Ringing Artifact Removal in Digital Restored Images Using Multi-Resolution Edge Map

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Abstract

This paper presents a novel approach to reducing ringing artifact in digitally restored images by using multi-resolution edge map. The performance of reducing ringing artifacts depends on the accurate classification of the local features in the image. The discrete wavelet transform (DWT) provides effective insight into both spatial and frequency characteristics of an image. Through the DWT analysis, we show that ringing artifacts can be suppressed to a great extent by using multiple-level edge maps, which provide enhanced matching to local edges. Base on the experimental results, the proposed method can reduce ringing artifacts with minimized edge degradation by using DWT analysis.

Keywords: Ringing Artifact, Multi-Resolution Edge Map, Discrete Wavelet Transform.

1. Introduction

In recent times, digital image restoration techniques have attracted increasing interests in various applications such as super-resolution and digital auto-focusing, to name a few. Therefore, the quality of the image is an important factor. As the image restoration technique has wider application areas, the ringing artifacts removal technique, which is the side effects of the image restoration process, becomes more necessary.

Conventional image restoration algorithms, such as the constrained least squares (CLS) and the Wiener filter, try to reduce the processing time by using fast fourier transform (FFT). These approaches are often inappropriate for real applications because of linear space invariance assumption, which regularizes the restoration operation uniformly across the entire image. Such frequency-domain image restoration techniques result in ringing artifacts in the neighborhood of abrupt intensity transitions due to the uniform amplification of the high-frequency component [1]. Ringing artifacts generally results from the poor match between the stationary image model and the actual image data [2]. There have been various researches for reducing ringing artifacts. The adaptive post-filtering approach extracts local statistics and constructs an edge map of the image [3]. Accurate localization of edge alleviates ringing artifacts by using quantized discrete cosine transform (DCT) coefficients of a block containing a straight edge [4]. In this paper, we present a multi-resolution, computationally simple post-filtering approach to reduce ringing artifacts in the restored images.

This paper is organized as follows. In section 2, we summarize a theoretical background. In section 3, we propose a novel ringing artifacts removal method, in which the DWT based adaptive edge map is introduced to suppress ringing and region classification. Experimental results and conclusions are respectively given in section 4 and 5.

2. Background on Discrete Wavelets Transform

The DWT represents a one-dimensional (1D) continuous-time signal $x(t)$, $t \in [0,1]$ in terms of shifted versions of a lowpass scaling function ϕ and shifted and dilated versions of a prototype band-pass wavelet function ψ [5]. For special choices of ϕ and ψ, the functions $\psi_{j,k}(t) := 2^{j/2}\psi(2^j t - k)$ and $\phi_{j,k}(t) := 2^{j/2}\phi(2^j t - k)$ with $j, k \in \mathbb{Z}$ form an orthonormal basis. The parameter j corresponds to the scale of the analysis, whereas k corresponds to the location. A finite-resolution approximation x^J to x is given

$$x^J(t) = \sum_{k=0}^{N_{j_0}-1} s_{j_0,k}\phi_{j0,k}(t) + \sum_{j=j_0}^{J} \sum_{k=0}^{N_j-1} w_{j,k}\psi_{j,k}(t), \tag{1}$$

where the scaling coefficients $S_{j_o k} := <x, \phi_{j_0 k}>$ and wavelet coefficients $w_{jk} := <x, \psi_{j_0 k}>$. J controls the resolution of the wavelet reconstruction x^J of x. In fact, the L_2 norm $\|x^J - x\|_2$ as $J \to \infty$.

For a discrete-time signal with N samples, the N wavelet coefficients can be efficiently computed in $O(N)$ operations using a filterbank consisting of lowpass filters, highpass filters, upsamplers, and decimators [5]. For periodic signals, which are natural when analyzing circular convolution, filterbanks implementing circular convolution are employed. Multidimensional DWTs are computed by wavelet-transforming alternately along each dimension [5][6].

3. Ringing Artifacts Removal Using the DWT-Based Adaptive Edge Map

In this section we describe the proposed ringing reduction algorithm. The basic idea of the proposed algorithm is the application of DWT for making an edge map. Based on the human visual system, each pixel in an image plays a different role in describing the image. Since the human visual system is very sensitive to high frequency changes and especially to edges in the image, the edges are very important to the perception of the image [3]. Therefore, the proposed algorithm is to classify local features in the restored image, and adaptively apply the smoothness constraints. As mentioned in the previous section, the restored image has ringing artifacts. In order to reduce ringing artifacts in the restored Image, we present detailed descriptions for edge extraction and the post filtering in the following subsections, respectively.

3.1. Wavelet Analysis for Extracting Edge Region

We suppose to have a restored image with ringing artifacts, which is the output of the well-known constraint least square (CLS) filter [7]. We use the incorporation of wavelet decomposition for finding the edge. The 1D transforms given in the previous section are easily extended to two-dimensional (2D) functions like images. A 2D scaling function,

$\phi(x, y)$, and three 2D wavelets, $\psi^H(x, y)$, $\psi^V(x, y)$, and $\psi^D(x, y)$, are required for 2D DWT. Each is the product of a 1D scaling function φ and corresponding wavelet ψ. The 2D separable scaling function

$$\phi(x, y) = \phi(x)\phi(y),\tag{2}$$

and three 2D separable, "directionally sensitive" wavelets are defined as

$$\psi^H(x, y) = \psi(x)\phi(y),\tag{3}$$

$$\psi^V(x, y) = \phi(x)\psi(y),\tag{4}$$

and

$$\psi^D(x, y) = \psi(x)\psi(y).\tag{5}$$

These wavelet measure functional variations along different directions: ψ^H measures variations along columns (for example, horizontal edges), ψ^V responds to variations along rows (like vertical edges), and ψ^D corresponds to variations along diagonals. The directional sensitivity is a natural consequence of the reparability imposed by equations (3) to (5); Decomposition using these for subimages provides the 2D of $f(x, y)$ of size $M \times N$ as

$$W_\phi(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\phi_{j_0, m, n}(x, y),\tag{6}$$

and

$$W_\psi^i(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y)\psi_{j, m, n}^i(x, y), \quad \text{for } i = \{H, V, D\},\tag{7}$$

where index i identifies the directional wavelets in equations (3) to (5). Superscript i has one of H, V and D.
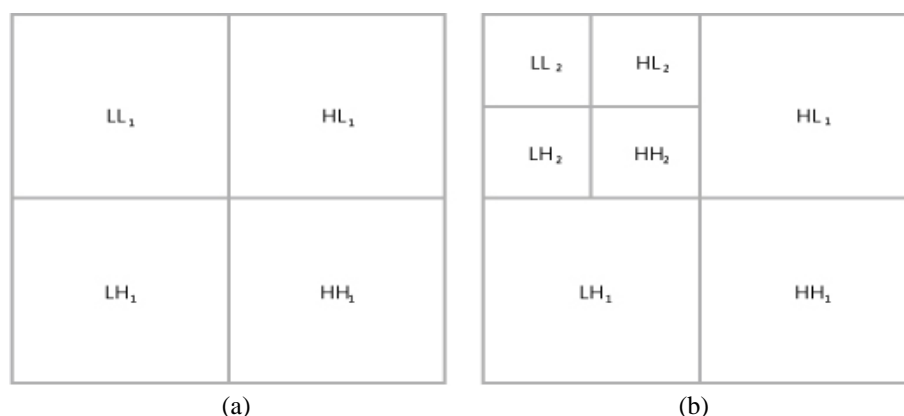

Figure. 1. Two-dimensional wavelet transform (a) First-level decomposition (b) Second-level decomposition, L denotes a low band, H denote a high band, and the subscript denotes the number of the level.
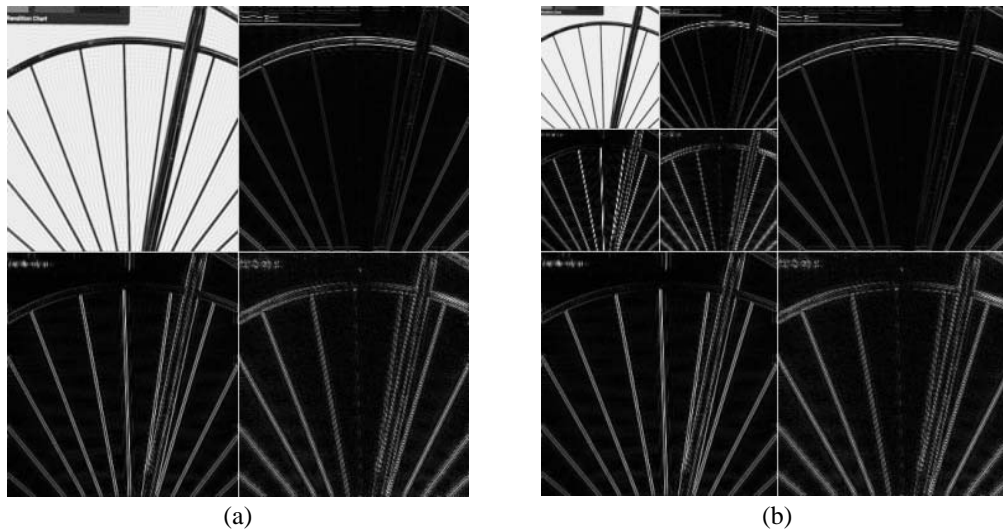
(a) (b)

Figure. 2. First and second level decomposition (a) Degraded image of size 512X512 first-level decomposition (b) Degraded image of size 512X512 second-level decomposition.
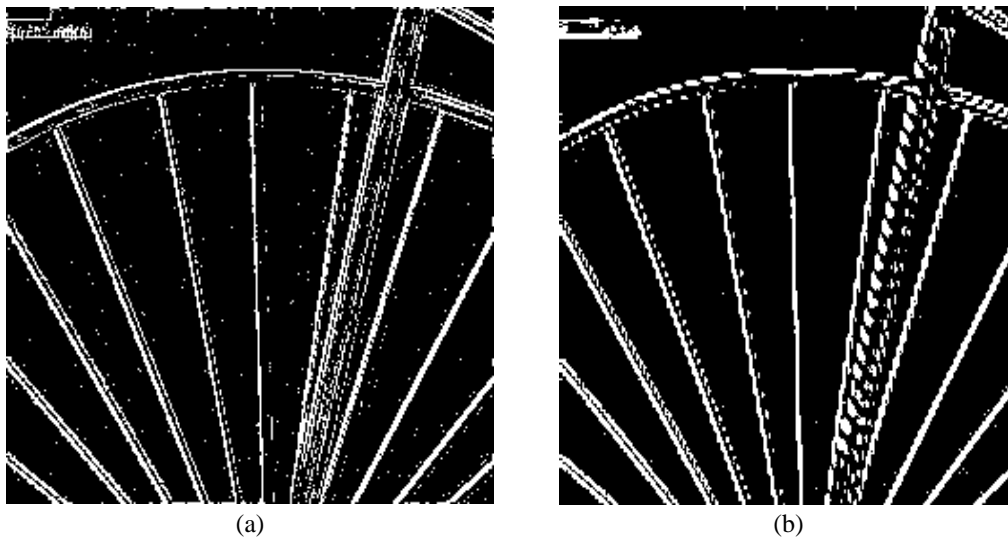

(a) (b)

Figure. 3. Wavelets in edge detection (a) The edge resulting from computing the absolute value of the inverse transform in first-level, (b) The edge resulting from computing the absolute value of the inverse transform in second- level.

Fig. 1. shows a 2D wavelet transform. The horizontal, vertical, and diagonal component of the wavelet transform using Daubechies D4 wavelet is shown in Fig. 2(a). Note, for example, that the horizontal edges of the original image are present in the horizontal detail coefficients of the upper-right quadrant of Fig. 2(a). The vertical edges of the image can be similarly identified in the vertical detail coefficients of the lower-left quadrant. To combine this information into a single edge image, we simply set the approximation coefficients to zero, compute the inverse transform, and take the edge image resulting from the absolute value. In

the same way, we take the edge image resulting in second-level decomposition Fig. 2(b). Fig. 3(a) shows edge detection results by computing the absolute value of the inverse transform coefficients in the first level and Fig. 3(b) in the second level.

The main idea of the proposed method comes from the observation that the edge image resulting from the second level is clearer than the first level. A compromise between the two images obtains the more accurate edge map.

3.2. Ringing Artifacts Removal

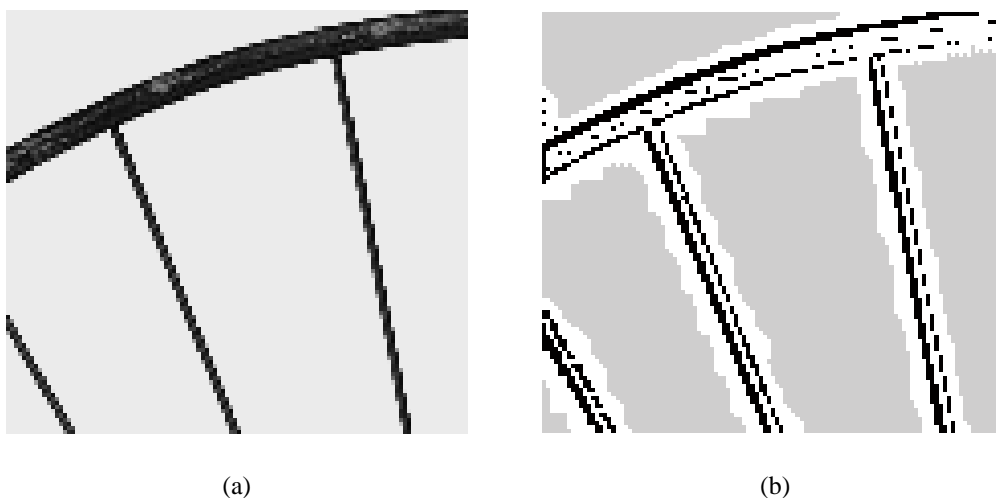(a)   (b)

Figure. 4. Mask used to control filtering for alleviation of ringing artifacts. (a) Original image, (b) Mask generated by selecting the proposed edge map (black), the pixel surrounding the edges (white).

According to the previous analysis, we find the major edge map. Ringing artifacts generally occur in the neighborhood of sharp edges in the image [8]. Such regions are marked both by the occurrence of high frequency entailed in the description of the sharp edge together with smooth regions on both sides of the edge. Ringing–artifact-prone regions are detected by a series of morphological operations. The edge map is dilated to indicate the region around the major edges. Then the actual edges are excluded. Fig. 4 (b) shows the ringing-artifact-prone region rendered by white color. Variation of grayscale values inside the detected region are due to the oscillations introduced by the ringing artifacts. Therefore the average variance of the pixel values in the DWT domain can be used to quantify the degradation. The classification is obtained by applying a pre-specified threshold to the variance values. Candidate edge regions (e_i) are obtained as

$$e_i[m,n] = \begin{cases} 1, & if \; |y_i[m,n]| \; > \; T \\ 0, & otherwise \end{cases}, \tag{8}$$
$$for \; i \in \{HL, LH, HH\}$$

where y_{HL}, y_{LH}, and y_{HH} respectively represent vertical, horizontal, and diagonal wavelet transform coefficients.
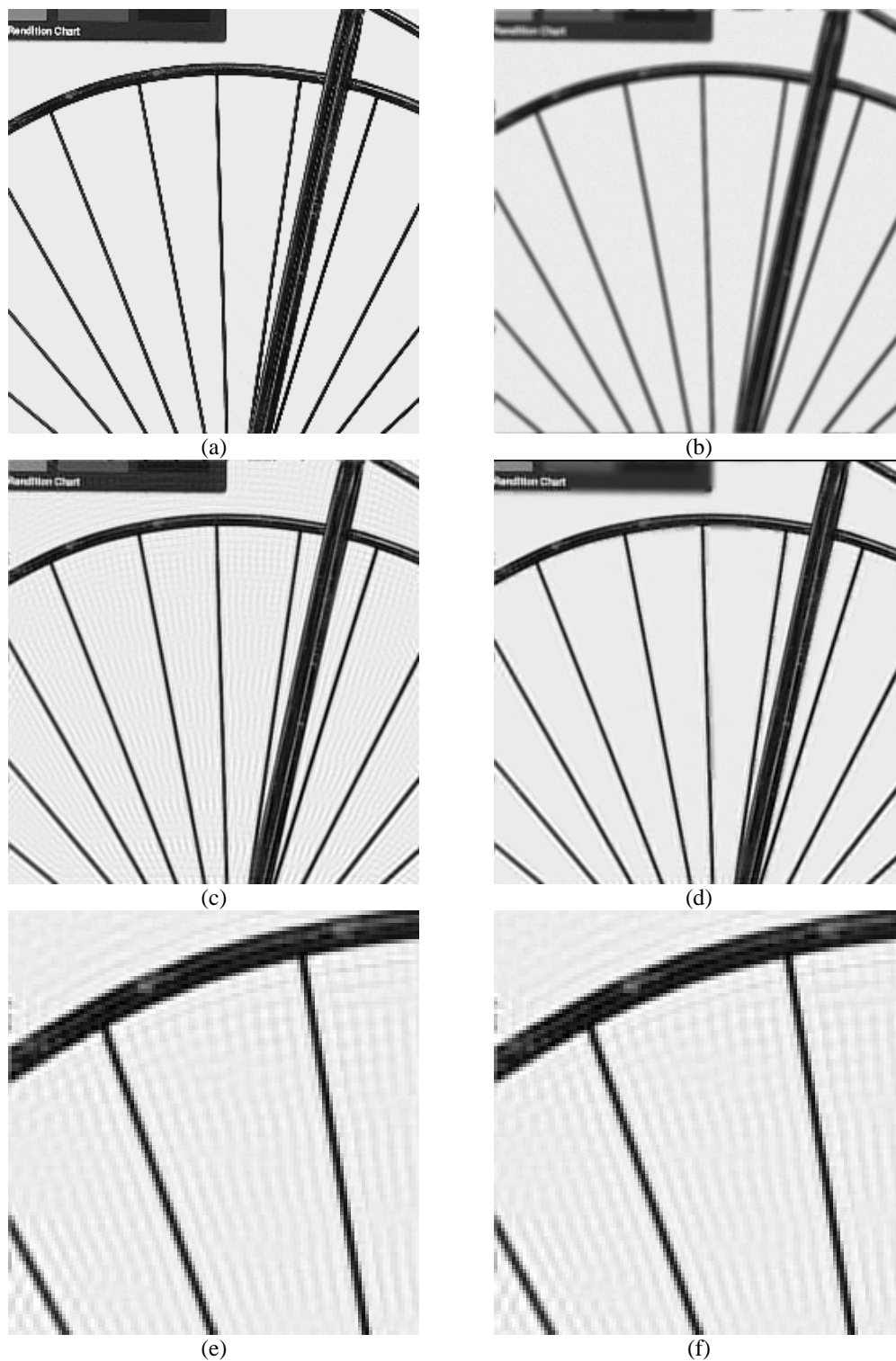
Figure. 5. (a) Original image, (b) Degraded image, (c) Image restored by CLS filter with ringing artifacts, (d) Result image using proposed algorithm, (e) Crop by 115X105 image from c, (f) Crop by 115X105 image from d.

A smoothing operator, such as Gaussian filtering, alleviates ringing artifacts at the cost of blurring the sharp edges and other detail in the image. This trade-off has motivated adaptive methods. One approach is to locate edges in the image and to perform filtering operation on condition to the proximity to edges [4]. The regions are marked as smooth, edge, and texture regions. An adaptive 3x3 low pass filter is applied to the pixel surrounding the edges as shown with white color. Since ringing noise and texture pixels have similar variance values, the filter with the large central weight is applied to the texture pixels far away from the edges to preserve the details, and the smoothing filter is applied to the pixels close to edges to selectively filter out the ringing noise.
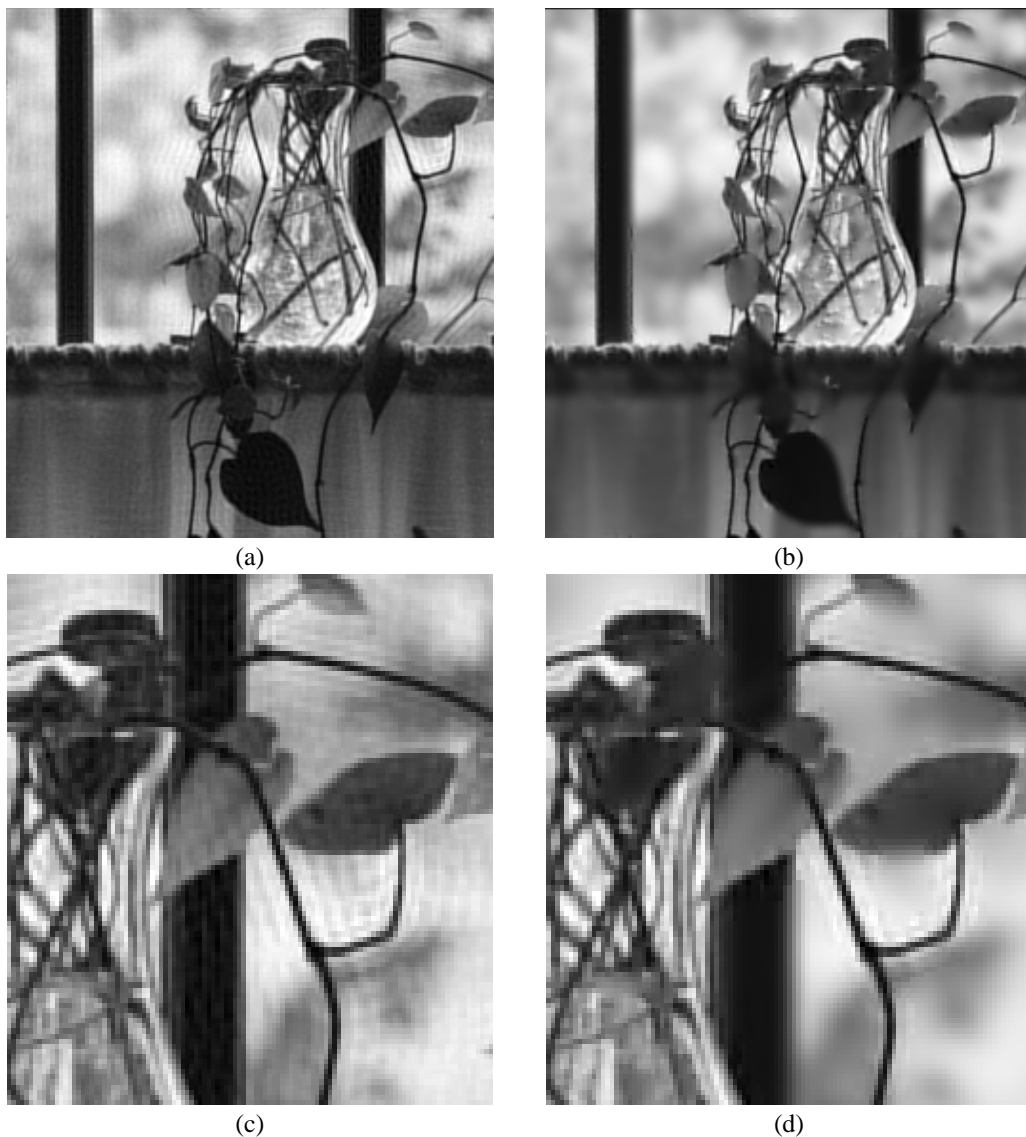

Figure. 6. (a) Image restored by CLS filter with ringing artifacts for the vase image with ringing, (b) Result image using proposed algorithm, (c) Crop by 115X105 image from a, (d) Crop by 115X105 image from b.

Figure. 7. (a) Original Lena image, (b) Blurred image with 11X11 uniform blur and 50dB gaussian noise, (c) Restored image by iterative method [1], (d) Restored image by adaptive iterative method, (e) Restored image by CLS filter with ringing artifact, (f) Bilateral filtering image with sigma 2, (g) Bilateral filtering image with sigma 20, (h) The result using proposed region classification and adaptive gaussian filtering (i) The result using proposed algorithm.

Table 1. PSNR values of various image restoration algorithms

Image in Fig. 7.	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
PSNR(dB)	23.11	26.92	26.94	27.11	27.24	27.85	28.81	31.36

4. Experimental Results

In this section, we analyze the performance of the proposed ringing reduction algorithm using both objective and subjective measures. For the experiment, we used standard test images, 512x512, 8bit, Bike and Lena. Figs. 5(a) and (b) show the degraded image by 7X7 uniform blur and 40dB Gaussian noise, and Fig. 5(c) shows the restored Bike image by using the CLS filter. Fig. 5(d) shows the filtered result by using the proposed ringing reduction algorithm. Figs. 5(e) and (f) show the magnified versions of Figs. 5(c) and (d), respectively.

Fig. 6(a) shows the restored image by using the CLS filter with the same degraded model. Fig. 6(b) shows the result of the proposed algorithm. Figs. 6(c) and (d) show the magnified versions of Figs. 6(a) and (b), respectively.

The proposed algorithm is compared with various ringing reduction algorithms such as an iterative method [9] and bilateral filtering [10] in the sense of peak-to-peak signal-to-noise ratio (PSNR). As shown in Fig. 7, the proposed algorithm can effectively reduce ringing artifacts with preserving edge details near eyes and the hat and PSNR values are summarized in Table 1.

5. Conclusion

In this paper, we propose an adaptive ringing reduction algorithm using wavelet-based multi-resolution analysis. The proposed method shows significant improvement in accuracy over existing methods. The location of edges can be accurately estimated due to the wavelet representation. The proposed algorithm can also be applied to the ringing artifact removal in compressed images. Experimental results show effectively removed ringing artifacts with significant reduction in computational load. The simplified algorithm using the first and the second level of wavelet decomposition has the advantage over many post-processing algorithm.

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