IMPROVED GRADIENT PROFILE SHARPNESS TRANSFORMATION BASEDSUPER-RESOLUTION USING DE-HAZING

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Abstract— This paper presents a Super Resolution (SR)technique considering atmospheric scattering models of hazy images. In which a SR image is considered as combination of radiance of the scene and atmospheric light. This assumption helps us to remove the hazy part in any SR image using dark channel prior. An edge sharpness metric called Gradient Profile Sharpness (GPS) is used in transforming the Low Resolution (LR) image to High Resolution (HR). This results in improved image quality. Extensive simulation results show that proposed method improves the performance of existing SR techniques, in terms of Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

Index Terms— Super Resolution from single image, Gradient Profile Sharpness transformation, Haze removal, Dark channel prior.

I. INTRODUCTION

The process of generating a High resolution (HR) image from one or many Low Resolution (LR) image(s) is called Super Resolution (SR). These SR techniques can be broadly classified into two categories: (i) classical multi image SR techniques and (ii) Single image based SR techniques.

Classical multi image approach assumes the multiple input images as down-sampled versions of the desired HR image. Then the sub-pixel shifts among LR images are used to estimate HR image.The multi-image Super Resolution approach is a well constrained problem and many methods have been proposed [1].The main drawback of this approach is that the multiple images of same scene are to be presented as input. This may not be possible in many applications like surveillance, remote sensing, etc. Hence, this approach is less preferred by researchers.
In the single image based SR techniques. The single image itself is considered as input. In recent years much work has been done in this area, these works can be classified into three categories: (i) Interpolation based approaches, (ii) learning based approaches and (iii) reconstruction based approaches.In interpolation based approaches speed is key factor which prompts researches to work in this direction and many sophisticated interpolation based models were developed. Butif upscaling ratio is high, these approaches tend to blur high frequency details.

The learning based approaches assume that high frequency details are lost in LR images and these can be hallucinated from dictionary containing image patch pairs. Some of these methods in this approach use dictionary constructed of external data set containing image pairs [2]. But, this makes the performance of these techniques dependent on similarity between input image and the data set. In order to reduce this dependence, self-example based approaches were proposed. These are based on the observation that across different scales of image, patches tend to recur redundantly [3]. Although these approaches are robust, there will be some artifacts in HR image generated and the computational complexity is also very high.
Reconstruction based approaches were developed over the years to tradeoff between performance and computational efficiency of algorithm. As the single image SR is an inherently ill constrained, these approaches enforce a constraint that synthesized HR image is to be consistent with its LR image. To make this problem solvable and to find the best estimated HR image, an effective regularization term is added as a model constraint. Since edges of the image are prominent inits visuality; edge sharpness metrics are often used as regularization terms. The gradient profile isintroduced to describe resolution of edges it is described using three features: (i)magnitude of intensity change, (ii) distance from center pixel which is having maximum gradient to pixel whose gradient magnitude is zero and (iii) the standard deviation of edge profile [4].

This paper proposes a two part model in which first part uses reconstruction based approach to synthesize an HR image using GPS transformation and second part de-hazes itto produce final image which is having higher resolution and is free from scattered atmospheric light.

This remaining paper is organised into four sections. Section II explains the reconstruction based approach using GPS transformation term to synthesize HR image, section III explains how the synthesized image is de-hazed and section IV provides with our experimental results and compares our model's performance with performance of HR image reconstruction using GPS transformation both structurally and visually. The conclusion of our work is given in section V of this paper.

II. RECONSTRUCTION OF HR IMAGE FROM LR IMAGE

This section explains how an HR image can be synthesized from single LR image using reconstruction based approach introduced in section I. This section is segmented into three parts. Part A formulates the problem statement. Part B defines the regularization parameter used in this model i.e. gradient profile sharpness (GPS). Part c details the algorithm used to reconstruct HR image.

A. Formulating the relation between input LR image and HR image

This paper deals with single image super resolution methods. Hence, we focus on problem of estimating $\hat{X}$, the estimate of target HR image X from input image Y. All SR techniques in literature are based on assumption that the available LR images are down-sampled, wrapped, blurred and noisy versions of target HR image. Supposing x, y are vector representations of images X and Y. We can write

$$y = sHx + \eta \tag{1}$$

Where, s represents subsampling operator, H represents blur kernel and η is representation of additive white Gaussian noise (AWGN) added to degrade LR image.

B. Defining regularization term used (GPS)

Equation (1) specifies the relation between input image and target HR image. But the problem is, there can be many HR images which may result same LR image under different blurring and wrapping factors. Hence, there should be a regularization term which ensures that synthesized HR image is consistent with target image. In this paper we use GPS defined in [5].

Gradient profile is described by modeling image's gradient magnitude at edges present in images. Traditionally generalized Gaussian description (GGD) model is used but it tends to cause large fitting errors. Hence triangular and Gaussian mixed model were proposed to model edges. For the ease of description of gradient profile a normalized coordinate system is used for each gradient profile is used. Where, profile peak is located at center.

Triangle model is suited for gradient profiles around short and asymmetric edges. Two sides of center are fitted separately. The linear function can be formulated as

$$m_{TR}(x) = \begin{cases} kd_x + h, & \text{if the value} \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Where, $m_{TR}(x)$ is the magnitude of gradient at pixel in the model, d_x is the absolute distance of pixel from centre, h is the peak value of profile, k is the slope of edge of triangle and it can be fitted using

$$k = \min_k \sum_{x \in p} [m_{TR}(x) - k.d_x - h]^2 \tag{3}$$

The key features of any description model are its height and spatial scattering.A metric of gradient profile is defined based on eccentricity of gradient profile description models as

$$\eta = h/d \tag{4}$$

Where, h is maximum gradient magnitude and d is spatial scattering. For triangle model it is horizontal distance between the center to the point where the gradient magnitude is zero. A larger GPS value means a sharper edge and smaller GPS value means smoother edge and is consistent with human perception of edges.

C. Algorithm used to transform LR image to HR image using GPS transformation

The algorithm of generating a HR image using single image and its GPS value can be divided into four steps. The first step is to extract GPS from the gradient profile description model given in (2).

The second step is to estimate GPS transformation relationship between different image resolutions. To reconstruct HR image we should have its gradient field. Toobtain target gradient field the Gradient profiles in LR image should be transformed into ones in HR image. The gradient transformation model can be formulated only if the relationship of GPSs in various resolutions is known. The parameter in GPS relationship can be estimated using the model in [5]. An up-scaled image (UR) is formed which is of same size as the HR image. After UR image is formed, the edge pixels of the image are found and their corresponding edge pixels in HR image are searched by comparing spatial difference and gradient difference.

$$x_0^{HR} = \arg\min_{x \in N}\left(d(x, x_0^{UR})^2 + \beta.\left\|\overrightarrow{G_H}(x) - \overrightarrow{G_U}(x_0^{UR})\right\|^2\right) \tag{5}$$

Where, the first term $d(x, x_0^{UR})^2$ in (5) correspond to spatial difference and the second term in (5) $\left\|\overrightarrow{G_H}(x) - \overrightarrow{G_U}(x_0^{UR})\right\|^2$ corresponds to gradient difference. Pair of gradient profiles is extracted from I_{HR} and I_{UR} at the positions of x_0^{HR} and x_0^{UR} then the GPS pairs $(\eta(x_0^{HR}), \eta(x_0^{UR}))$ are calculated according to (4). GPS transformation relation can be written as

$$\eta^{HR} = \alpha.\eta^{UR} \tag{6}$$

Where α determines the degree of enhancement.

The third step is to generate target gradient field in HR image using transformation of gradient profiles. In gradient profile transformation total energy and shape of original gradient profile are to be preserved. Three constraints are proposed in [5]to keep the transformation consistent. First constraint is there should not be a change in sum of gradient magnitude in a gradient profile. This preserves the luminance difference around the edges. Even with the transformation of gradient profile its shape should not change from its original shape. Shifting of edges should be avoided and to avoid it, the peak in transformed profile should not change its position. Gradient profile transformation models are developed using these three constraints. Weconsidered triangular model, as the shape is fixed and sum of gradient magnitude should also be unchanged, the area should remain unchanged.

$$\begin{cases} h_{TR}^{HR}.\, d_{TR}^{HR} = h_{TR}^{UR}.\, d_{TR}^{UR} \\ h_{TR}^{HR}/d_{TR}^{HR} = \alpha^{*}.\, h_{TR}^{UR}/d_{TR}^{UR} \end{cases} \quad (7)$$

Where h_{TR}^{HR} and d_{TR}^{HR} are gradient profile's parameters of triangle model in HR image, h_{TR}^{UR} and d_{TR}^{UR} are their counterparts in UR image. Hence we can draw relation between known parameters of gradient profile in UR image and unknown parameters of gradient profile in HR image.

$$\begin{cases} h_{TR}^{HR} = \sqrt{\alpha^{*}}.\, h_{TR}^{UR} \\ d_{TR}^{HR} = \sqrt{1/_{\alpha^{*}}}.\, d_{TR}^{UR} \end{cases} \quad (8)$$

The slopes of triangle model in HR image can also be calculated as

$$k_{TR_{left}}^{HR} = \frac{-h_{TR}^{HR}}{d_{TR_{left}}^{HR}} = \propto^{*} k_{TR_{left}}^{UR} \quad (9)$$

Using slope and peak values of a triangle model, the gradient magnitude of each location in gradient profile can be written as

$$\widehat{m}_x^{HR} = \begin{cases} k_{TR_{left}}^{HR} d_x + h_{TR}^{HR} & \text{if } d_x \leq d_{Tleft}^{HR} \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

Where, d_x is the distance between current pixel and edge pixel and d_{Tleft}^{HR} is maximum scattering allowed.$k_{TR_{left}}^{HR}$ is the slope of left side of triangular profile,h_{TR}^{HR} is the peak gradient magnitude located at edge.

The final step is HR image reconstruction from estimated target gradient field. Based on transformation models used in [6] target gradient field can be generated from gradients in UR image. This is the prior for HR image reconstruction. When this introduced in HR image reconstruction model, HR image can be found by minimizing reconstruction error in image field and gradient field.

$$\begin{aligned} I_{HR}^{*} &= \min_{I_{HR}} E\left(I_{HR}|I_{LR}, \nabla\widehat{I_{HR}}\right) \\ &= \min_{I_{HR}}(E_I(I_{HR}|I_{LR}) \\ &\quad + \beta.\, E_G(\nabla I_{HR}|\nabla\hat{I}_{HR})) \end{aligned} \quad (11)$$

Wherethe first term in (11) $E_I(I_{HR}|I_{LR})$implies that there should be consistency between down sampled version of HR image and LR image

$$E_I(I_{HR}|I_{LR}) = \|\downarrow(I_{HR} \otimes G) - I_{LR}\|^2 \quad (12)$$

Second term in (11) $\beta.\, E_G(\nabla I_{HR}|\nabla\hat{I}_{HR})$ implies that there should be a consistency between HR image and estimated gradients

$$E_G\left(\nabla I_{HR}\middle|\nabla\hat{I}_{HR}\right) = \left\|\nabla I_{HR} - \nabla\hat{I}_{HR}\right\|^2 \quad (13)$$

III. DE-HAZING OF GENERATED HR IMAGE

This section is dedicated to explain how effect of haze can be removed from image and why is this haze removal necessary. Part A of this section explains the need of de-hazing. Part B of this section gives the standard atmospheric scattering model of scene radiance of hazy image. Part c explains dark channel prior and its calculation. Part D explains how transmission parameter is estimated. Part E explains how original radiance of scene is recovered.

A. Need for De-hazing

Presence of haze or fog in images will degrade the visibility of image.This can become a major problem in many applications like video surveillance, target identification, remote sensing etc. these also are major applications for super resolution. Almost all computer vision algorithms assume that input image's intensity is original radiance of scene. This is not true in the presence of atmospheric light. This assumption leads to inevitable loss of performance is. Hence, to enhance performance of SR techniques haze is to be removed.

B. Atmospheric scattering model of hazy images

The atmospheric scattering model is first proposed in [16] and later developed by Narasimhan and Nayar in [9]. The model can be expressed as following:

$$I(x) = J(x)t(x) + A(1 - t(x)) \quad (14)$$

$$t(x) = e^{-\beta d(x)} \quad (15)$$

It is to be noted that depth of scene$d(x)$ is the key information. As β can be treated like a constant in the conditions of homogenous atmosphere. And the medium of transmission $t(x)$is easily available from (15) if depth of scene is given. The range of depth is [0,?) as the objects visible in the image can be very distant from the point of observation, and so we have

$$I(x) = A \quad \text{as } d(x) \to \infty \quad (16)$$

Equation (16) shows that the intensity of pixel at infinite depth can be atmospheric light. Hence, we can say if the pixel is sufficiently distant to make the transmission parameter small then the intensity of pixel can be approximately equal to the atmospheric light. We can estimate the atmospheric light by the following equation if a sufficient threshold is given.

$$A = I(x) \quad if\ d(x) > d_{threshold} \quad (17)$$

C. Dark channel prior

The dark channel prior is based on observation on haze-free outdoor images in [10]. The observation made is that in most of local patches not having sky, one color channel is having very low intensity at some pixels. In other words, the minimum intensity in non-sky patches is very low. We define dark channel as

$$J^{dark}(x) = \min_{C\in\{r,g,b\}}(\min_{y\in\Omega(x)}(J_C(y))) \quad (18)$$

Where $\Omega(x)$ the patch with center at x, $J_C(y)$ is radiance of scene at pixel y. We can say that for non-sky region the intensity of dark channel is quite low and may tend to zero, given that the image is non-hazy. This statistical observation is termed as dark channel prior.

D. Estimating the transmission parameter

As mentioned in part B of this section a haze-free image can be formed from the atmospheric scattering model if the atmospheric light and transmission parameter are known. The atmospheric light can be found using (16) or (17). Now to estimate the transmission parameter we use the atmospheric light and the dark channel prior. We assume that transmission parameter $t(x)$ is constant locally. Taking the min operator on (14) we get:

$$\min_{y\in\Omega(x)}(I^C(y)) = \tilde{t}(x)\min_{y\in\Omega(x)}(J^C(y)) + (1-\tilde{t}(x))A^C \quad (19)$$

This operation is performed on all three color channels separately and operation in each color channel is independent of other color channels. Hence the min operation operating on each color can be written as

$$\min_C(\min_{y\in\Omega(x)}(\frac{I^C(y)}{A^C})) = \tilde{t}(x)\min_C(\min_{y\in\Omega(x)}(\frac{J^C(y)}{A^C})) + (1-\tilde{t}(x)) \quad (19)$$

But from dark channel prior the first term in right hand side of equation tends to zero.

$$J^{dark}(x) = \min_C\left(\min_{y\in\Omega(x)}\left(J^C(y)\right)\right) = 0 \quad (20)$$

This gives the estimate of transmission parameter as:

$$\tilde{t}(x) = 1 - \min_C(\min_{y\in\Omega(x)}(\frac{I^C(y)}{A^C})) \quad (21)$$

Even though the dark channel prior does not apply to sky regions, this equation still holds good because the color of sky is approximately equal to the atmospheric light and the second term in (21) tends to one. And the transmission parameter tends to zero, which is consistent with atmospheric scattering model when distance tends to infinity. But in practice, the atmosphere is never absolutely free of ant particle. In fact, according to the phenomenon called aerial perspective, the presence of haze is cue for human to perceive depth. If haze is removed thoroughly, the obtained image may seem unnatural and perception of depth may be lost.Hence we may add small amount of haze for distant objects by introducing a constant parameter in (21):

$$\tilde{t}(x) = 1 - \omega\min_C(\min_{y\in\Omega(x)}(\frac{I^C(y)}{A^C})) \quad (22)$$

Where, ω allows preserving haze adaptively. The value of ω is application specific.

E. Recovering radiance of scene

With the transmission map the radiance of scene can be recovered using (22). But the direct attenuation term may be zero when transmission parameter tends to zero. The transmission parameter is restricted to a lower bound t_0. Which means for high dense haze regions a small amount of haze is preserved. Equation (14) can be written in its modified form as

$$J(x) = \frac{I(x)-A}{\max(t(x),t_0)} + A \quad (23)$$

The aim of lower bound t_0 is to make sure that the denominator in (22) never equals to zero.

IV. EXPERIMENTAL RESULTS

This paper generates HR image from an LR image. We collected standard images in pairs. One image is of higher resolution and other is decimated version of the first one. We are using magnification factor of three. So the decimation factor should also be three. The color image is first converted into YCBCR formand Super resolution is applied on Luminance channel only. To reduce color distortion in generated HR image. We have used triangular gradient profile description model. To de-haze generated HR image, we consider $t_0 = 0.1$ and ω is set to 0.95.The simulation is run on MATLAB r2013a, running on Windows 10 backed by Intel i5 processor. We compare the results of our technique with the results produced by reconstructing HR image alone.

The list of images used in testing is

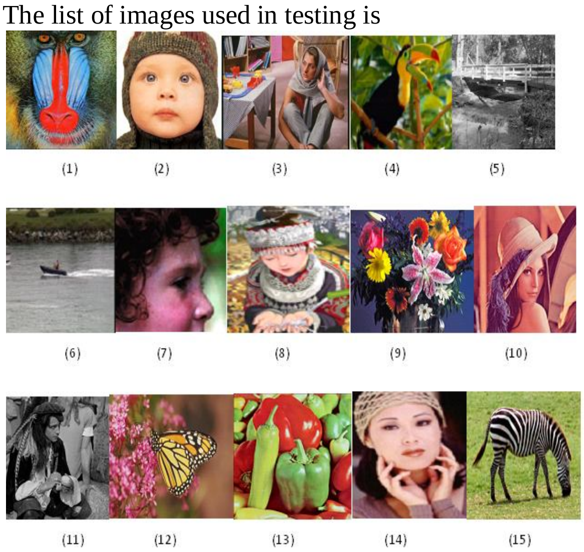

Fig 1: The input images taken to test our algorithm (1) Baboon, (2) Baby, (3) Barbara, (4) Bird, (5) Bridge, (6) Coastguard, (7) Face, (8) Comic, (9) Flowers, (10) Lena, (11) man, (12) Monarch, (13) Pepper, (14) Woman ,(15) Zebra

Their corresponding HR images are shown in figure 2

Fig 2: The HR images synthesized by our algorithm (1) Baboon, (2) Baby, (3) Barbara, (4) Bird, (5) Bridge, (6) Coastguard, (7) Face, (8) Comic, (9) Flowers, (10) Lena, (11) man, (12) Monarch, (13) Pepper, (14) Woman ,(15) Zebra

The merit of a SR technique is given by comparing the generated HR images with ground truth. The comparison can be done qualitatively and structurally. Picture to Signal Noise Ratio (PSNR), gives qualitative analysis and Structural Similarity index (SSIM), gives structural analysis. We now compare the values of PSNR and SSIM obtained only when HR reconstruction (using GPS transformation) is used and those values obtained when the de-hazing is also applied. They are tabulated in table (1) where, image number corresponds to the respective image mentioned in fig (1).

Table 1: comparison of PSNR and SSIM values (a) HR reconstruction without de-hazing (b) HR reconstruction with de-hazing

Image	(a) HR reconstruction without de-hazing		(b)HR reconstruction with de-hazing	
	PSNR	SSIM	PSNR	SSIM
1	23.45	0.8989	28.05	0.902
2	23.58	0.9047	29.01	0.9277
3	23.46	0.9269	29.84	0.9270
4	24.46	0.6837	30.80	0.7961
5	23.41	0.9355	26.22	0.9364
6	23.42	0.9238	27.84	0.9045
7	23.34	0.9394	27.21	0.9328
8	24.54	0.6636	27.93	0.6961
9	23.60	0.8359	26.47	0.8222
10	23.52	0.9264	25.78	0.8850
11	24.05	0.8470	27.74	0.8764
12	23.42	0.9413	24.18	0.9001
13	23.77	0.8797	29.75	0.8914
14	24.01	0.8172	24.91	0.8478
15	23.71	0.9436	29.54	0.9666

CONCLUSION

The proposed algorithm uses a haze removal technique to improve performance of SR. The images were enhanced both visually and structurally. It is worth mentioning that haze removal method is based on dark channel prior which may fail for images containing large sky regions. This work can be extended by using improved haze models and advanced priors like color attenuation prior.

REFERENCES

[1] Tsai and Huang R. Y. Tsai and T. S. Huang, "Multiframe image restoration and registration," tech. rep., Greenwich, CT, 1984.

[2] S. Mallat and G. Yu, "Super-resolution with sparse mixing estimators," IEEE Trans. Image Process., vol. 19, no. 11, pp. 2889–2900, Nov. 2010

[3] M. Ebrahimi and E. R. Vrscay, "Solving the inverse problem of image zooming using 'self-examples,"' in Image Analysis and Recognition. Berlin, Germany: Springer-Verlag, 2007, pp. 117–130.

[4] J. Sun, J. Sun, Z. Xu, and H.-Y. Shum, "Gradient profile priorand its applications in image super-resolution and enhancement,"IEEE Trans. Image Process., vol. 20, no. 6, pp. 1529–1542,Jun. 2011.

[5] Qing yan, Yi Xu Xiaokang Yang, Nguyen "Single image super resolution using gradient profile sharpness", IEEE Transactions on Image Processing.,vol.24 , no: 10 pp 3187-3202 19 march 2015.

[6] M. Ebrahimi and E. R. Vrscay, "Solving the inverse problem of image zooming using 'self-examples,"' in Image Analysis and Recognition. Berlin, Germany: Springer-Verlag, 2007, pp. 117–130.

[7] M. Bevilacqua, A. Roumy, C. Guillemot, and M.-L. Alberi Morel, "Single-image super-resolution via linear mapping of interpolated selfexamples," IEEE Trans. Image Process., vol. 23, no. 12, pp. 5334–5347, Dec. 2014.

[8] E. J. McCartney, Optics of the Atmosphere: Scattering by Molecules and Particles. New York, NY, USA: Wiley, 1976

[9] S. G. Narasimhan and S. K. Nayar, "Vision and the atmosphere," Int. J. Comput. Vis., vol. 48, no. 3, pp. 233–254, Jul. 2002.

[10] H. Kaiming, S. Jian, and T. Xiaoou, "Single image haze removal using dark channel prior," Processing of 2009 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2009, pp. 1956-1963.

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