Chapter 6

Single image super resolution in color images

Single image super resolution for grey level image is extended to color images in this chapter. Two color image super resolution methods are implemented. In the first method color image in RGB format is converted to YCbCr format. The luminance component Y alone is super resolved and other two components are interpolated using standard methods. At the end the YCbCr format is converted back to RGB format. In the second method the three color components R, G, B are super resolved separately to obtain super resolved color image. It is found that the second method needs more computation time compared with the first method.
6.1 Introduction

The previous chapters presented single image super resolution methods in grey images. In this chapter the method is extended to color images.

6.2 Overview

6.2.1 Color Fundamentals

The colors that human beings observe in an object are determined by the nature of the light reflected from the object. The visible light is composed of frequencies that ranges from 400 to 700 nanometers in the electromagnetic spectrum. A body that reflects light that is balanced in all visible wavelengths appears white to the observer. However a body that favors reflectance in a limited range of the visible spectrum exhibits some shades of color. For example, green objects reflect light with wavelengths primarily in the 500 to 570 nm range, while absorbing most of the energy at other wavelengths [76]. There are two ways to characterize the color of an object: color of the pigments (the color of the light that is reflected) or the color of the light that is absorbed. (the complementary of the pigment color) [98].

Three basic quantities are needed to describe the quality of a chromatic light source: radiance, luminance, and brightness. Radiance is the total amount of energy that flows from the light source, and is usually measured in watts. Luminance, measured in lumens, gives a measure of the amount of energy an observer perceives from a light source [76].

Cones are sensors in the eye responsible for color vision. Due to the absorption characteristics of the human eye, colors are seen as variable combinations of the so-called primary colors red, green, and blue. These primary colors are added to produce the secondary colors of light-magenta (red plus blue), cyan (green plus blue), and yellow (red plus green). Mixing the three primaries or secondary with its opposite primary color, in the right intensities produces white light.
The characteristics generally used to distinguish one color from another are brightness, hue, and saturation. As already explained brightness embodies the chromatic notion of intensity. Hue is an attribute associated with the dominant wavelength in a mixture of light waves. It represents the dominant color as perceived by an observer. Saturation refers to the relative purity or the amount of white light mixed with hue. The pure spectrum colors are fully saturated.

### 6.2.2 Color Model

A color model is a specification of a coordinate system within which each color is represented by a single point. Several popular color formats are used for image and video processing. A color model is an abstract mathematical system for representing color and has 3 dimensional abstractions for three primary colors along three dimensions. They can represent only limited number of colors and hence often can’t represent all colors in the visible spectrum.

**Gamut or Color Space**

The range of colors that are covered by a color model is called Gamut or color space. Color models can be classified as either additive or subtractive.

Additive color describes the situation where color is created by mixing or adding the visible light emitted from differently colored light sources. Additive color uses transmitted light to display color. Human perception is additive since black is the absence of light and white the presence of all wavelengths of light. Subtractive colors are in contrast to additive colors. In this type color system light is removed from various part of the visible spectrum to create colors.

Figure [6.1] shows additive and subtractive models. The most common examples for additive light are computer monitors and televisions. Subtractive color is used in paints and pigments and color filters. The additive reproduction process usually uses red, green and blue light to produce the other colors. Combining one of these additive primary colors with another in equal amounts produces the additive secondary colors cyan, magenta, and yellow. The different color models are
RGB Color Format

In the RGB model which is also called additive model, each color is represented as a combination of primary colors red, green, and blue. Figure 6.1 shows RGB color system. The primary colors can be added to produce the secondary colors of light - magenta (red plus blue), cyan (green plus blue), and yellow (red plus green). The combination of red, green, and blue at full intensities makes white. The importance of the RGB color model is that it relates very closely to the way that the human eye perceives color. This model is a basic color model for computer graphics because color displays use red, green, and blue to create the desired color. The number of bits used to represent each pixel in RGB space is called pixel depth.
A RGB color cube can be used to display smooth transitions between these colors. To generate any color within the RGB color cube, all three RGB components need to be of equal pixel depth and display resolution. This model is based on a Cartesian coordinate system. Schematic of RGB color cube is shown in Figure 6.3. Here RGB values are at three corners; cyan, magenta, and yellow are at three corners; black is at the origin; and white is at the corner farthest from the origin. The gray scale extends from black to white along the line joining these two points. Different colors are points on or inside the cube, and are defined by vectors extending from the origin [76]. Each color is in the range [0,1].

In RGB model, images consist of three component images, one for each primary color. Any modification of the image requires modification of all the three planes. If 8 bits are needed to represent each primary color image, then 24 pixels are needed to represent a RGB color pixel. The total number of colors in a 24 bit RGB image is $2^8$.

**CMY Color Format**

Cyan, Magenta, and yellow are the secondary colors of light. When a surface coated with cyan pigment is illuminated with white light, no red light is reflected from the surface. That is Cyan subtracts (absorbs) red light from reflected white
light, which itself is composed of equal amounts of red, green, and blue light. The CMY color space is subtractive.

Figure 6.3: RGB color cube

Usually most devices like color printers and copiers convert RGB to CMY internally. Converting from RGB to CMY is done using the equation 6.1.

\[
\begin{bmatrix}
C \\
M \\
Y
\end{bmatrix} = \begin{bmatrix}
1 \\
1 \\
1
\end{bmatrix} - \begin{bmatrix}
R \\
G \\
B
\end{bmatrix}
\] (6.1)

Here normalised color values are used. Equation 6.1 demonstrates that light reflected from a surface coated with pure cyan does not contain red (C=1-R), pure magenta does not contain green, yellow does not contain blue.

**CMYK Color Format**

In actual practice, mixing maximal amounts of cyan, magenta and yellow pigments creates a color that is not really black (dark muddy instead). So in order to produce true black a fourth color black is added giving rise to the CMYK color model.
HSB Format

Color models like RGB, CMY consider a color image as being composed of three primary images that combine to form single image. They are not suited for describing colors for practical human interpretation. HSB color model decomposes color according to perception rather than according to how it is physically sensed. A point within the HSB gamut is defined by Hue (the chromaticity or pure color), Saturation (the vividness or dullness of the color), Brightness (the intensity of the color).

According to this model, any color is represented by 3 numbers as in Figure 6.4. The first number is the hue, and its value ranges from 0 to 360 degrees. Each degree represents a distinct color. First there is the red color (0 or 360 degrees,) and then there are all other colors (for example yellow at 120 degrees, green at 180 degrees and blue at 240 degrees), up to the violet color. All the VIBGYOR colors are represented here. The second number is the saturation. It represents the amount of color or, more exactly, its percentage. It is the purity of the color and is the amount of pure color mixed with white color. Its value ranges from 0 to 100, where 0 represents no color, while 100 represents the full color. Finally, the third number is the brightness. One can enhance the color brightness adding the white color, and can reduce it by adding the black color. In this case 0 represents the white color and 100 represents the black color. The more this value tends to 0, the brighter the color is. The more this value tends to 100 the darker the color is. The RGB values have been normalised to the range [0,1]. Given an RGB color format,
H component of each RGB pixel is obtained by

\[
H = \begin{cases} 
\theta; & \text{if } B \leq G \\
360 - \theta; & \text{if } B > G 
\end{cases}
\]

where,

\[
\theta = \cos^{-1} \left\{ \frac{1/2[(R - G) + (R - B)]}{(R - G)^2 + (R - B)(G - B))^{1/2}} \right\}
\]

The Saturation component is given by

\[
S = 1 - \frac{3}{(R + G + B)} \min(R, G, B) 
\]

The intensity is given by

\[
I = \frac{1}{3}(R + G + B)
\]

This is used by NTSC, PAL, and SECAM television standards. Like HSB, YIQ separates color into luminance Y and color channels (I and Q). Y is the luminance or gray scale component, I is the in phase component (amount of red-green) and Q is the quadrature (amount of blue-yellow). The YIQ color space is a rotation and distortion of RGB such that the Y axis lies along the RGB gray scale, the I axis is oriented roughly to red-green and the Q axis to blue-yellow. Converting RGB to YIQ is done by the equation

\[
\begin{bmatrix}
Y \\
I \\
Q
\end{bmatrix} = \begin{bmatrix}
0.299 & 0.587 & 0.114 \\
0.596 & -0.274 & -0.321 \\
0.211 & 0.523 & -0.312
\end{bmatrix} \begin{bmatrix}
R \\
G \\
B
\end{bmatrix}
\]

**YUV Color Model**

The YUV color model is the basic color model used in analogue color TV broadcasting. Initially YUV is the recoding of RGB for transmission efficiency (minimizing bandwidth) and for downward compatibility with black and white television. The YUV color space is derived from the RGB space. It comprises the luminance (Y) and two color difference U, V components. The luminance
can be computed as a weighted sum of red, green and blue components; the color
difference, or chrominance, components are formed by subtracting luminance from
blue and from red.

**YC\(_b\)C\(_r\) Color Model**

![Color image and its Y, C\(_b\) and C\(_r\) components.](image)

YC\(_b\)C\(_r\) color space used for component digital video is a scaled and offset version
of the YUV color space. Y is the luminance component and C\(_b\) and C\(_r\) are the blue
difference and red-difference chroma components. Figure 6.5 shows a color image
and its Y, C\(_b\) and C\(_r\) components. It can be noted that the Y image is essentially
a grey scale copy of the original image. The principal advantage of the YC\(_b\)C\(_r\)
model in image processing is decoupling of luminance and color information. The
importance of this decoupling is that the luminance component of an image can
be processed without affecting its color component. For example, the histogram
equalization of the color image in the YC\(_b\)C\(_r\) format may be performed simply by
applying histogram equalization to its Y component. There are many combinations
of $YbCr$ values from nominal ranges that result in invalid RGB values, because the possible RGB colors occupy only part of the $YbCr$ space limited by these ranges.

Conversion from RGB to YCbCr using equation 6.5:

$$
\begin{bmatrix}
Y \\
Cb \\
Cr
\end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112 & -93.786 & -18.214 \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix}
$$

(6.5)

### 6.3 Single image super resolution using directionlets for color images

There are different ways to extend the gray image super-resolution algorithm for processing color images in RGB format. The typical solution involves applying monochromatic SR algorithms to each of the color channels independently, while using the color information to improve the accuracy of motion estimation [90]. This process can result in better performance than super-resolving only the luminance components, both in terms of SNR values and in visual plausibility. But it is at the expense of three times larger run-time complexity. Humans are more sensitive to the brightness information (luminance) than color information (chrominance components). Another approach is transforming the problem to a different color space, where chrominance layers are separated from luminance, and super resolution method is applied only to the luminance channel. The chrominance or color channels, are then upsampled using interpolation methods (eg. bilinear, bicubic) and the final RGB is computed by recombining the new SR luminance image with the interpolated chrominance. Processing the luminance information does not reduce the quality of resultant image, but this method reduces the computation time [88].

Above mentioned two methods are implemented here. The simplest way is the second method which super resolves only the luminance component of a given
color image.

6.3.1 Color image Super resolution with super resolution on luminance component only

Methodology

In this method the RGB color image is converted into $YC_bC_r$ model and the super-resolution is performed only on the Y component. The main advantage of the $YC_bC_r$ model in image processing is that the luminance and the color information are independent. Thus, the luminance component can be processed without affecting the color contents. The details information in a digital image is mainly present in the image luminance component. Therefore, one can take advantage of the high sensitivity of the human visual system to the brightness variation than to the chrominance variation. Consequently, more computational resources can be allocated to enlarge the brightness values while color components can be enlarged using a simpler approach. The final result is then obtained by combining the super-resolved Y component with the interpolated $C_b$ and $C_r$ components. As mentioned earlier, this scheme has the important advantages of enabling the gray level model being applied directly to color images, resulting in the run-time complexity to be the same as that of gray level case. Finally, the $YC_bC_r$ model is converted to the RGB model to generate the synthetic image.

Implementation

High resolution color images are obtained from the Internet and are used to form training set. The images are obtained from Canon digital Gallery [1]. One of the training set image is shown in Figure 6.6. It is of size 333x500 and in tiff format. Some of high and corresponding low resolution images are shown in Figure 6.7. The low resolution images are obtained by subsampling the each R, G, B components of their high resolution images separately.

In this method the RGB formatted images are converted into $YC_bC_r$ format. The luminance component Y alone is super-resolved using the new directionlet method. For this the training set is formed using the luminance components of high and low
resolution color images. The low and high resolution luminance components are divided into patches and directionlet transform is applied on these patches. These coefficients form the training set. The missing high resolution Y component is learned from this training set. The other two components $C_b$ and $C_r$ are upsampled using cubic spline interpolation. The super resolved Y component and cubic spline interpolated $C_b$, $C_r$ components are converted back to RGB format to obtain the high resolution image.
Figure 6.7: (a),(c) Original images of girl1 and girl2 (b),(d) Low resolution images, contd.......
Results

For color images, results obtained using new directionlet method is compared with Yang et al sparse method [36] and Shan et al method [75]. The paper [75], is based on an image formation process that models how a coarselevel image is produced from its clear finer-resolution version.

SNR values are calculated and shown in table 6.1 for new directionlet method, Yang et al and Shan et al super resolution methods. Table shows that the super resolved image girl1 using directionlet method has SNR of 43.5548dB while super resolved images using Yang et al method and Shan et al method have SNR of
Table 6.1: SNR values of Super resolved Color images

<table>
<thead>
<tr>
<th>method</th>
<th>SNR in DB</th>
</tr>
</thead>
<tbody>
<tr>
<td>super resolved using Shan et al method</td>
<td>39.2839</td>
</tr>
<tr>
<td>super resolved using Yang et al method</td>
<td>39.3904</td>
</tr>
<tr>
<td>Directionlet method</td>
<td>43.5548</td>
</tr>
<tr>
<td>girl1</td>
<td>39.2839</td>
</tr>
<tr>
<td>girl2</td>
<td>32.1571</td>
</tr>
<tr>
<td>tiger</td>
<td>23.7560</td>
</tr>
<tr>
<td>queen</td>
<td>25.5211</td>
</tr>
<tr>
<td>super resolved using Yang et al method</td>
<td>33.8038</td>
</tr>
<tr>
<td>super resolved using Shan et al method</td>
<td>26.6926</td>
</tr>
<tr>
<td>Directionlet method</td>
<td>29.2922</td>
</tr>
<tr>
<td>queen</td>
<td>27.6746</td>
</tr>
<tr>
<td>Directionlet method</td>
<td>31.5619</td>
</tr>
</tbody>
</table>

39.3904dB and 39.2839dB only. Same is the case with the images of girl2, tiger and queen.

Figure 6.8 (a), (c), (e), (g) show original image, super resolved images of low resolution image Figure 6.7 (b) of girl1 using existing methods (Yang et al method and Shan et al method) and new directionlet method. Here the low resolution image of size 166 × 250 is super resolved to an image of size 332 × 500. Figures 6.8 (b), (d), (f), (h) represent the zoomed portions of forehead of girl in Figure (a), (c), (e), (g) respectively. It is clear that the image obtained by directionlet super-resolution method, consists of sharper details than the images from other methods. Blocking effect is present in hair strands of image using existing methods but it is almost removed in the new method.

Figure 6.9 shows another color image of girl2 in which new super resolution method is applied. The low resolution image is of size 215 × 251 and is shown in Figure 6.7 (d). Figure 6.9 (b), (d), (f), (h) show zoomed portions of original image (a), super resolved using Yang et al method (c), Shan et al method (e) and super resolved method using directionlet (g) respectively. The artifacts in the hair band present in super resolved image using existing method is almost removed in directionlet based super resolution method. Also the eyebrows and hair strands are sharper and close to original in the directionlet method. Table 6.1 shows that the directionlet based super resolved image has SNR of 37.3295dB while super resolved images with Yang et al method and Shan et al method have SNR value 33.8038dB and 32.1571 respectively.
Figure 6.8: (a) original image (c) super resolved using Yang et al method (b), (d) zoomed portion of the face of (a), (c) respectively. contd......
Figure 6.8: (e) super resolved using Shan et al method (g) super resolved image using directionlets (f), (h) zoomed portion of the face of (e), (g) respectively.
Figure 6.9: (a) original image (c) super resolved using Yang et al method (b), (d) zoomed portion of the face of (a), (c) respectively. Contd......
Figure 6.9: (e) Super resolved using Shan et al method, (f,g) super resolved image using directionlets, (f,h) zoomed portion of the face of (e),(g) respectively.
Figure 6.10: (a) original image (c) super resolved using Yang et al method (b), (d) zoomed portion of the face of (a), (c) respectively. contd...........
Figure 6.10: (e) super resolved using Shan et al. method. (g) super resolved image using directionlets. (f), (h) zoomed portion of the face of (e), (g) respectively.
Figure 6.11: (a) original image (c) super resolved using Yang et al method (b), (d) zoomed portion of the face of (a), (c) respectively. contd..................
Figure 6.11: (e) super resolved using Shan et al method (g) super resolved image using directionlets (f), (h) zoomed portion of the face of (e), (g) respectively
The third low resolution image used is shown in 6.7f. It is of size 200 × 150. Figures 6.10(a), (c), (e), (g) show original image, super resolved image using Yang et al method, super resolved using Shan et al method and directionlet based super resolved image (400 × 300). Figures 6.10(b), (d), (f), (h) show zoomed portions of (a), (c), (e), (g) respectively. The ringing effects present in the mustache of tiger in the super resolved images using Yang et al method and Shan et al method is almost removed in directionlet based method.

In Figures 6.11(a), (c), (e), (g) show original image, super resolved image using Yang et al sparse method, Shan et al method and new super resolved image of low resolution image in Figure 6.7h. Low resolution image is of size 196x292 and it is super resolved to the size of 392x584. The block effect in the marked area of super resolved images using Yang et al method and Shan et al method is almost removed in the new super resolved image.

6.3.2 Super resolution on R, G, B components

Methodology

To form the training set, each high and low resolution color component is divided into patches and directionlet transform is applied on these patches. Thus there are three groups of directionlet coefficients corresponding to three color components. The training set contains three groups of directionlet coefficients. Each group contains directionlet coefficients of low and high resolution color component patches. In MATLAB, the format of input color image is in RGB. The high resolution color components R, G, B are learned from the training set individually.

To super resolve an input low resolution color image, it’s three high resolution components corresponding to different colors are learned separately from the training set. Each color component is super resolved separately.
Figure 6.12: (a) Original image (c) image super resolved by super resolving luminance components only (e) image super resolved by super resolving R, G, B components (b), (d), (f) zoomed portion of the face of (a), (c), (e) respectively
Implementation

The same high resolution images which are used in the first method are used as the training set images. The low resolution image of girl1 is super resolved to its double size.

Results and discussions

Figure 6.12(a), (c), (e) show the original image, the SR image by super resolving luminance the components only and SR image by super resolving all the three color components separately and (b), (d), (f) are the zoomed portions of (a), (c), (e) respectively. The super resolved image in Figure 6.12(e) has almost same subjective quality compared to the image in Figure 6.12(c), which is obtained by super resolving the luminance component only. Also SNR of Figure 6.12(e) is 43.9447dB while that of Figure 6.12(c) is 43.5548dB. But the time taken for the second method is very large (three times) compared with the first method.

6.4 Super resolution of LR color images to 4 times its original size (magnification factor 4)

The LR color image of size MxM is super resolved to an image of size 4Mx4M using new directionlet method. It is compared with the super resolved image obtained using Yang et al’s sparse method.

As in the case of grey images, the zooming factor 4 is obtained by iterating the critically sampled directionlet method two times with output image of first iteration as the input low resolution image of the second iteration. SNR values obtained for different methods are shown in table 6.2.

From table 6.2 SNR values obtained for the image Lena for zooming factor 2 and 4 are 22.5731dB and 13.8592dB for directionlet method, 22.0944dB and 13.8316dB for Yang’s method respectively. So is the case with image bush. From SNR values, it is clear that directionlet method gives better result.
Table 6.2: SNR values for color images with zooming factor 2 and 4

<table>
<thead>
<tr>
<th>Method</th>
<th>SNR in DB for zooming factor 2</th>
<th>SNR in DB for zooming factor 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lena</td>
<td>Bush</td>
</tr>
<tr>
<td>Yang et al’s sparse method</td>
<td>22.0944</td>
<td>9.6565</td>
</tr>
<tr>
<td>Directionlet method</td>
<td>22.5731</td>
<td>10.6168</td>
</tr>
</tbody>
</table>

Figure 6.13: (a) low resolution image (64x64) (b) original image (128x128) (c) original image (256x256) (c),(d) 2 times SR images (128x128) using Yang et al. method and directionlet method (f),(g) 4 times SR images (256x256) using Yang et al. method and new directionlet method respectively.
Figure 6.14: (a) low resolution image (64x64) (b) original image (128x128) (c) original image (256x256) (d) 2 times SR images (128x128) using Yang et al method and directionlet method (f), (g) 4 times SR images (256x256) using Yang et al method and new directionlet method respectively.

Blocking effect along the edges of the leaves are noticed in Yang et al method. Triangular protrusions along the leaf are missing in directionlet method and but it is sharper than the image by the other method.
Figures 6.14(a) low resolution image (64x64) (b) original image (128x128) (e) original image (256x256) (c), (d) 2 times SR images (128x128) using Yang et al method and directionlet method (f), (g) 4 times SR images (256x256) using Yang et al method and new directionlet method. Here ringing effect present in the edge of hat of Yang et al method is less in new directionlet method.

6.5 conclusion

In this chapter directionlet based super resolution method is extended to color images. Two super resolution methods are implemented here. In the first method, RGB format is converted to YC\textsubscript{b}C\textsubscript{r} format and super resolution method is applied to the luminance component, Y alone. In the second method each R, G, B components are super resolved separately. The two methods (YCbCr method) give almost same result both in numerical and visual quality, but the second method needs more time compared with first method. They are compared with the Yang’s method which is proved to be the best among existing methods. It is seen that directionlet based super resolved method outperforms the existing super resolution methods, in the case of color images also.