Image Super Resolution in Wavelet Domain Using Edge Enhancement via a Sparse Representation

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Abstract: In Wavelet domain, generating super resolution (SR) image from a single low resolution image create a problem. This paper has been proposed that sharper image can be achieved by an intermediate stage for estimating the high frequency (HF) sub bands. This includes edge preservation procedure & mutual interpolation between the input LR (low resolution) image & the HF sub band images as performed via the discrete wavelet transform (DWT). A sparse signal representation in the LR image is provides by sparse mixing weights which are calculated over blocks of coefficients in an image .

Keywords-Super resolution (SR), wavelet domain Edge extraction, interpolation, sparse mixing Estimators.

I. Introduction

Resolution plays an important role in many image processing applications, like improvement in video resolution, extraction of particular feature in an image, resolution enhancement of satellite image, Medical appliances.

Few of the logically used techniques for resolution improvement is to enlarge the given low resolution image so that the finally obtained one is sharper. In any fields, the high resolution image is very helpful, such as in the fields as remote sensing, medical diagnostics, military information gathering & video frame freezing etc. But these high resolutions are very difficult to obtain because there will be some restrictions of the image sensors & high precision optics such as their physical capacity & high cost. There comes the need for the techniques to convert low resolution to high resolution images, so that they could be applicable for various applications.

In many of the applications sensors with simple & cheap hardware will be used hence we have to compromise with low resolution images. One such example is in navigation missions LR sensors with simple & cheap hardware, such as unfocused fractional SAR systems & optical cameras are used .Thus get low resolution images. When processing these images for the required information, there will be a need to convert these images into high resolution images.

The interpolation based image resolution improvement is one of the famously used techniques to enlarge the low resolution Medical image. Our medical image is of having pixel 256x256 & enlarged high resolution output image will be 4096x4096 by using 16 x interpolations.

The difference of SR approach in comparison with existing method consist mutual interpolation via lanczos interpolation techniques for Wavelet transform high frequency (HF) sub band images & edge extracting images via DWT. Additionally LR image interpolation is computed by estimating sparse image mixture models in a DWT image. To obtain robustness for the SR process in presence of noise, the novel framework uses special denoising filtering, employing the non-local means (NLM) technique for the input LR image. To obtain robustness for the SR process in presence of noise, the novel framework uses special denoising filtering, employing the non-local means (NLM) technique for the input LR image. Finally, all of the subband images are combined, reconstructing via inverse DWT (IDWT) the output HR image that appears to demonstrate superiority of the designed algorithm in terms of the objective criteria and subjective perception, in comparison with the best existing techniques.

To justify the objective criteria (PSNR & SSIM) we have compared with NLM & without NLM technique. Here Section II presents a short introduction to the NLM filtering method and to implementation of the interpolation through the inverse mixing estimator for a single image in WT space. The proposed technique is presented in Section III. Section IV discusses the qualitative and quantitative results of the proposed algorithm & how objective criteria & subjective criteria improving the image resolution. Finally, the conclusions are drawn in the final section.

II. PRELIMINARIES

A. NLM Filtering

In the denoising stage, the pixel \( \hat{x}(m, n) \) is estimated using NLM algorithm by applying the weighted mean of neighboring noise-contaminated
pixels $y(m,n)$. The position of pixel $(m, n)$ is estimated by the equation

$$
\hat{x}(m, n) = \frac{\sum_{(r,s) \in Q(m,n)} y[r,s] w[m,n,r,s]}{\sum_{(r,s) \in Q(m,n)} w[m,n,r,s]}
$$

Where

$Q(m,n) =$ neighborhood of the pixel $y(r,s)$,

$w[m,n;r,s]=$ weight for the $(m,n)^{th}$ neighborpixel. Using radiometric & geometric similarity between the pixels, the weights for the filter are computed as

$$
w[m,n;r,s] = \exp \left\{ -\frac{(y[m,n]-y[r,s])^2}{2\delta^2} \right\},
$$

g \left( \sqrt{(m-r)^2+(n-s)^2} \right)

The $\delta$ controls the gray-level difference between the two pixels, and $g$ is the geometric distance. In the next steps, denoised image $\hat{x}(m,n)$ is used.

**B. Interpolations with Sparse Wavelet Mixtures**

Once we get the sub sampled image $\hat{x}(m,n)$, it is then decomposed with one level DWT in the LL, LH, HL, and HH image sub bands. These are then treated as matrices $\Psi$, whose columns approximations and details are the vectors of a wavelet image on a single scale $\{\psi_{d,n}\}_{0 \leq d, 0 \leq n < e}$. Dual frame matrix $\Psi$ is used to perform decomposition whose columns are the dual wavelet frames $\{\tilde{\psi}_{d,n}\}_{0 \leq d, 0 \leq n < e}$ [15]. Then coefficients of wavelet are given by

$$
z(d,n) = (\hat{x}, \tilde{\psi}_{d,n}) = \tilde{\psi}(m,n).
$$

The low-frequency image $z_l$ is separated by wavelet transform & is projected over LF scaling filters $\{\tilde{\psi}_{d,n}\}_{d \in G}$ and HF image $z_h$ that is projected over the finest scale wavelets HF in three directions $\{\tilde{\psi}_{d,n}\}_{d \leq 1, 0 \leq n < e}$, i.e.,

$$
z_l = \sum_{n \in G} z(0,n) \tilde{\psi}_{0,n} z_h = \sum_{d=1}^3 z(d,n) \tilde{\psi}_{d,n}
$$

Aliasing effect on $z_l$ is little & thus can be interpolated with a Lanczos interpolator $V^+$. Directional interpolators $V^+_{\theta}$ for the $\theta$-used to interpolate $z_h$. Where $\theta$s set of angles uniformly discretized between $0$ and $\pi$. Directional interpolator $V^+_{\theta}$ is applied to a block $B_{Q_{\theta}}$ that is interpolated with a directional interpolator $V^+_{\theta}=V^+_{\theta}$. For each angle.

The interpolator output is given by

$$
X_{LL}(m,n)=V^+z_l(m,n)+\sum_{\theta \in \Theta} (V^+_{\theta} - V^+) \times
\tilde{\psi} \sum_{Q_{\theta}} \hat{a}(B_{Q_{\theta}}) B_{Q_{\theta}} z_h(m,n)
$$

For every angle $\theta$, a new value is calculated over wavelet coefficients of every block of direction $\theta$ multiplied by their mixing weight $\hat{a}(B_{Q_{\theta}})$, which has difference between separable Lanczos interpolator $V^+$ and $V^+_{\theta}$ (directional interpolator) along $\theta$. This overall interpolator is calculated for as any of 20 angles, with blocks of width 2 pixels and a length between 6 and 12 pixels based on their orientation.

**III. PROPOSED SR TECHNIQUE**

Here input image is decomposed using one level of DWT that applies different wavelet families. Image is separated into different sub bands using DWT, namely LL, LH, HL; HH were last 3 sub bands contain the high frequency component from the image. This interpolation is applied to all sub bands. The noise level is reduced by a denoising procedure using NLM technique for input low resolution image.

**LR** Image is used as input data in the proposed SR procedure as the input data in the sparse representation for the high resolution images, in the following steps. The LR image is found out by 1-D interpolation in a given direction $\theta$ & then computations of new samples along the oversampled row, columns or diagonals. In the last step, the algorithm calculates the missing samples along the direction of $\theta$ from the previously calculated new samples, where complete sparse process is done with lanczos interpolation ($\tilde{a}=2$), reconstructing the LL subbands & LR image differ in their HF components, because of this difference is performed in HF bands by interpolating each band via the NNI process along with HF features into the HF images. To get more edge information, we have proposed on extraction step of the edges using HF sub bands HH, HL, & LH images. Then the edge information is used in HF sub bands using NNI process. The extracted edges are calculated as

$$
E = \sqrt{HH^2 + HL^2 + LH^2}
$$

At the end we perform additional interpolation with the lanczos interpolation ($\tilde{a}=2$) to get the require size for the IDWT process.
Adding the difference image & edge extraction stage contain additional HF features, & generate sharpened SR image. This sharpness is increased by the fact the Interpolation of the isolated HF components in HH, HL & LH appears to store more HF component than interpolating from LR image directly.

IV. SIMULATION RESULTS AND DISCUSSION

The results of statistical simulations as well as performance evaluation is conducted via objective metrics [PSNR, MSE, MAE and SSIM] are reported here. In addition subjective visual comparison of the SR images performed by NLM technology & without NLM technology was employed & thus made it possible to evaluate the performance of the analyzed techniques in a different manner. The medical images were studied by applying the designed & better existing SR procedures.

In simulations, the pixels of LR image have been obtained by down sampling the original HR Image by a factor of 4 in each pixel. The NLM filter from equation (2) applied in the denoising stage to find neighborhood Q in the simulation as $5 \times 5$ pixels & parameter $\delta=2$ was chosen.

From the table I we can clearly observed that the PSNR for the test image [Medical image] is Greater in with NLM than without NLM, i.e PSNR of with NLM is $63.3863$dB were as without NLM is $47.1615$dB & also we can observe that the performance criteria of MSE (Mean squared error), MAE (Mean absolute error), and SSIM (Structural similarity index matrix) is improved.

The figures on the next page show the output of intermediate stages of super resolution process. Figure 4 shows the comparison of low resolution input image and the high resolution output image and figure 5 shows the cropped area of low resolution input and high resolution output image.
TABLE 1:
Evaluation Parameter with NLM & without NLM

<table>
<thead>
<tr>
<th>Sr. No</th>
<th>Evaluation Parameter</th>
<th>Without NLM</th>
<th>With NLM</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>MSE</td>
<td>1.1230</td>
<td>0.1728</td>
</tr>
<tr>
<td>02</td>
<td>MAE</td>
<td>0.2219</td>
<td>0.0411</td>
</tr>
<tr>
<td>03</td>
<td>PSNR</td>
<td>47.1615</td>
<td>63.3863</td>
</tr>
<tr>
<td>04</td>
<td>SSIM</td>
<td>5.0448e−013</td>
<td>4.4358e−013</td>
</tr>
</tbody>
</table>

Fig 2: Wavelet Decomposition on Original image.

Fig 3: Edge Extraction for LH, HL, and HH sub-bands image enhancement

Fig 4: Low Resolution Input Image & Super resolved output Image.

Fig 5: Cropped area of Low Resolution Image & Super Resolved output Image.

References


