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An Improved Algorithm Based on Super-Resolution Techniques in the Frequency Domain for Video Image Processing

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ABSTRACT

In this paper, a novel method for image quality enhancement based on super-resolution algorithms in the frequency domain is presented. The proposed algorithm improves image quality by amplifying high-frequency components, which are crucial for preserving fine details and sharp edges. Unlike many existing super-resolution techniques that rely on multiple image frames, the proposed approach operates efficiently using only a single input frame. This characteristic not only simplifies implementation but also makes the method applicable in scenarios where acquiring multiple frames is impractical. A significant advantage of the proposed method is its reduced computational complexity compared to traditional super-resolution techniques, which often involve iterative optimization processes or deep learning models requiring extensive training datasets. By leveraging the frequency domain for enhancement, the algorithm achieves superior processing efficiency, making it particularly suitable for real-time applications such as video image processing. In such applications, computational speed is a critical factor, and the ability to enhance image quality without introducing excessive processing delays is highly desirable. To evaluate the effectiveness of the proposed method, extensive experiments were conducted on various image datasets, and the results demonstrate that the algorithm successfully enhances image sharpness while maintaining computational efficiency. The promising outcomes suggest potential applications in medical imaging, surveillance, and satellite image processing, where high-quality image reconstruction is essential.

1. INTRODUCTION

Enhancing image quality has always been a significant research area in image processing. While numerous methods and algorithms exist for increasing the resolution of still images, the field of video image enhancement remains relatively unexplored. For single images, complex and iterative algorithms can be employed; however, in video processing, due to constraints on execution speed, such computationally intensive and iterative methods are not practical.

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Super-resolution is one of the key approaches for image quality enhancement, differing from conventional image enhancement techniques. Various algorithms have been proposed in this field [1-5]; however, most of these methods are highly complex and iterative in nature. Consequently, they are not suitable for video processing applications, where real-time performance at frame rates of 50 or 60 frames per second is required. In fact, most of these algorithms are unsuitable for real-time applications. Since this study focuses on real-time image processing, iterative algorithms due to their execution speed limitations and the resulting delays in information processing are not considered in this research.

Super-resolution techniques aim to take one or multiple low-quality images as input and generate a high-resolution output image, typically with different input and output dimensions. Single-frame super-resolution techniques are categorized into three main groups:

Interpolation-based techniques: These methods, such as bilinear interpolation, often result in blurring and block artifacts in the output image.

Reconstruction-based techniques: These approaches solve optimization problems to restore image edges, but they require substantial iteration, making them computationally expensive.

Statistical methods: These algorithms also require significant iteration for implementation.

Among these three categories, none provide both high-speed execution and acceptable output image quality[6]. The algorithm presented in this paper builds upon the work of Seiichi Gohshi [7-9] conducted between 2012 and 2015, which focuses on reconstructing low-quality images using frequency-domain super-resolution techniques. However, modifications have been introduced to improve computational speed.

In frequency-domain super-resolution techniques, the input consists of a single low-resolution image. One common approach in this domain involves enhancing edge details to produce a high-resolution output. Among the various edge-enhancement methods, image sharpening is a widely used technique for improving visual quality. One well-known sharpening approach is the unsharp mask method, which remains a standard feature in television display devices due to its low implementation cost and high efficiency. Implementing this algorithm in television systems requires only a few delay lines, adders, and multipliers. However, the primary limitation of this method is its inability to generate frequency components beyond the Nyquist limit of the input image [7].

In the following sections of this paper, the proposed method is first introduced. Subsequently, the simulation results are analyzed in the next section. Finally, the paper concludes with a summary of findings.

2. PROPOSED METHOD

The initial concept of this algorithm was first introduced by Seiichi Gohshi in 2012, as illustrated in Figure 1 [7].

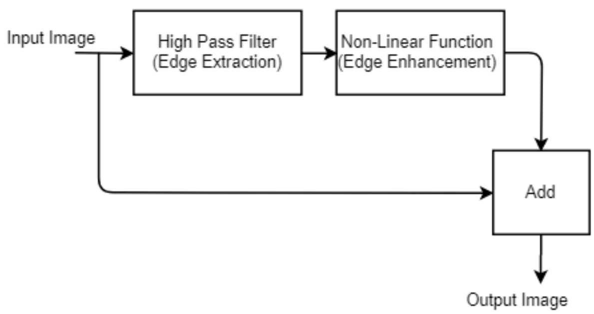


Fig. 1. The Initial Concept of the Super-Resolution Algorithm Proposed by Gohshi in the Frequency Domain [7].

To better understand the behavior of this algorithm, it is essential to consider the Fourier series expansion of the input image. For simplicity, we assume a one-dimensional image function f(x)f(x)f(x) with the following expansion:

$$f(x) = \sum_{n=-N}^{+N} a_n \cos(\omega_n x) + b_n \sin(\omega_n x) \tag{1}$$

The high-pass filter in Figure 1 eliminates low frequencies, including the zero frequency of the input image. The output of this stage can be expressed in accordance with Equation (2).

$$g(x) = \sum_{n=-N}^{-M} a_n \cos(\omega_n x) + b_n \sin(\omega_n x) + \sum_{n=M}^{N} a_n \cos(\omega_n x) + b_n \sin(\omega_n x) \tag{2}$$

where M and N are positive integers, and N>M. The highest energy in images is concentrated in the DC frequency content, which in some cases leads to image saturation. This issue is resolved in the proposed algorithm due to the presence of the high-pass filter. The frequency components between -M and M are eliminated by the high-pass filter. For instance, if the nonlinear function is defined as in Equation (3), then:

$$y = \begin{cases} x^2 & x > 0 \\ -x^2 & x < 0 \end{cases} \tag{3}$$

Edges are represented in the form of $\sin(\omega_n x)$ and $\cos(\omega_n x)$. Squaring these values, as expressed in Equation (3), results in terms of $sin^2(\omega_n x)$ and $cos^2(\omega_n x)$, which in turn contain frequency components of the form $\sin(2\omega_n x)$ and $\cos(2\omega_n x)$. Consequently, the nonlinear function utilized in the algorithm generates frequency components higher than those in the input, thereby enhancing the quality of the output image. Additionally, by implementing a low-pass filter before the high-pass filter in Figure 1, the artificial artifacts introduced in the image can be mitigated [10].

Based on the algorithm in Figure 1 and the discussions presented in reference [11], an improved algorithm can be proposed as illustrated in Figure 2. The advantages of this algorithm include its ease of implementation using FPGA chips for real-time applications and the acceptable quality of the output image.

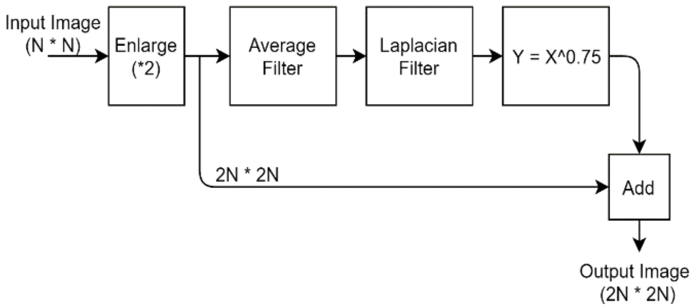


Fig. 2. Proposed Improved Algorithm

In the algorithm presented in Figure 2, the averaging filter plays a crucial role in eliminating artificial artifacts in the output image, while the Laplacian filter is employed as the high-pass filter. The nonlinear function used in this algorithm is defined as $y = x^{0.75}$, which generates higher-order frequency components in the output compared to the input image. Additionally, the *Enlarge* block utilizes bilinear interpolation to upscale the image.

For the high-pass filter, alternatives such as the Canny filter which provides significantly better performance than the Laplacian filter could be used. However, since this algorithm is intended for video image processing, execution speed is a critical factor for hardware implementations. Thus, the filters selected must offer a balance between acceptable output quality and high processing speed.

3. SIMULATION RESULTS

In this section, the results of applying the proposed algorithm (Figure 2) to several sample images, shown in Figure 3, are presented. The output quality of this algorithm is compared with the unsharp masking method and the bicubic interpolation technique. All simulations were conducted using MATLAB.

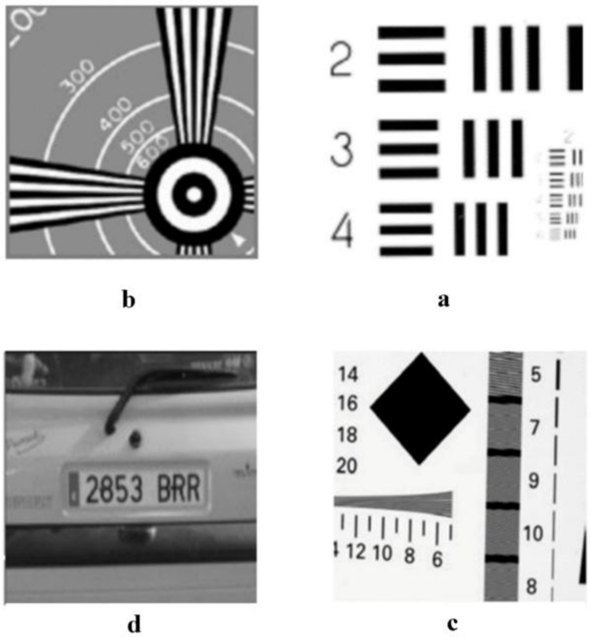


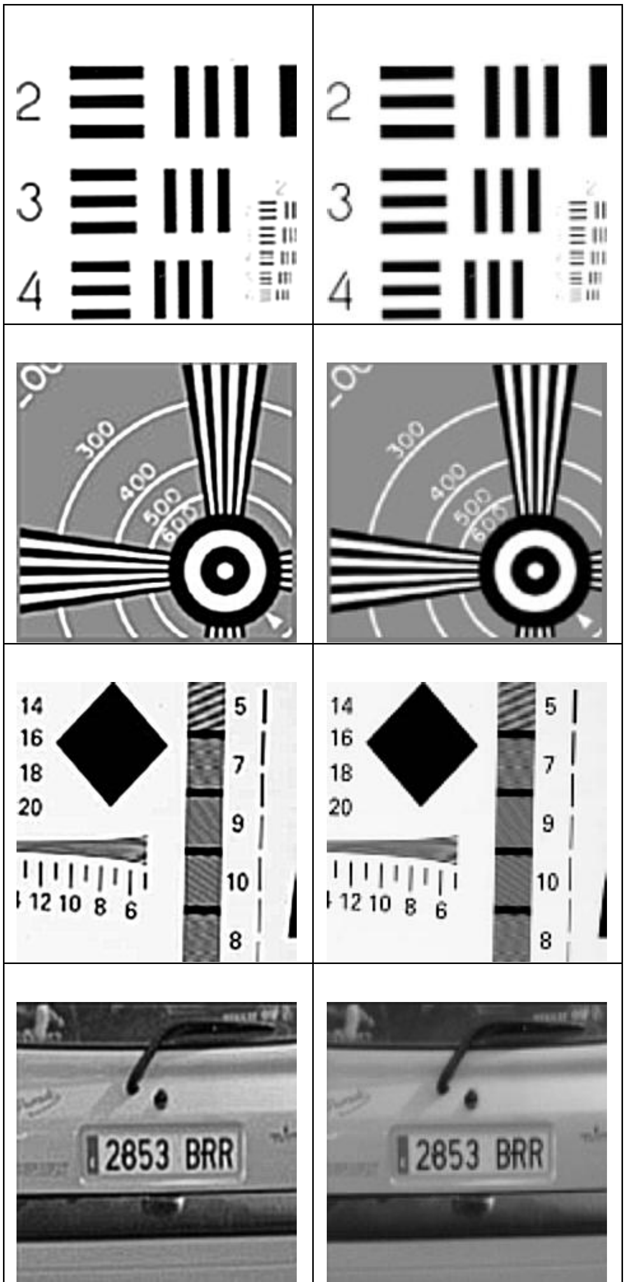
Fig. 3. Original Images (220 × 220 pixels)

To compare the outputs of the proposed algorithm, we adopt the evaluation method introduced by Gohshi in [7]. In this approach, the two-dimensional Fourier transform of the images is used for comparison. This metric demonstrates that the proposed method effectively generates high-frequency components in the output image—information that is absent in the input image.

For this evaluation, we utilize the normalized logarithm of the magnitude of the shifted two-dimensional Fourier transform of the image, as expressed in Equation (4). In the resulting Fourier transform matrix, moving away from the center corresponds to higher-frequency components of the image.

$$\frac{\log(abs(fftshift(fft2(input\_image))))}{Max(\log(abs(fftshift(fft2(input\_image)))))} \tag{4}$$

The low-resolution images for the input of the proposed algorithm were obtained using the nearest neighbor interpolation algorithm with a factor of 0.5. The outputs of the proposed algorithm are presented in Figure 4.



b	a

Fig. 4. Output of the non-sharp mask (a) and the proposed algorithm (b).

As shown in Figure 4, the proposed algorithm not only generates high-frequency components in the output images but also improves the contrast of the images. Figure 5 presents the data related to the quantitative metric mentioned in Equation 4 for comparing the algorithm's outputs, which are equivalent to the images in Figure 3. As observed in these outputs, the images generated by the proposed algorithm contain high-frequency components that are absent in the input images.

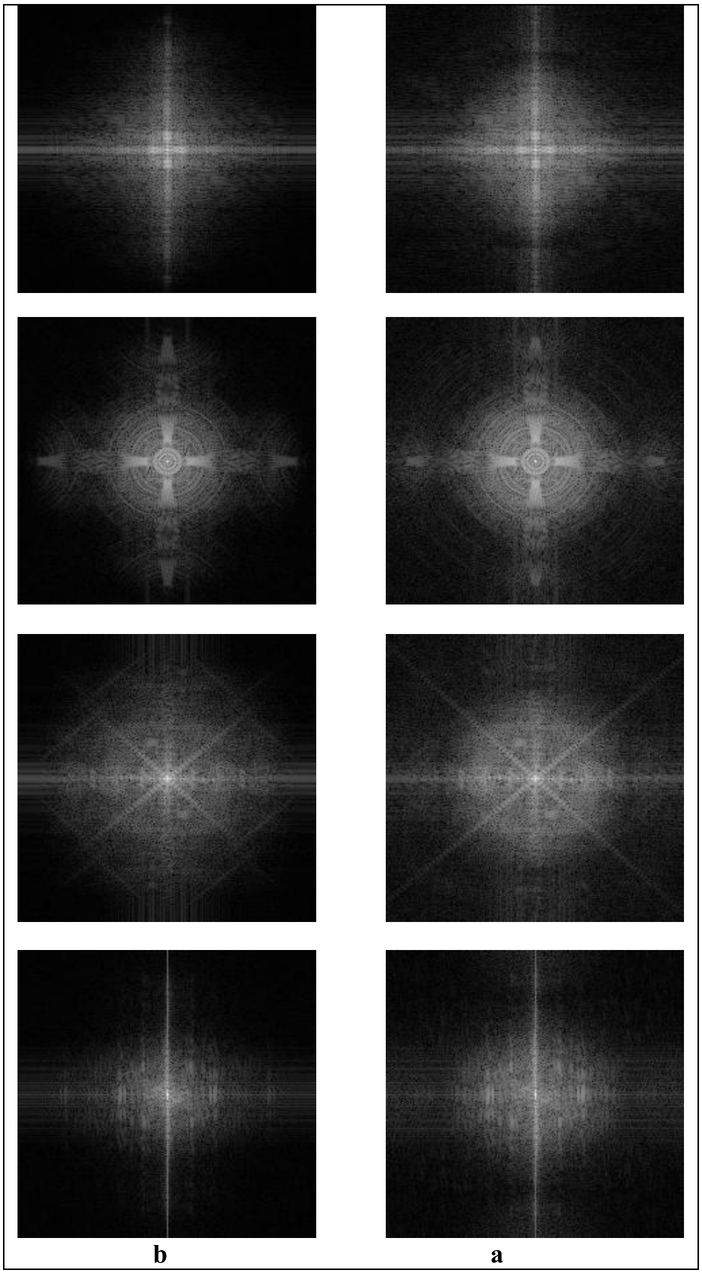


Fig. 5. Fourier Transform of the output (a) and input (b) images of the proposed algorithm.

To perform a quantitative comparison of the output images of the algorithm with the original images (a and b) in Figure 3, the Mean Square Error (MSE) between the output image and the original image is calculated for the Bicubic, Unsharp Masking, and proposed algorithm. The results for the images in Figure 3, with different SNR values, are presented in Table 1.

Table 1. Comparison of MSE for the Proposed Algorithm with Various Algorithms at Different SNR Levels for Images (a) and (b) in Figure 3. (1) Bicubic Algorithm, (2) Proposed Algorithm, (3) Non-Sharp Mask Algorithm

SNR 15 dB	SNR 5 dB	Image	Algorithm
0.0104	0.0105	(a)	1 (Bicubic)
0.0084	0.0086	(b)	
0.0127	0.0128	(a)	2 (Proposed)
0.0106	0.0110	(b)	
0.0211	0.0211	(a)	3 (Non-Sharp Mask)
0.0196	0.0200	(b)	

The results in Table 1 show that the MSE of the proposed algorithm is very close to that of the Bicubic method for various images and has an acceptable difference compared to the Unsharp Masking algorithm. Therefore, since implementing the Bicubic algorithm on hardware platforms like field-programmable gate arrays (FPGA) requires significant resources, the proposed algorithm can be used, as its output accuracy is very close to that of the Bicubic method, while the hardware resources required for its implementation are significantly reduced.

4. CONCLUSION

In this paper, an optimized algorithm based on super-resolution techniques in the frequency domain was presented. The proposed algorithm offers notable advantages, including high processing speed and reduced computational complexity compared to many existing super-resolution methods. These characteristics make it particularly well-suited for real-time applications requiring efficient image enhancement.

Furthermore, the improved algorithm is designed to facilitate seamless implementation on field-programmable gate arrays (FPGAs) for video image processing. The reduced computational burden and efficient structure contribute to its suitability for hardware-based acceleration, enabling real-time performance in practical applications. Given these advantages, an essential future direction involves implementing the proposed enhanced algorithm on FPGA with an optimized hardware design to further improve its efficiency and applicability in real-world scenarios.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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