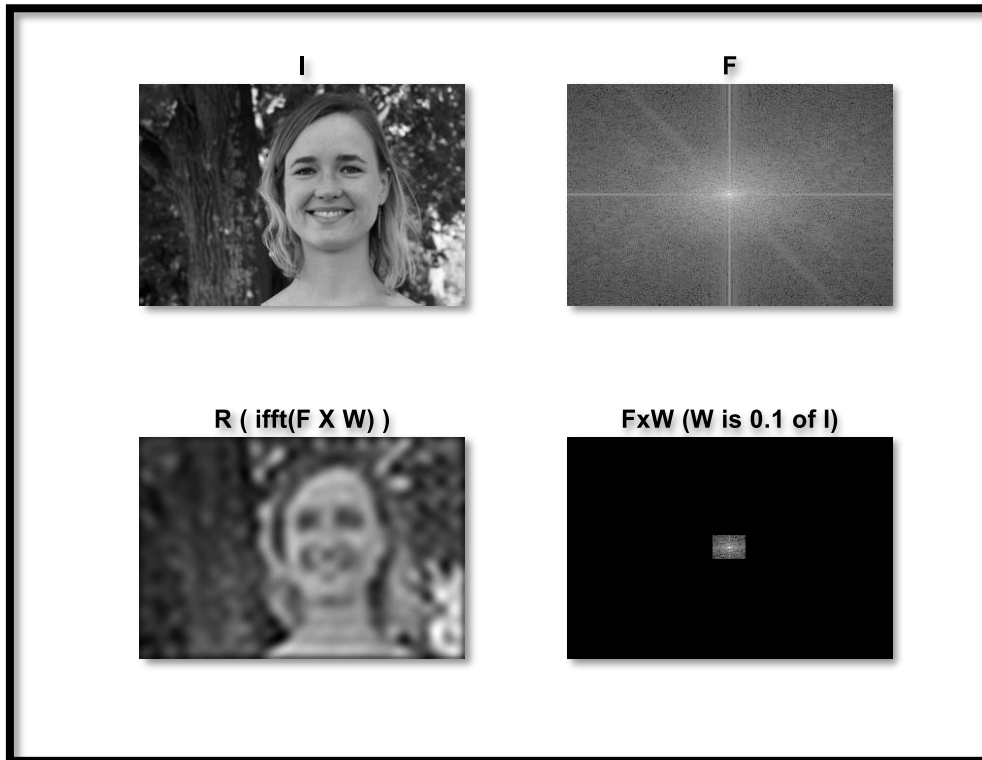

Figure 6. R1 for image1, rectangles of white with 10% of picture sizes
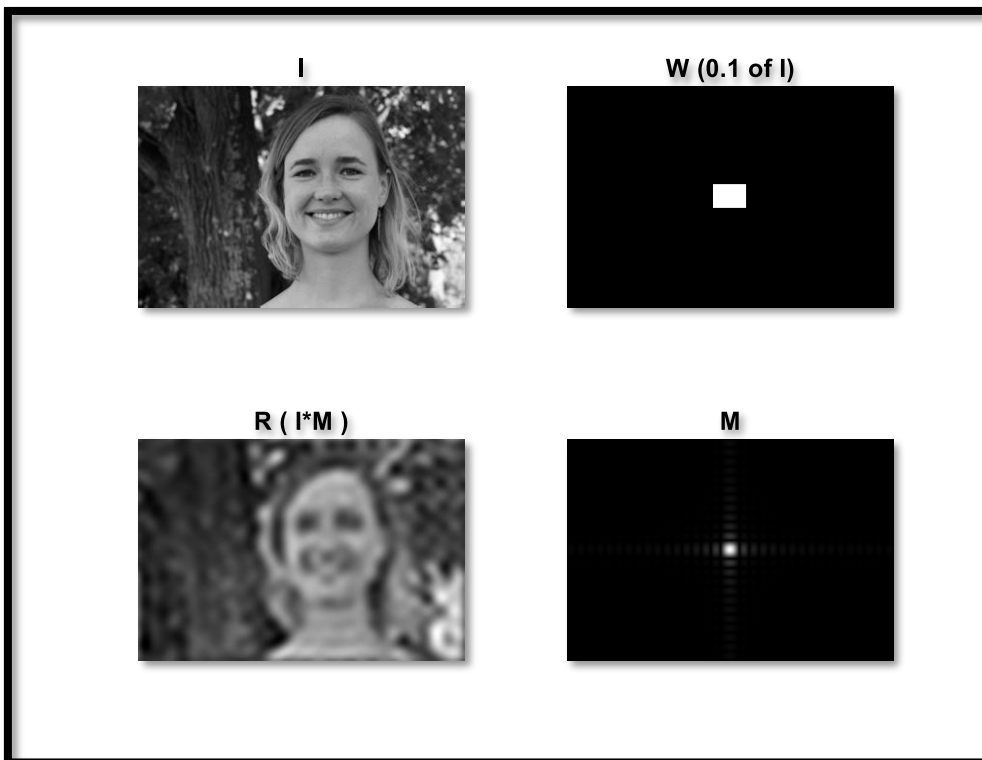

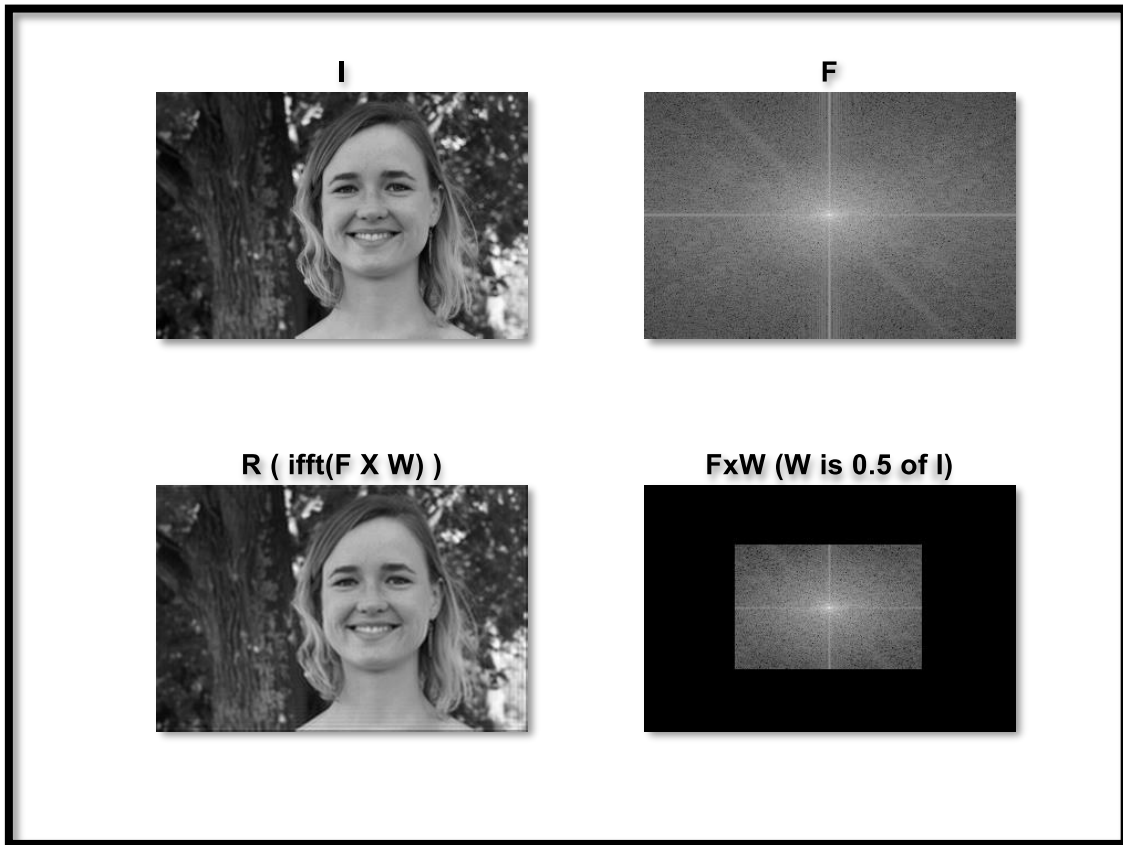Figure 7. R2 for image1, rectangles of white with 10% of picture sizes

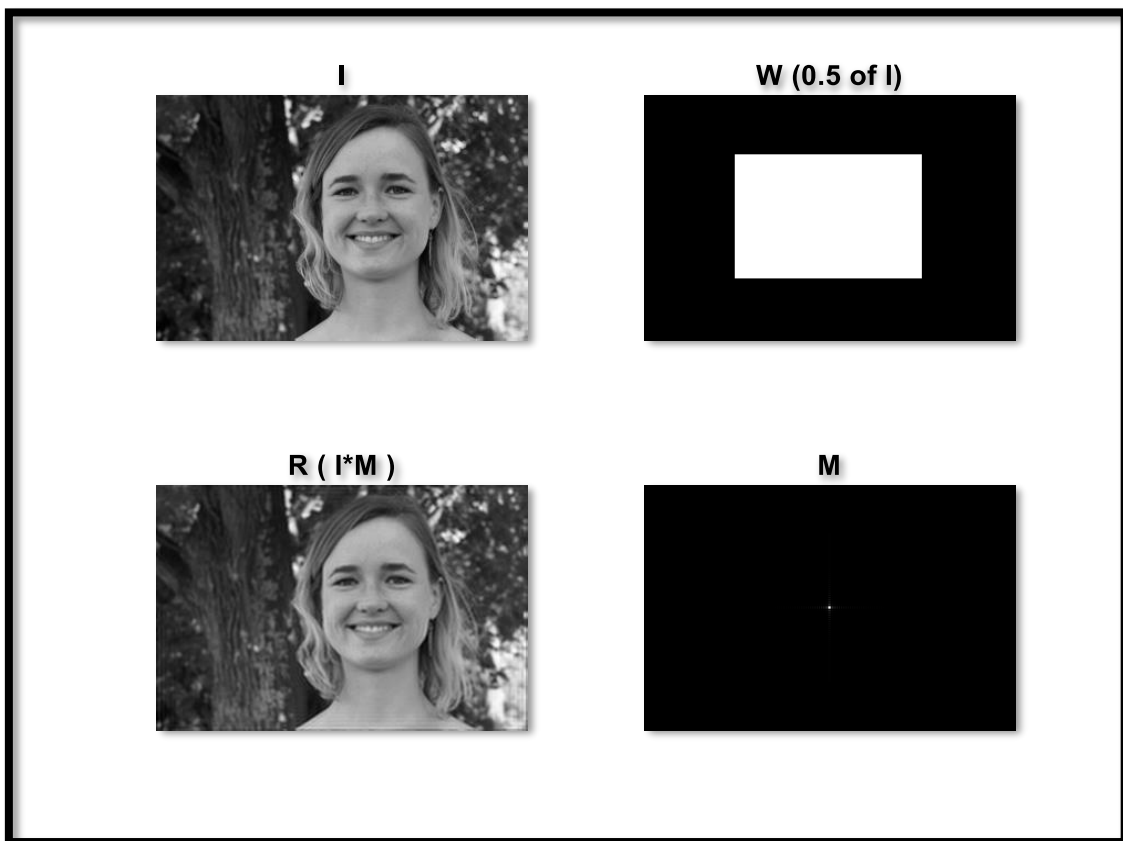Figure 8. R1 for image1, rectangles of white with 50% of picture sizes

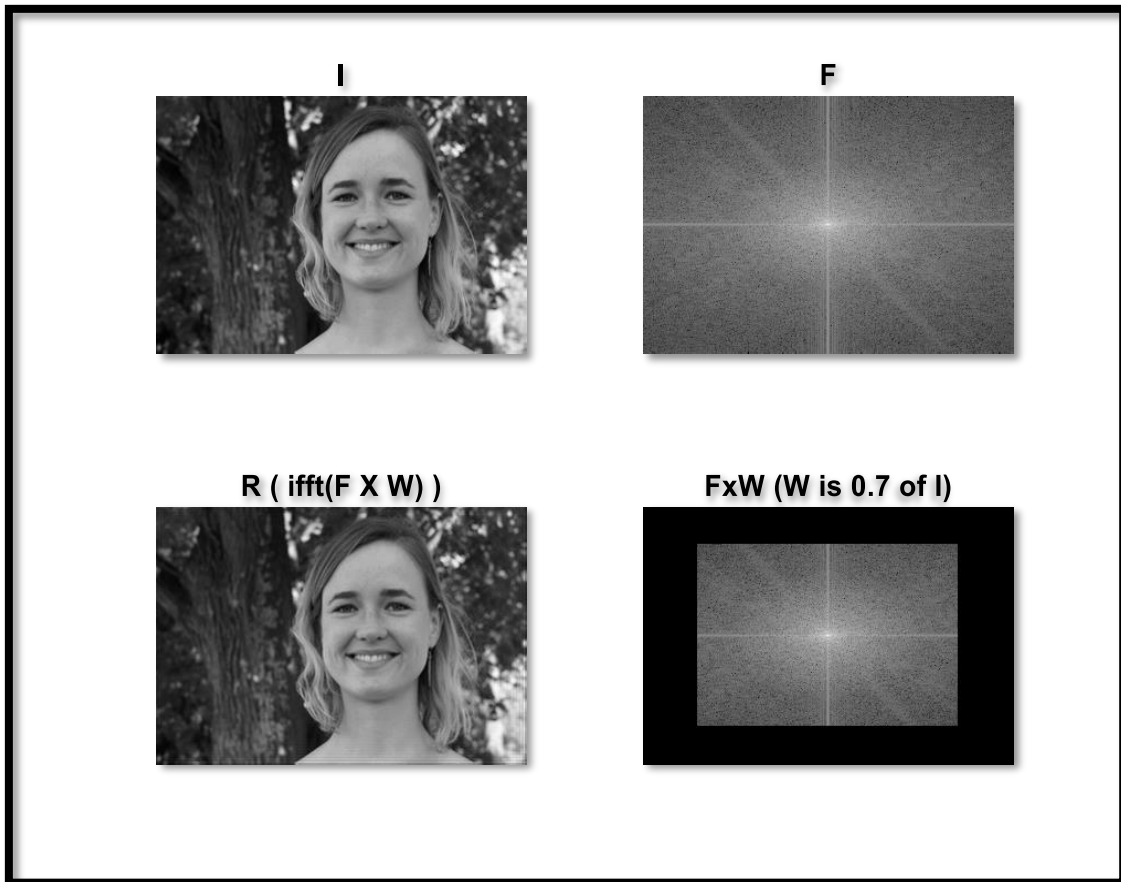Figure 9. R2 for image1, rectangles of white with 50% of picture sizes

Figure 10. R1 for image1, rectangles of white with 70% of picture sizes
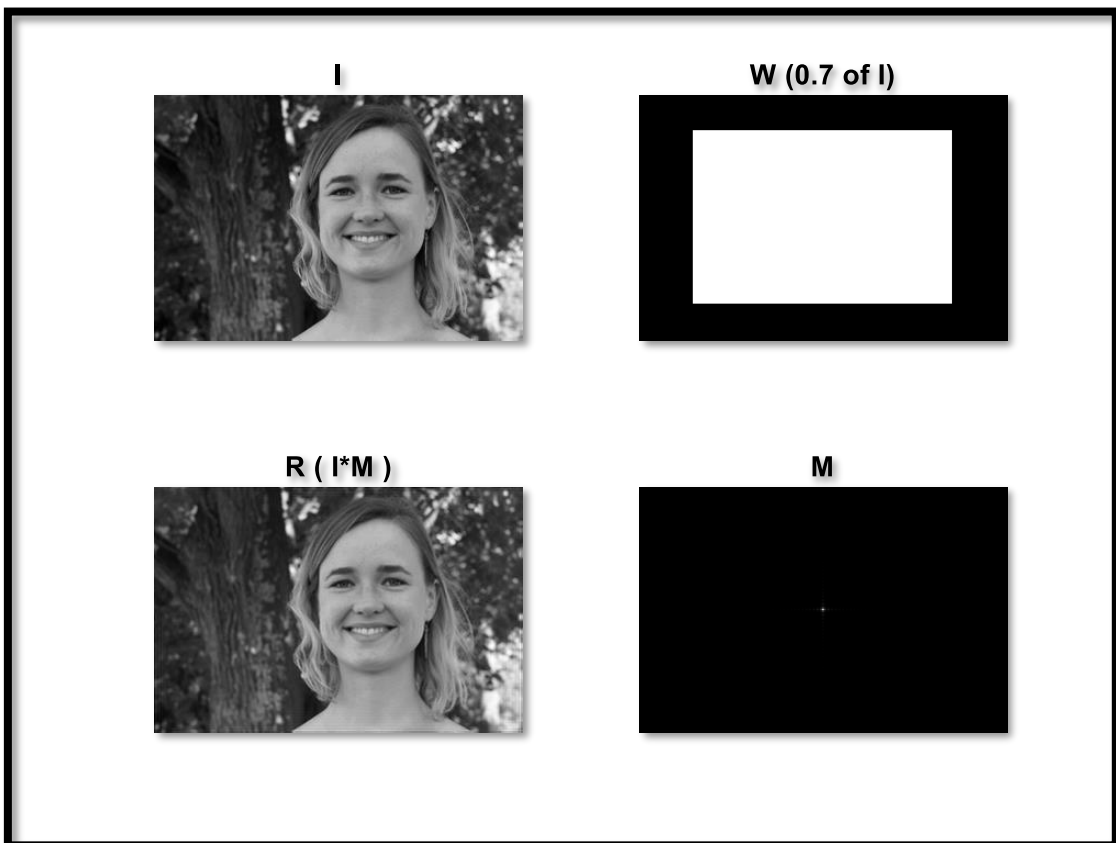

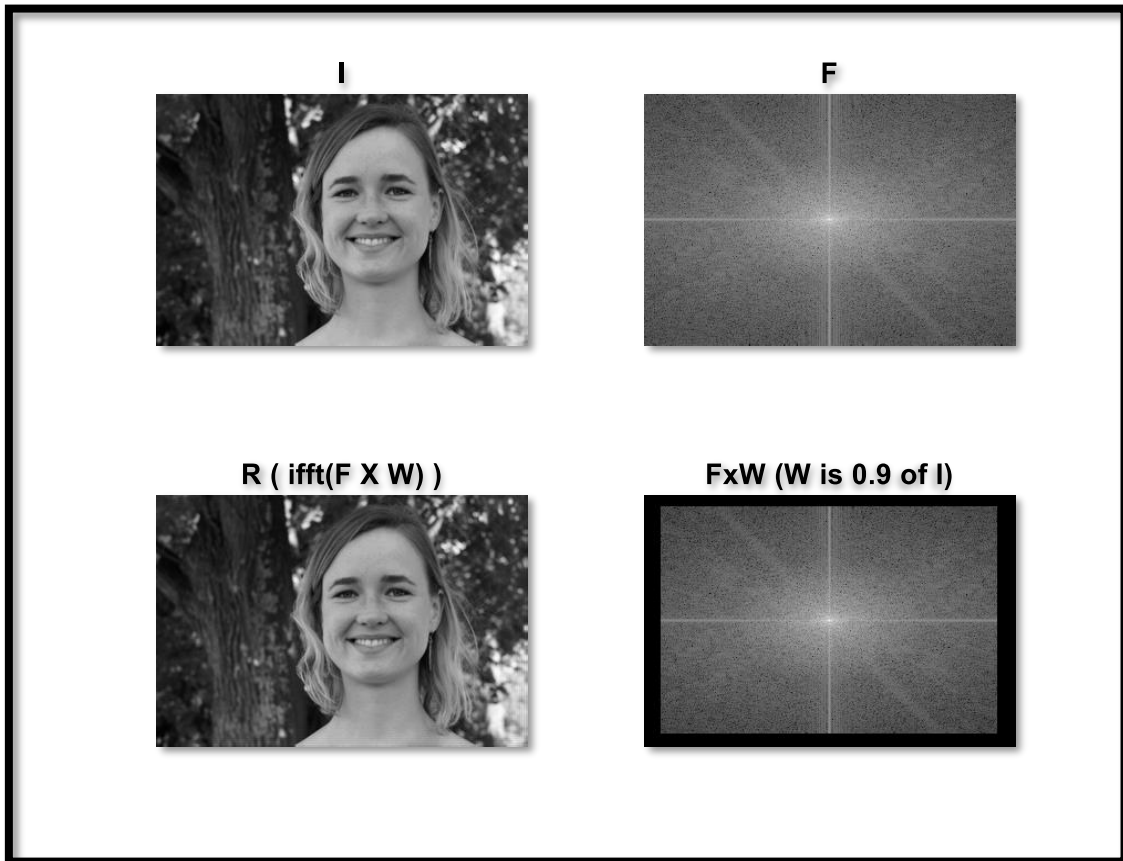Figure 11. R2 for image1, rectangles of white with 70% of picture sizes

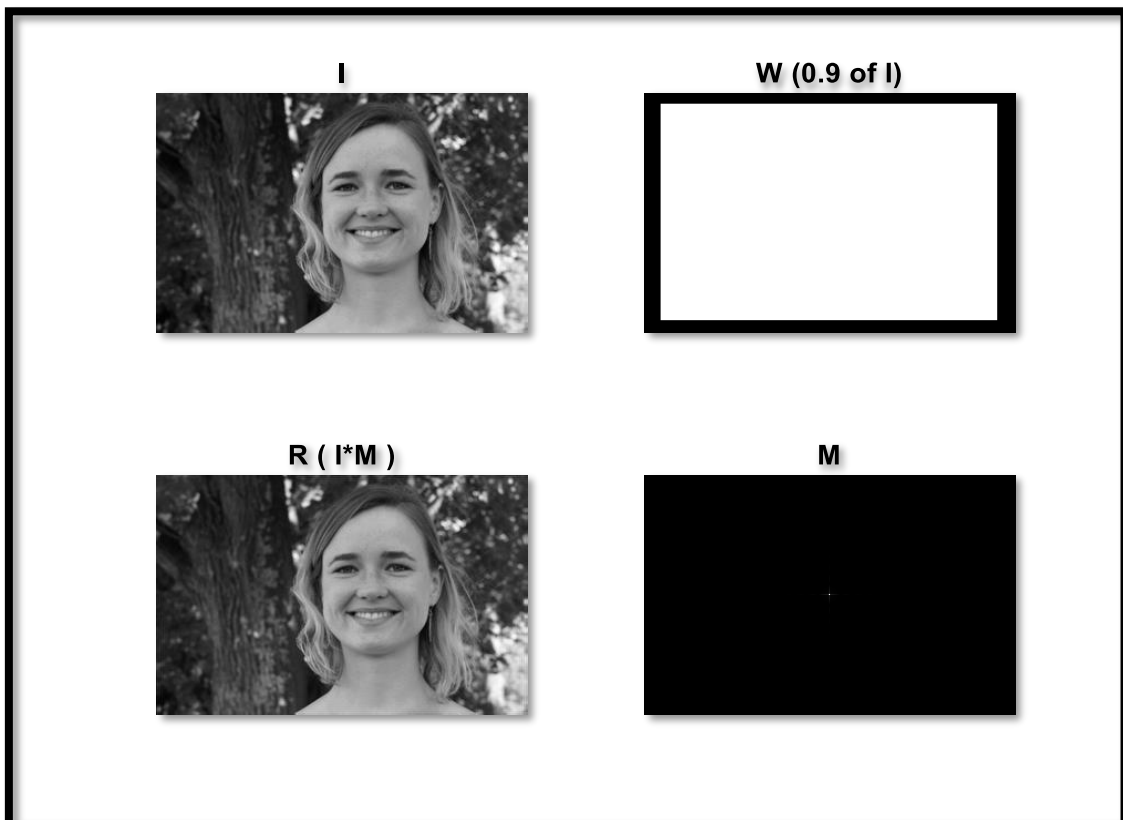Figure 12. R1 for image1, rectangles of white with 90% of picture sizes

Figure 13. R2 for image1, rectangles of white with 90% of picture sizes

In this paper we will use two indicators of peak signal to noise ratio and structural similarity to judge the image quality. Generally, the use of peak signal-to-noise ratio is a common method in image processing. It determines the image quality by calculating the error between corresponding pixels. The calculation is expressed as follows [5]:

$$MSE = \frac{1}{H * W} \sum_{i=1}^{H} \sum_{i=1}^{W} (X[i,j] - Y[i,j])^2,$$

$$PSNR = 10 * \log_{10}^{(2^n - 1)^2 / MSE}.$$

……………………………………….(1)

According to the above formula, when the calculation result of PSNR is larger, it means the image quality will be better. In addition, MSE represents the mean square error value calculated based on the pixel point difference between the reference image and the image filtered by the result algorithm, which represents the number of pixel bits in the image, and H,W represent the length and width of the image.

This paper analyzes and processes the image from the aspects of contrasts, structural information, and brightness of the image from these indicators, which are expressed as follow [8]

$$SSIM(X,Y) = L(X,Y)^{\propto} * C(X,Y)^{\beta} * S(X,Y)^{\gamma}$$ ……………………………..……..(2)

Therefore, we will obtain PSNR and SSIM for image (1) with Rectangles of white 90% of picture sizes
And comparison with some methods as indicated in table 1

Table 1. Comparison of PSNR and SSIM for image1 on different methods

Algorithms	PSNR	SSIM
Proposed algorithm	24.78	0.98
Deep learning model [5]	23.45	0.85
DCPDN [5]	13.74	0.74
Over filtered decomposition model [9]	16.65	0.74

Let's use an input image I with lower resolution than the one we used earlier in place of the image we used above for the white rectangle whose dimensions are 30% of the image's overall dimensions. Figure 14 depicts the outcome of this investigation. Let's swap out the high-resolution picture above for a lower-resolution one I, so that the white rectangle's dimensions are 30% of the image's overall dimensions. The findings are presented in Figure 14.
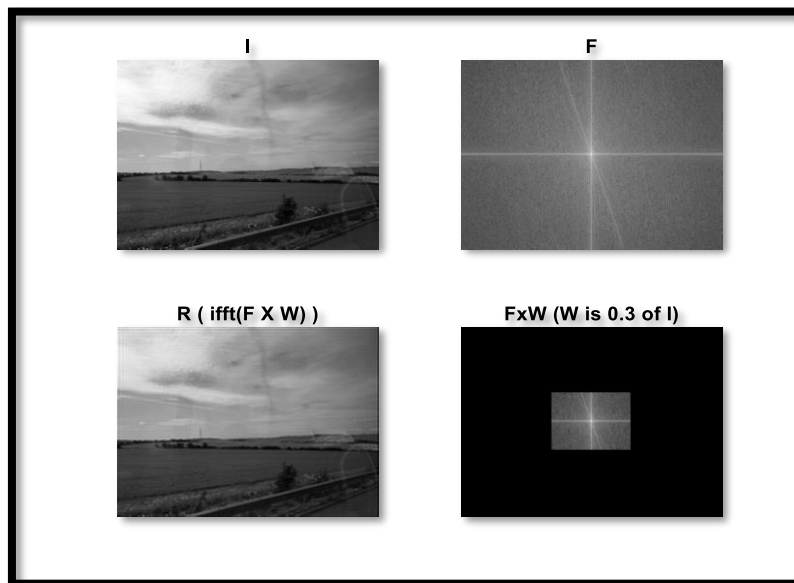

Figure 14. R1 for a low detail image, rectangles of white with 30% of picture sizes

Figure 14 appears less blurry than Figure 4 result, despite both using the same W. Because the input picture in the experiment depicted in Figure 14 contains fewer details. Compared to a low-detail version of the same white rectangle W in area, the high-detail version loses more information and appears blurrier (i.e., looks more blurred). High-detail images have more information packed into their high-frequency components, so applying the same pass filter to both images causes the high-detail image to lose more information (and look more blurry) than the less-detailed one. The end output is shown in Figure 15 when a moderately detailed image is used as input. Image filtering by convolution can be adopted along with wireless communication elements as in [10-14], for better wireless transmission of images.
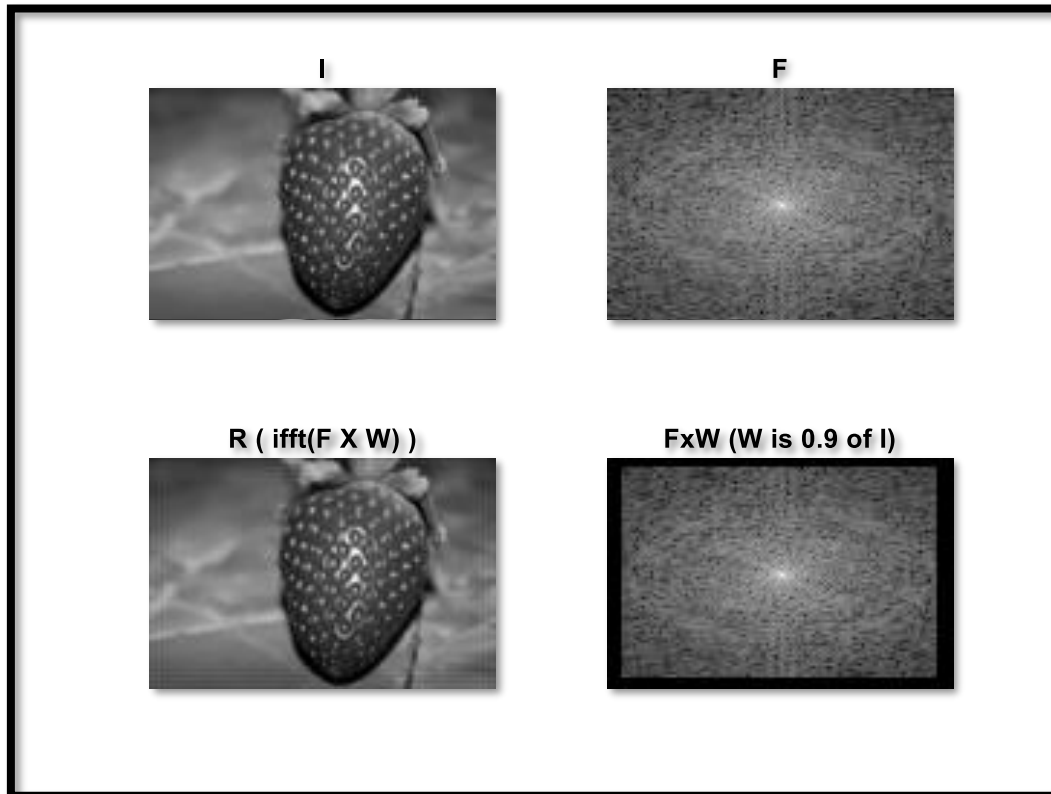

Figure 15. R2 for a medium detail image, rectangles of white with 90% of picture sizes

4. Conclusion

In this paper, we discussed some of the filtering techniques in spatial and frequency domain for removing noise from image. The result of image filtering in either way more or less the same. However, frequency-based algorithms are designed to process frequency components of images in frequency domain instead of processing pixels in spatial domain which can be seen as major difference in the two approaches. Therefore, we can say that frequency-based algorithms depend on features of images that exist in the frequency domain. Hence, it can be concluded that Fourier transformation is more accurate and easier to manipulate and that spatial filters offer considerably more versatility because they can be used also for nonlinear filtering.

Conflict of Interest

The authors declare that they have no conflict of interest, and all of the authors agree to publish this paper under academic ethics.

Author Contributions
All the authors contributed equally to the manuscript.

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