Color Image Super-resolution through POCS Approach

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Abstract: For color image Super-resolution (SR) reconstruction, the common practice is to transform the images from the Trichromatic (RGB) color space to YUV or some other color spaces that separate the luminance from chrominance and saturation components, and implement SR reconstruction only on the luminance component (Y). As for the color components (U, V), usually directly use interpolation algorithms for enlargement. Although interpolation process is high-efficiency, it often produces “jaggy” and “ringing” artifacts. When the images are complex or the applications want better quality, this simple process cannot satisfactory. This paper proposes an approach using Projection Onto Convex Sets (POCS) theory, integrating SR reconstructed Y component into the local constraint to improve the edge performance of the reconstructed high-resolution U, V, and setting a global constraint to ensure the whole performance. Experimental results demonstrated that compared with the bicubic-interpolation method and the colorization-based U, V component process method which has the same focus as us, our algorithm can reconstruct the high-resolution U, V component with higher Peak Signal Noise Ratio (PSNR) and Structural Similarity (SSIM) and the efficiency of our approach is acceptable.

Keywords: Color image, Color components, Super-resolution, Projection onto convex sets (POCS), Guided filter.

1. Introduction

Consider the memory space and the transfer channel limited, the original high-resolution images are usually compressed or blurred into low-resolution ones. Image Super-resolution (SR) reconstruction is an inverse problem that figure out the high-resolution images from the low-resolution counterparts using the information processing approaches [1]. Multiple images SR is reconstruct the high-resolution image from a group of low-resolution images, which usually based on the single image SR [2]. In this paper, we researched on the single image SR reconstruction.

Currently, the single image SR methods can roughly divide into three kinds: the methods based on interpolation, the methods based on learning, and the methods based on recovery. The first kind of methods directly use the interpolation approaches to up-sample the low-resolution image [3, 4], without considering the prior constraints and high frequency information. As a result, the interpolation based methods have the highest computational efficiency, but usually along with ‘jaggy’ and ‘ringing’ artifacts. Learning based methods require to construct the training sample sets, and use the prior knowledge acquired from the sample sets to complement the high frequency information, such as Example-based method [5], Neighbor-embedding method [6], Support-vector Regression method [7], sparse representation method [8], etc. Recovery based methods make use of the prior information of the image, set prior constraints and solve the
optimization problems to get the high-resolution image, such as Maximum Posterior Probability (MAP) method [9], Iterative Back-projection (IBP) method [10], Regularization method [11], Projection Onto Convex Sets (POCS) method [12, 13], etc.

For color image SR reconstruction, except for some Example-based methods [5], the common practice was transferring the original Trichromatic image (in RGB color space) to YUV or some other color spaces that separate the luminance from chrominance and saturation components, then did SR operation on the Y component only. Because of the less sensitive of human eyes on chrominance and saturation change than the luminance change, the low-resolution U and V components (represent as U_L and V_L) were usually up-sampled by simple interpolation methods. But when the images are complex, rich in details and edges, or the application occasions want more sophisticated color information, shortcoming of simple interpolation is obviously [14].

Interpolation methods, take bicubic for example, calculate the value of the object pixel through substituting the neighbor pixels value into the bicubic equation, regardless of edges or flat regions the pixel located. In view of the Y component possesses distinct edge information, and in the SR circumstance, the reconstructed Y component of high-resolution (represent as Y_H) is available, Y_H can be used as a constraint to improve the edge accuracy of the reconstructed U and V components. Liu [14] firstly adopted the colorization algorithm proposed by Levin [15] to get the color information of single image SR reconstruction. It adjusted the position of the initial U_L and V_L points in the enlarged images according to the correspondence of the Y_L and Y_H values. Then it did colorization [15] which utilized the Y_H information to get the high-resolution U and V. This method has good visual effect and color difference calculated by CIEDE2000 color difference formula, but its subjective quality (calculated by Structural Similarity, SSIM) and objective quality (calculated by Peak Signal-to-noise Ratio, PSNR) is not satisfactory. Moreover, its position adjust process is a little tedious, and the colorization [15] algorithm need to solve the matrix equation, when the image is large, the computation time will be too long.

In this paper, we employ the POCS approach to handle the color information of single image SR reconstruction. As an inverse problem, there are many solutions to the reconstruction task, the POCS approach makes reasonable assumptions as constraints, each constraint lead POCS solution to a convex set, and the feasible solution is the intersection of all these constraint convex sets. We take the SR reconstructed Y_H as the edge information reference, calculate the value of the pixel under the constraint that if the two neighbor pixels have similar Y values, they should have similar U and V values. This is the local constraint of our POCS approach. Unlike Liu’s [14] method, we utilize the idea of guided filter [16] instead of Levin’s colorization [15] algorithm to shorten the running time. Meanwhile, we take the fact that through the same processes the similar input should have the similar output as the global constraint to get the high-resolution U and V.

In Section 2, we briefly describe the POCS approach. Section 3 introduces the color image SR through POCS approach. Section 4 presents the experimental results. Section 5 is the conclusion.

2. POCS Approach

Convex set is the closed set that if two points are lie in the set, then the point between the two points is still lie in the set. For N convex sets C_i ~ CN, if exists the common point \( x \in \prod_{i=1}^{N} C_i \), the POCS approach can get the \( x \). If the projection operator from point \( f \) to the convex set \( C_i \in H, i = 1, 2, ..., N \), is \( P_i \), the projection of \( f \) to \( C_i \) will be \( P_if \), and continuous projection to all the N convex sets will be \( P_NP_{N-1}...P_1f \). Then given the original value \( f^{(0)} \), the iterative process will be:

\[
 f^{(n+1)} = P_N\cdots P_1f^{(n)}, n = 0, 1, 2, ..., \tag{1}
\]

where \( n \) is the number of iterations. More generally, there is:

\[
 f^{(n+1)} = T_NT_{N-1}\cdots T_1f^{(n)}, n = 0, 1, 2, ..., \tag{2}
\]

where \( T_i = (1 - \lambda_i)I + \lambda_i P_i, 0 < \lambda_i < 2, i = 1, 2, ..., N \). \( \lambda_i \) is the relaxation operator using to adjust the convergence speed, \( I \) is the unit matrix.

In the image SR reconstruction, the degraded model from the high-resolution image to the low-resolution image could be expressed as:

\[
 I_L = (LP*I_H)D + \eta, \tag{3}
\]

where \( LP \) is the low-pass filter operator, \( D \) is the down-sampling operator, \( I_L \) is the observed low-resolution image and \( I_H \) is the original high-resolution image, \( \eta \) is the additive noise.

Take U component as a representative, if the reconstructed U_H is similar to the original high-resolution U (represent as U_H), then through the same degraded operation of eq(3), the outcome U_L should be similar to the observed low-resolution U (represent as U_L). This feature is used as a global constraint in POCS, defined as:

\[
 \hat{U}_H \in \{ \hat{U}_H^{(n)} : \| f^{(n)}_{\hat{U}_H} \| \leq \varepsilon \}, \tag{4}
\]
and 
\[ d^{(n)}_{U_H} = U_{LR} - (LP * \hat{U}_{H}^{(n)})D, \]
where \( \hat{U}_{H}^{(n)} \) is the reconstructed high-resolution U after the \( n \) times iteration, \( \xi \) is the small number to end the iteration. The residual \( d^{(n)}_{U_H} \) correspondence to the additive noise \( \eta \), its statistical properties can be defined by \( \eta \).

To get the high-resolution U component, the SR reconstructed Y component is available. For a color image, the luminance Y and color information U have similar contour, and Y contains more details. We utilize the reconstructed Y component to constraint the local parameter:

\[ W_{sy}(Y) = \frac{1}{|w_s|} \sum_{x,y \in w_s} \left( 1 + \frac{(Y_x - \mu_x)(Y_y - \mu_y)}{\sigma_x^2} \right), \]
where \( w_s \) is the local window, \( |w| \) is the number of the pixels in the window, \( \mu_x, \sigma_x^2 \) are the mean and variance of Y in \( w_s \), and \( x \) and \( y \) represent the pixel position. Then the process is:

\[ O_s = \sum_y W_{sy}(Y)I_y, \]

The up two equations are the basis to get the initial estimation and local constraint of the POCS approach. Then the iteration process will run until the global constraint is satisfied.

3. Color Image SR Through POCS Approach

3.1. The Local Constraint

To work out the local constraint of eq. (6) and eq. (7), we avoided to solve the time-consuming matrix equation and adopt the solving process of guided filter \[ [16] \] whose filter kernel is similar to eq. (6). The guided filter assumed the output \( O \) is a linear transform of the guidance image \( G \) in a window \( w_s \), where \( s \) is the centered pixel:

\[ O_i = a_s G_i + b_s, \forall i \in w_s, \]
where \( a_s \) and \( b_s \) are the local coefficients in \( w_s \).

For the input image \( I \), the purpose is to minimize the cost function:

\[ E(a_s, b_s) = \sum_{i \in w_s} ((a_s G_i + b_s - I_i)^2 + \epsilon a_s^2), \]
where \( \epsilon \) is the parameter penalizing large \( a_s \). Through derivation, \( a_s \) and \( b_s \) can be efficiently calculated by a few multiplication and addition processes:

\[ a_s = \frac{1}{|w_s|} \sum_{i \in w_s} G_i I_i - \bar{G}_s \bar{T}_s}{\sigma_{G_x}^2 + \epsilon}, \]

\[ b_s = \bar{T}_s - a_s \bar{G}_s, \]

where \( \bar{G}_s \) is the mean of guidance image \( G \) in \( w_s \), \( \bar{T}_s = \frac{1}{|w_s|} \sum_{i \in w_s} I_i \) is the mean of input image \( I \) in \( w_s \), \( \sigma_{G_x}^2 \) is the variance of \( G \) in \( w_s \). Then the output image \( O \) can be worked out by eq. (8).

3.2. The Initial Estimation

In the POCS approach, the initial estimation of the iteration is important. Obviously, the low-resolution \( Y_L \) and high-resolution \( Y_H \) are known, using \( Y_H \) as reference to get the initial estimated \( U_H^{(0)} \) will overcome the shortcoming exists in the edges of the interpolation methods.

For clarity, let’s restate the abbreviations. \( Y_{LR} \) is the initial low-resolution Y component, \( U_{LR} \) is initial low-resolution U component, \( Y_{H} \) is the SR reconstructed Y component. The operation to get the initial estimation \( U_H^{(0)} \) is as follows:

Firstly, utilizing \( Y_{LR} \) as the guidance image, \( U_{LR} \) as the input image, substituting into eq.(10)(11), to get the low-resolution coefficients \( a_1, b_1 \);

Secondly, up-sampling \( a_1, b_1 \) by the bicubic interpolation method to get \( a_h, b_h \);

Lastly, obtaining \( U_H^{(0)} \) through \( U_H^{(0)} = a_h Y_H + b_h \).

3.3. The Global Constraint

Having the initial estimation \( U_H^{(0)} \), if it is similar to the original high-resolution \( U \), after the same degradation process, the result should be similar to the original observed \( U_{LR} \). But usually there are residuals, which need adopting the iterative
approaches to reduce. The pseudocode is demonstrated in Algorithm 1. In the algorithm, \( f_{\text{bicubic}} \) is the bicubic interpolation operator.

**Algorithm 1.** Iteration to reduce the global residual.

Input: Initial estimation \( U_H^{(0)}, a_h, b_h \), original observed \( U_{LR} \), SR reconstructed \( Y_H \), the low-pass filter operator \( LP \), the down-sampling operator \( D \), iterative step-length \( \lambda \), the maximum number of iterations \( p \), error limit \( \xi \).

Output: The SR reconstructed \( U_H \).

1: Initialize \( U_H^{(0)} = (LP \ast U_H^{(0)})D, \)
   \( e_l^{(0)} = U_{LR} - U_l^{(0)}, \)
   \( e_h^{(0)} = f_{\text{bicubic}}(e_l^{(0)}), \)
   \( a_h^{(0)} \leftarrow a_h, b_h^{(0)} \leftarrow b_h, k \leftarrow 0 \)
2: \( k \leftarrow k + 1 \), If \( \| e_h^{(k-1)} \|_2^2 \leq \xi \) or \( k \geq p + 1 \), stop the iteration;
3: Compute \( a_h^{(k)} \), \( b_h^{(k)} \) given \( e_h^{(k-1)}, Y_H \);
4: \( a_h^{(k)} \leftarrow (a_h^{(k-1)} + \lambda a_h^{(k)}), \)
   \( b_h^{(k)} \leftarrow (b_h^{(k-1)} + \lambda b_h^{(k)}); \)
5: Compute \( U_H^{(k)} \) given \( a_h^{(k)}, b_h^{(k)}, Y_H \);
6: Compute \( U_l^{(k)} = (LP \ast U_l^{(k)})D, \)
   \( e_l^{(k)} = U_{LR} - U_l^{(k)}, \)
   \( e_h^{(k)} = f_{\text{bicubic}}(e_l^{(k)}); \)
7: Goto step 2, until the stop condition is satisfied, and \( U_H^{(k-1)} \) is the wanted output.

4. Experimental Results and Analysis

In order to verify the performance of our method, in the experiments, we use the original high-resolution color images as reference. Take 4× magnification for example, we filter the high-resolution color image by a gauss low-pass filter (9×9 window, variance 2) and uniform sample 1 pixel from every 4×4 pixel window.

We compare our method with the usually employed bicubic-interpolation method and Liu’s [14] method. Fig. 1 is one experiment image, Fig. 2 is its experimental results.

Observing the images of Fig. 2 row (1), the results of our method is much clearer than the bicubic-interpolation and Liu’s [14] results, especially in the edges, obviously, our method has better deblurring ability.

In Fig. 2 row (2), quantizing the difference between the reconstructed high-resolution \( U_H \) and original \( U_{HR} \) as residual, our result has little residual in the whole image, while the other two methods have very distinct residual along the edges. Compare the images of Fig. 2 row(3) and Fig. 1.(a), our result image has more similar color to the original high-resolution image.

Fig. 3 gives the test images of the experiment. Fig. 4 to Fig. 7 are the enlarged local patch results. From these figures, it can be seen that our approach reconstructs the high-resolution U and V component with higher PSNR and SSIM values, then has less color distortion than the bicubic-interpolation and Liu’s [14] methods. Table 1 lists the result values of the whole test images given by Fig. 3. In the experiment, Liu’s results were generated with executable code available on the author’s project webpage.

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![Fig. 1. (a) The original high-resolution color image, (b) The observed low-resolution U component image.](image-url)
Fig. 2. Column (a) are results of the bicubic-interpolation method, column (b) are results of the Liu’s [14] method, column (c) are results of our method. And row (1) are the reconstructed high-resolution U components images, row (2) are the residual images, row (3) are the reconstructed color images.

Fig. 3. The test images.
Fig. 4. The reconstructed local patch of image ‘Flower’.

Fig. 5. The reconstructed local patch of image ‘Fruit’.

Fig. 6. The reconstructed local patch of image ‘Rollercoaster’.

Fig. 7. The reconstructed local patch of image ‘Race’.
Table 1. The PSNR(dB) and SSIM values of the whole test images.

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<tbody>
<tr>
<td></td>
<td></td>
<td>PSNR (dB)</td>
<td>SSIM</td>
<td>PSNR (dB)</td>
</tr>
<tr>
<td>Flower</td>
<td>U</td>
<td>39.09</td>
<td>0.9398</td>
<td>37.93</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>35.85</td>
<td>0.8958</td>
<td>34.64</td>
</tr>
<tr>
<td>Fruit</td>
<td>U</td>
<td>39.74</td>
<td>0.9464</td>
<td>38.87</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>44.11</td>
<td>0.9758</td>
<td>42.62</td>
</tr>
<tr>
<td>Rollercoaster</td>
<td>U</td>
<td>36.54</td>
<td>0.9419</td>
<td>34.99</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>36.96</td>
<td>0.9481</td>
<td>35.32</td>
</tr>
<tr>
<td>Race</td>
<td>U</td>
<td>41.26</td>
<td>0.9732</td>
<td>39.25</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>41.90</td>
<td>0.9779</td>
<td>38.69</td>
</tr>
<tr>
<td>Horse</td>
<td>U</td>
<td>46.72</td>
<td>0.9857</td>
<td>45.97</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>42.60</td>
<td>0.9709</td>
<td>41.59</td>
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<tr>
<td>Fish</td>
<td>U</td>
<td>42.46</td>
<td>0.9742</td>
<td>40.50</td>
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<tr>
<td></td>
<td>V</td>
<td>42.30</td>
<td>0.9756</td>
<td>41.12</td>
</tr>
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</table>

In the experiment, both ours and Liu’s algorithm take the SR reconstructed Y component as reference. Through practice, we found that our approach is less affected by the YSR’s accuracy. Even though we just got YSR by simple interpolation following back-projection process, our approach got better result than the other algorithms. Our approach is universal under the color image SR reconstruction frame, that is no matter what SR method be taken, as long as YSR is known, our approach is workable. And it’s no doubt that if YSR is better reconstructed, UH reconstructed by our approach will be better too.

Compare with Liu’s method, our approach avoids time-consuming operation of solving the matrix equation, replaces with multiplication and addition operations. Taking an image has 512×512 pixels for example, the running time of Liu’s method is nearly 2 minutes while ours is less than 2 seconds in a PC with an Intel core i5 2.4GHz CPU and 4G RAM.

5. Conclusions

This paper is focus on the obtaining of the high-resolution color components, other than the usual SR reconstruction works only research on the Y component. Compare with the interpolation method which is the common process to the color components of the SR reconstruction frame, our approach takes YSR as reference to improve the edge performance. Compare with Liu’s method which had the same research focus as us, we integrate YSR into the local constraint to get the initial estimation and the coefficients of local pixels, along with the assumed global constraint, our POCS approach produces high-resolution color components with sharper edges and less dependence on the YSR performance.

Quantitative comparison our approach has higher values than the other two methods both in PSNR and SSIM. And our approach has higher efficiency than Liu’s method. However, like Liu’s method, in regions with different color component but similar Y values, the color bleeding may affect the result, how to solve this problem is the follow-up work.

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