Super-Resolution using Combination of Wavelet Transform and Interpolation Based Method

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Abstract - Super-resolution is a technique of producing a high-resolution (HR) image from one or more low-resolution (LR) images. Classical interpolation based magnification techniques like nearest-neighbor, bilinear and bicubic interpolation results in a larger image along with undesirable artifacts like blurring, aliasing and ringing effects. So the aim of super-resolution is to provide a larger image with good quality (quality means an image with less undesirable artifacts). Previous super-resolution techniques are based on using multiple images and learning based methods but the idea here is to use a single image in the super-resolution process. Here we have used the combination of wavelet transform and interpolation based technique to achieve the super-resolution using a single image. First the edges of the image are enhanced using wavelet transform and then the magnification is done using an interpolation based method. A comparison of this algorithm with other technique is also done to provide the quantitative and qualitative result to prove the effectiveness of the methods.

Keywords: Super-resolution, Magnification, Edge detection, Edge enhancement, Up-sampling

1 Introduction

Super-resolution (SR) produces a high-resolution (HR) image from one or more low-resolution (LR) images, which has become a popular research area due to fact that larger images are to be filled with such information which does not directly exist in the smaller images. The simple techniques for HR image production like pixel replication or linear interpolation are not satisfactory due to the creation of visual undesirable artifacts (blurring, ringing etc) though these produce good quantitative results [1]. The images captured by low resolution imaging devices produces low quality images (blur, distort, noisy) that can be improved in two ways: enhance the resolution of the imaging device or apply super-resolution methods to improve its quality [2]. SR is widely applied in image compression and transmission, medical image analysis, face recognition and image zoom [3]. SR techniques can be divided into three categories: Interpolation based methods, reconstruction based methods and learning based methods.

Interpolation based methods (e.g. [4, 9, 10, 14, 16, 17, 18, 19, 21, 22, 23]) matches the LR images with the grid point of its HR images, after which non-uniform interpolation techniques are used to obtain the pixels of HR images. Post-processing (e.g. deconvolution) can also be used to enhance HR images clarity.

Reconstruction based methods (e.g. [7, 8, 11, 13, 15, 24]) uses the pair relationship between LR images and HR images. Using this relationship, linear equations that connect the pixel values of HR and LR images are obtained. By solving these linear equations, HR images are obtained.

Learning based methods (e.g. [2, 3, 5, 20]) emphasizes on learning about the structure or content of images based on relevant prior knowledge, which helps in obtaining better results. Learning based methods are somewhat dependent on the training set hence it is only suitable for such images whose training set is available.

In this paper, we propose a method that uses the combination of wavelet transform and interpolation based method to achieve super-resolution. It is well known that in super-resolution or magnification process, the loss occurs in the high-frequency region that it across the edges. Our method tries to enhance the edges using the wavelet transform so that blurriness is reduced and then algorithm for magnification is proposed so that the undesirable artifacts (ringing or aliasing effect) are minimized.

Rest of the paper is arranged as follows: In section 2 states the proposed algorithm in detail that involves two basic steps: wavelet based edge boosting and interpolation based image magnification. Image magnification is further divided into three steps: expansion, edge detection and enhancement and filling the rest of the unknown pixels (referred here as holes) in comparison with the neighbor pixels. Section 3 presents the quantitative and qualitative results in comparison with other techniques and section 4 gives some concluding remarks on the method.
2 Proposed Method

The proposed algorithm is shown diagrammatically in figure 1.

2.1 Wavelet based Edge Boosting

Wavelet transform decomposes the image into four sub-band images, namely, low-low (LL), low-high (HL), high-low (LH) and high-high (HH). Discrete Wavelet Transform (DWT) and Stationary Wavelet Transform (SWT) are two types of wavelet transform. Here we have used SWT as the sub-bands retain its size as compared to DWT, where in DWT the sub-bands size to down sampled. The three sub-bands (LL, HL and HH), represents the image edges so these are enhanced by multiplying with an appropriate threshold “Th”. To calculate the value of threshold ‘Th’ CCC, PSNR and MSE (mentioned in section III) for 84 images were analyzed and appropriate value of ‘Th’ was selected. Table 1 outlines the value of “Th” that can be selected in the process.

Table 1: "Th" value for Wavelet based Edge Boosting

<table>
<thead>
<tr>
<th>Image properties</th>
<th>Threshold value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Images with less edges (single face, animal image etc)</td>
<td>(2 \leq \text{Th} \leq 4)</td>
</tr>
<tr>
<td>Images with maximum edges (crowd, satellite images etc)</td>
<td>(1 &lt; \text{Th} \leq 2)</td>
</tr>
</tbody>
</table>

The enhanced image “In” can be obtained using the inverse of SWT. This process is depicted in figure 2.

2.2 Interpolation based Image Magnification

The edges of the input image are enhanced in the first step so that when the image is enlarged the blurriness is reduced. Here we have proposed a separate algorithm for image magnification instead of using any existing strategy because we want to avoid the ringing and aliasing effect.

2.2.1 Expansion

In this phase the HR image is produced from the enhanced image In(nxm) as Out(2n-1x2m-1). The mapping between the In and Out is done using equation 1

\[
\text{Out}(2r-1,rc-1)=\text{In}(r,c)
\]  

Where \(r=1,2,\ldots,n\) and \(c=1,2,\ldots,m\)

Figure 3 shows the expansion and mapping process.
2.2.2 Edge Detection

At this stage, the edges in the enhanced input image are detected. Four types of edges are shown in figure 4.

![Edge Types](image)

**Figure 4: Four Types of Edge**

For detecting the edge a threshold “T” is to be selected. There are 16 safe colors in 256 color RGB system [4]. So to calculate “T”, median of 16 safe colors is calculated using the equation

\[
M_d=(X_{n/2}+X_{n/2+1})/2 \\
T=M_d
\]

(2a) (2b)

Where n=16 and X₁=0, X₁=1…..X₁=n-1. After calculating “T” edge is detecting using equation 3, with reference to Out(x,y) which corresponds to an unknown pixel value

\[
\begin{align*}
\text{MAX} &= \max\{\text{Out}(x-1,y-1), \text{Out}(x-1,y+1), \\
& \text{Out}(x+1,y-1), \text{Out}(x+1,y+1)\} \\
\text{MIN} &= \min\{\text{Out}(x-1,y-1), \text{Out}(x-1,y+1), \\
& \text{Out}(x+1,y-1), \text{Out}(x+1,y+1)\} \\
|\text{MAX-MIN}| &> T
\end{align*}
\]

(3a) (3b) (3c)

Where “max” and “min” selects the maximum and minimum intensity values from the given list respectively. This detects the existence of edge but it must be further categorized into one of the defined edges. To be classified as a 0° edge equation 4 must be satisfied.

\[
\text{Out}(x-1,y-1)-\text{Out}(x-1,y+1)<T \quad \| \quad \text{Out}(x+1,y-1)-\text{Out}(x+1,y+1)<T
\]

(4)

Similarly, 90°, 45° and 135° edge is classified using equation 5, 6 and 7 respectively.

\[
\text{Out}(x-1,y-1)-\text{Out}(x+1,y-1)<T \quad \| \quad \text{Out}(x-1,y+1)-\text{Out}(x+1,y+1)<T
\]

(5)

\[
\text{Out}(x-1,y-1)-\text{Out}(x+1,y+1)<T \quad \& \quad \text{Out}(x-3,y+1)-\text{Out}(x+1,y+1)<T
\]

(6)

\[
\text{Out}(x-3,y-1)-\text{Out}(x+1,y+1)<T \quad \& \quad \text{Out}(x+1,y-1)-\text{Out}(x+1,y+1)<T
\]

(7)

2.2.3 Edge Enhancement

The edge enhancement technique used is different from other. Other techniques tend to find pixel “Q”, shown in figure 5a, but in this technique “P1” and “P2”, the pixels forming the edge are found first.

The value of “P1” and “P2” are calculated using the equation 8 after the classification of edge into one of the defined types because the intensity value of “T1”, “T2” and “T3” depends on the type of edge.

\[
\begin{align*}
P1 &= T1+T2/2 \\
P2 &= T2+T3/2
\end{align*}
\]

(8a) (8b)

![Edge Representation in Matrices](image)

**Figure 5: Edge Representation in Matrices**

2.2.4 Fill the Holes in Comparison with Neighbor Pixels

The remaining unknown pixels are found iteratively using equation 2 from one of the neighbors relationship shown in figure 6(a or b). The reason for using median (equation 2) of neighbor pixels instead of average is that noise, extreme low or high value, are also averaged thus infecting the output pixels. But as median takes the
midpoint of the values so in this way noise doesn’t infect the pixels.

![Pixel Neighborhood](image)

**Figure 6: Pixel Neighborhood of Central Hole**

3 Experimental Results

The proposed method was compared against bilinear (BL), bicubic (BC), cubic spline interpolation [14], DCC [17], DFDF [16], NEDI [22] and ICBI [9].

3.1 Qualitative Comparison

Figure 7 and 8 presents the visual comparison of the proposed techniques with other mentioned techniques. The “Th” value used in both figure is 4. It can clearly be seen that the edge are much sharper in the proposed methodology.

3.2 Quantitative Comparison

For image quality assessment cross-correlation coefficient (CCC), mean-square error (MSE) and Peak Signal-to-Noise ratio (PSNR) are used, whose formulas are given in equation 9, 10 and 11 respectively. High value of PSNR, CCC value closer to 1 and low value of MSE represents good quality image. Structural Similarity (SSIM) is not used for quality assessment as SSIM fails in blurred images [23].

\[
\text{CCC} = \frac{\sum_{m} \sum_{n} (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\sum_{m} \sum_{n} (A_{mn} - \bar{A})^2 \sum_{m} \sum_{n} (B_{mn} - \bar{B})^2}}
\]  

(9)

\[
\text{PSNR} = 10 \log_{10} \frac{(2^n - 1)^2}{\sqrt{MSE}}
\]  

(10)

Where \( \bar{A} \) is the mean value of A, \( \bar{B} \) is the mean value of B and MSE is calculated using (11).

\[
\text{MSE} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i, j) - y(i, j))^2
\]  

(11)

For fairness of comparison study, we selected 84 images on which the mentioned methods were applied but due to the limited space only six images are used, which are shown in figure 9.

Table 2, 3 and 4 lists the CCC, PSNR (db) and MSE values of 2 times magnified test images. The proposed method is quite competitive with the other techniques as it provides consistent results with good image quality.

4 Conclusion

In this paper, super-resolution technique has been proposed that takes a single image details. The edges are boosted first in wavelet domain after which an interpolation based magnification algorithm is proposed. In magnification algorithm, first the edges are found and enhanced (edges are enhanced in a way that the unknown pixels that are a part of the edge, gets the value of the edge) after which the remaining unknown pixels (holes) are filled in correspondence with the neighborhood pixels. This method is applied to the grayscale images only. After the detail experimentation, this technique produces artifacts free HR image and its results (both quantitative and qualitative) are comparable with other well known techniques as mentioned in the paper.

This work can be extended in a way that instead of manually selecting the value of threshold (mentioned in section II), an algorithm can be devised that calculates the value of this threshold based on the input image.
Figure 7: 2x Magnification Result Comparison


Figure 8: 2x Magnification Result Comparison

Table 2: CCC Values of Test Images in Figure 8 Magnified 2 Times

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<tbody>
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<td>0.9639</td>
<td>0.9643</td>
<td>0.9584</td>
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Table 3: PSNR (db) Values of Test Images in Figure 8 magnified 2 Times

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<tbody>
<tr>
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Table 4: MSE Values of Test Images in Figure 8 magnified 2 Times

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<tbody>
<tr>
<td>Mouse</td>
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<td>53.9572</td>
</tr>
</tbody>
</table>
5 Reference


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