ABSTRACT
This paper presents a novel real-time super-resolution (SR) method using directionally adaptive image interpolation and image restoration. The proposed interpolation method estimates the edge orientation using steerable filters and performs edge refinement along the estimated edge orientation. Bi-linear and bi-cubic interpolation filters are then selectively used according to the estimated edge orientation for reducing jagging artifacts in slanting edge regions. The proposed restoration method can effectively remove image degradation caused by interpolation using the directionally adaptive truncated constrained least-squares (TCLS) filter. The proposed method provides high-quality magnified images which are similar to or better than the result of advanced interpolation or SR methods without high computational load. Experimental results indicate that the proposed system gives higher peak-to-peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) values than the state-of-the-art image interpolation methods.

Index Terms— Super-resolution, image interpolation, image restoration, digital zooming

1. INTRODUCTION
A super-resolution (SR) method can provide high-resolution (HR) images without a high density image sensor or an expensive optical zooming system. In order to implement a SR method [1], in real-time, hardware simplicity and computational efficiency must be taken into consideration. However, most simple interpolation methods such as bi-linear and bi-cubic interpolation cannot avoid jagging artifacts in slanting edge regions and blur artifacts in high-frequency regions especially with a high magnification ratio [2].

To solve these problems, advanced interpolation methods have been proposed. Li et al. [3] have estimated local covariance coefficients from a low-resolution (LR) image and then use the estimated covariance estimates to adapt the interpolation at a higher resolution based on the geometric duality between the LR and the HR covariances. Zhang et al. [4] have proposed an edge-guided nonlinear interpolation method using directional filtering and data fusion. Giachetti et al. [5] have proposed an up-scaling method based on a two-step grid filling and iterative correction of the interpolated pixels by minimizing an objective function depending on the second-order directional derivatives of the image intensity. These advanced interpolation methods are, however, unsuitable for the real-time digital zooming in compact cameras which have limited computational power and memory space.

This paper presents a real-time SR method that minimizes interpolation artifacts and restores high-frequency details using a finite impulse response (FIR) filter. The proposed interpolation method precisely estimates the edge orientation using steerable filters with edge refinement. The input image is then adaptively interpolated along the estimated edge orientation. As a result, the proposed interpolation method can provide digitally interpolated images without interpolation artifacts such as jagged edges. Image details lost in the interpolation process are also recovered using the directionally adaptive truncated constrained least-squares (TCLS) filter [6].

2. DIRECTIONALLY ADAPTIVE IMAGE INTERPOLATION
The proposed directionally adaptive image interpolation algorithm consists of; (i) estimation of the edge orientation followed by edge refinement and (ii) selective one-dimensional...
(1D) bi-linear or bi-cubic interpolation along the estimated edge orientation.

2.1. Estimation of Edge Orientation Using Steerable Filters and Edge Refinement

In order to determine the edge orientation, the input image is convolved with four steerable filters [7] as

\[ R^\theta = G^\theta * I, \quad \text{for} \quad \theta \in \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}, \]

where \( G^\theta \) represents a 5 x 5 steerable filter rotated by angle \( \theta \), and \( I \) a 5 x 5 local block of the image.

For reducing the computational load of the digital zooming algorithm, four 5 x 5 steerable filters are used with the standard deviation \( \sigma = 1.0 \). The initial edge is estimated by minimizing (1) as

\[ \theta^I = \arg \min_{\theta} \{ R^\theta \}, \]

If \( R^\theta \) is less than a pre-specified threshold, the corresponding pixel is considered to be in a non-edge region. In this work, the threshold value of 0.075 was used with consideration of the amount of noise and sensitivity of steerable filters.

Given an initial edge direction \( \theta^I \), the refined edge orientation is selected from 18 angles, \( \{0^\circ, 10^\circ, 20^\circ, ..., 170^\circ\} \), as

\[ \theta^* = \frac{R^{0^\circ}}{R^{0^\circ} + R^{45^\circ}} \times 45, \quad \text{for} \quad \theta^I = 0^\circ, \]

\[ \theta^* = \frac{45 \times R^{0^\circ} + 90 \times R^{45^\circ}}{R^{45^\circ} + R^{90^\circ}}, \quad \text{for} \quad \theta^I = 45^\circ, \]

\[ \theta^* = \frac{90 \times R^{135^\circ} + 135 \times R^{90^\circ}}{R^{90^\circ} + R^{135^\circ}}, \quad \text{for} \quad \theta^I = 90^\circ, \]

and

\[ \theta^* = \frac{135 \times R^{0^\circ} + 180 \times R^{135^\circ}}{R^{135^\circ} + R^{0^\circ}}, \quad \text{for} \quad \theta^I = 135^\circ, \]

where \( \theta^I \) represents the initially estimated edge orientation, and \( \theta^* \) the refined edge direction, which is finally quantized with the interval of 10°.

Fig. 1 shows the estimation results of the edge orientation using four directionally steerable filters and the proposed edge refinement method. As shown in the figure the proposed method provides more accurate, continuous edge orientation, which makes the directionally adaptive interpolation more natural.

2.2. Directionally Adaptive Image Interpolation Selectively Using Bi-linear and Bi-cubic Interpolation

In order to interpolate the edge region, the proposed method computes the line on the point \( P3 \) with angle \( \theta^* \) as shown in Fig. 2.

The line crosses the vertical grid at \( P1 \), and crosses the horizontal grid at \( P2 \). The intensity value of \( P1 \) is determined by 1D cubic interpolation using four pixels in the vertical direction. The intensity value of \( P2 \) is also determined in the same manner in the horizontal direction.

\[ P3 = \frac{w_2}{w_1 + w_2} P1 + \frac{w_1}{w_1 + w_2} P2, \]

If a pixel to be interpolated is not on the edge, its value is determined by 2D bicubic interpolation. By using the directionally optimized 1D interpolation, the proposed method can significantly reduce jagging artifacts in the slanted edge region.

3. DIRECTIONALLY ADAPTIVE IMAGE RESTORATION

Kim et al. has proposed the original version of the TCLS restoration filter for removing spatially adaptive image degradation followed by a spatially adaptive noise smoothing filter based on local variance [6]. This section presents a directionally adaptive version of the TCLS restoration filter that can minimize image degradation caused by weighted linear and bi-cubic interpolation.
The input LR image can be considered as a low-pass filtered and subsampled version of the original HR image as

$$g(x, y) = T[f(p, q)*h(p, q)] + \eta(x, y)$$

where $g(x, y)$ and $\eta(x, y)$ respectively represent 2D arrays of the LR image and additive noise. $f(p, q)$ represents the HR image, and $h(p, q)$ represents the space-variant point spread function (PSF), which plays a role in anti-aliasing filter for the subsequent subsampling process $T[\cdot]$. Due to the nature of the anti-aliasing filter, the PSF $h$ is determined by the subsampling ratio.

Given the frequency response of the degradation system according to the subsampling ratio $s$, $H_s(u, v)$, the frequency response of the constrained least-squares (CLS) filter is given as

$$R_{CLS}(u, v) = \frac{H^*_s}{|H_s(u, v)|^2 + \lambda |C(u, v)|^2},$$

where $C(u, v)$ represents a frequency response of the high-pass filter, and $\lambda$ the regularization parameter that controls the relative amount of data fidelity and the smoothing constraint.

For the CLS filter to be spatially adaptive, four different smoothness constraints according to the edge orientation, $C^\theta(u, v), \theta \in \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$, are generated using the directional high-pass filter as

$$C^{0^\circ}(x, y) = \begin{pmatrix} -0.1677 & 0.8333 & -0.1677 \\ -0.1677 & 0.8333 & -0.1677 \end{pmatrix},$$

$$C^{45^\circ}(x, y) = \begin{pmatrix} -0.1677 & 0 & 0 \\ -0.1677 & 0.8333 & 0 \\ -0.1677 & -0.1677 & -0.1677 \end{pmatrix},$$

$$C^{90^\circ}(x, y) = \begin{pmatrix} 0 & -0.1677 & -0.1677 \\ 0 & 0.8333 & -0.1677 \\ 0 & -0.1677 & -0.1677 \end{pmatrix},$$

and

$$C^{135^\circ}(x, y) = \begin{pmatrix} -0.1677 & -0.1677 & -0.1677 \\ 0 & 0.8333 & -0.1677 \\ 0 & 0 & -0.1677 \end{pmatrix}.$$  (13)

In addition to directionally adaptive smoothness constraints, the regularization parameter $\lambda$ also changes according to the strength of the edge using the activity value as

$$\alpha(x, y) = \frac{1}{1 + \sigma v(x, y)},$$

where the tuning parameter $\sigma$ is chosen so that $\alpha(x, y)$ distributes as uniformly as possible in $[0, 1]$, and $v(x, y)$ represents the local variance at each pixel $(x, y)$ as

$$v(x, y) = \frac{1}{MN} \sum_{(x,y) \in S} (f(x, y) - m_{xy})^2,$$  (15)

where $S$ represents a rectangular region encompassing $(x, y)$, $M$ and $N$ respectively represent the vertical and horizontal sizes of the region, and $m_{xy}$ the local mean. The adaptive regularization parameter is determined as

$$\tilde{\lambda} = \alpha(x, y) \lambda, \text{ for } 0 \leq \alpha \leq 1,$$  (16)

where $\alpha(x, y)$ represents the activity value, and $\lambda$ the initial regularization parameter.

The proposed method experimentally used $\lambda = 0.4$, and $\tilde{\lambda}$ is quantized with the step of 0.1 for efficient implementation. The frequency response of the modified CLS filter is given as

$$\tilde{R}_{CLS}^\theta(u, v) = \frac{H^*_s}{|H_s(u, v)|^2 + \lambda |C^\theta(u, v)|^2},$$

where $C^\theta(u, v)$ and $\tilde{\lambda}$ respectively represent the directionally adaptive smoothness constraints and the spatially adaptive regularization parameter.

The proposed restoration algorithm requires the Fourier transform of the entire input image, which make the digital zooming system inappropriate for real-time implementation because of the large memory space and high computational load. The frequency-domain modified CLS filtering is approximately equivalent to the corresponding spatial-domain filter, which is obtained by the inverse Fourier transform of $\tilde{R}_{CLS}^\theta(u, v)$ in (17), of the support equal to the entire interpolated image. The adaptive spatial-domain restoration filter can be expressed as the inverse DFT of $\tilde{R}_{CLS}^\theta(u, v)$ as

$$r_{CLS}^\theta(x, y) = F^{-1}\left[\tilde{R}_{CLS}^\theta(u, v)\right],$$  (18)

where $F^{-1}[\cdot]$ represents the inverse DFT operation. Since a large filter support is impractical, the proposed method reduces the support by appropriately truncating the modified CLS filter because significant amount of energy is concentrated in the central part of the filter support. In this work, the proposed method designs a directionally adaptive TCLS filter using the raised cosine window. The size of the windows is confined to $13 \times 13$ which contains over 99% of the total energy of the modified CLS filter.

In this paper, the proposed method generates 120 directionally adaptive TCLS filters using directionally adaptive smoothness constraints $C^\theta(u, v)$, spatially adaptive regularization parameter $\lambda$, as PSFs according to the magnification ratio. For magnifying the input image by two times, for example, the proposed method selects the smoothness constraint $C^\theta(u, v)$ by estimating the initial edge orientation. The proposed method computes the activity value based on local variance of the interpolated image. Each activity value is discretized by the step size of 0.1. The proposed method calculates the adaptive regularization parameter $\lambda$ using the normalized activity value.

The proposed method performs 2D convolution using the adaptive TCLS filtering according to the directionally adaptive smoothness constraint $C^\theta(u, v)$ and spatially adaptive regularization parameter $\lambda$ as
\[ \hat{f}(x, y) = \hat{g}(x, y) * r_{\theta}^{\text{CLS}}(x, y), \]  
(19)

where * represents the 2D convolution operator, \( \hat{g}(x, y) \) the interpolated image, \( r_{\theta}^{\text{CLS}}(x, y) \) the impulse response of the directionally adaptive TCLS filter, and \( \hat{f}(x, y) \) the restored HR image.

4. EXPERIMENTAL RESULTS

The performance of the proposed method is compared with various conventional interpolation methods including bi-linear, bi-cubic, Li’s [3], Zhang’s [4], and Giachetti’s [5] method in terms of the peak-to-peak signal-to-noise ratio (PSNR) and the structural similarity measure (SSIM) [9].

![Fig. 3](image)

Fig. 3. Experimental results for two times magnification: (a) bi-linear interpolation, (b) bi-cubic interpolation, (c) Li’s method in [3], (d) Zhang’s method in [4], (e) Giachetti’s method in [5], and (f) proposed method.

As shown in Fig. 3(d), jagging and blur artifact are observed in Zhang’s method [5]. The proposed method can successfully remove both jagging and blur artifacts as shown in Fig. 3(f). In addition to subjective comparison as shown in Fig. 3, objective measures, such as PSNR and SSIM, are summarized in Table I.

Table 1. The PSNR / SSIM values comparison of five different method

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Interpolation Method</th>
<th>PSNR</th>
<th>SSIM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bilinear</td>
<td>23.6709</td>
<td>0.9066</td>
</tr>
<tr>
<td></td>
<td>Bicubic</td>
<td>23.6162</td>
<td>0.9102</td>
</tr>
<tr>
<td></td>
<td>Li’s method in [3]</td>
<td>21.4442</td>
<td>0.7883</td>
</tr>
<tr>
<td></td>
<td>Zhang’s method in [4]</td>
<td>25.7749</td>
<td>0.9415</td>
</tr>
<tr>
<td></td>
<td>Giachetti’s method in [5]</td>
<td>25.4202</td>
<td>0.9399</td>
</tr>
<tr>
<td></td>
<td>Proposed method</td>
<td>25.9208</td>
<td>0.9457</td>
</tr>
<tr>
<td></td>
<td>Bilinear</td>
<td>25.2408</td>
<td>0.9115</td>
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<tr>
<td></td>
<td>Bicubic</td>
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<td>0.9088</td>
</tr>
<tr>
<td></td>
<td>Li’s method in [3]</td>
<td>22.9224</td>
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<tr>
<td></td>
<td>Zhang’s method in [4]</td>
<td>26.8691</td>
<td>0.9251</td>
</tr>
<tr>
<td></td>
<td>Giachetti’s method in [5]</td>
<td>26.1184</td>
<td>0.9177</td>
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<tr>
<td></td>
<td>Proposed method</td>
<td>26.8725</td>
<td>0.9252</td>
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</table>

5. CONCLUSIONS

This paper presents a novel real-time super-resolution method based on directionally adaptive image interpolation and image restoration. The proposed method analyzes the edge orientation using computationally efficient steerable filters and edge refinement process. The selective use of 1D bi-linear and bi-cubic interpolation filters according to the estimated edge orientation can enhance image quality with reduced computational load. Various types of degradation artifacts caused by interpolation are removed by employing the directionally adaptive TCLS filter. Experimental results show that the proposed method can provide high-quality digitally zoomed images without interpolation artifact such as jagging and blur artifact in edge regions. Furthermore, the proposed method gives improved PSNR and SSIM values compared with existing state-of-the-art interpolation methods.
6. REFERENCES


