GROUPLET-BASED COLOR IMAGE SUPER-RESOLUTION

Aldo Maalouf, and Mohamed Chaker Larabi

XLIM-SIC Laboratory, UMR CNRS 6172, University of Poitiers,
SP2MI-2 Bd Marie et Pierre Curie, PO Box 30179
86962 Futuroscope Chasseneuil, France
{maalouf, larabi}@sic.sp2mi.univ-poitiers.fr

ABSTRACT

This paper addresses the problem of generating a super-resolution (SR) image from a single multi-valued low-resolution (LR) input image. The main application in our case lies in the exploitation of the cinema or TV archives for projections in higher resolutions (HD, 2K, 4K). We approach this problem from the perspective of image geometry-oriented interpolation. First, the geometry of the LR image is obtained by computing the grouplet transform. The grouplet orthogonal bases, that were introduced by Mallat in [1], are constructed with a multiscale association field that groups pixels to take advantage of geometrical image regularities. These bases are used to define a grouplet-based structure tensor in order to capture the geometry and directional features of the LR color image. Then, the SR image is synthesized by an adaptive directional interpolation using the extracted geometric information to preserve sharpness of edges and textures. This is accomplished by the minimization of a functional which is defined on the extracted geometric parameters of the LR image and oriented by the geometric flow defined by the grouplet transform. The proposed super-resolution algorithm outperforms the state-of-the-art methods in terms of the visual quality of the interpolated image.

1. INTRODUCTION

Image super-resolution is the process of increasing the resolution of a given image. One such application to image super-resolution can be found in streaming video websites, which often store video at low resolutions (e.g. 352×288 pixels CIF format) for various reasons. The problem is that users often wish to expand the size of the video to watch at full screen with resolutions of 1024×768 or higher, and this process requires that the images be interpolated to the higher resolution. Another application comes from the emergence of HDTV displays. To better utilize the display technical prowess of the existing viewing devices, input signals coming from a low-resolution source must first be converted to higher resolutions through interpolation. Moreover, filmmakers today are increasingly turning towards an all-digital solution, from image capture to post-production and projection. Due to its fairly recent appearance, the digital cinema chain still suffers from limitations which can hamper the productivity and creativity of cinematographers and production companies. One of these limitations is that the cameras used for high resolutions are expensive and the data files they produce are large. Because of this, studios may chose to capture some sequences at lower resolution (2K for example). These sequences can later be interpolated to 4K sequences by using a super resolution technique and projected in higher resolution display devices.

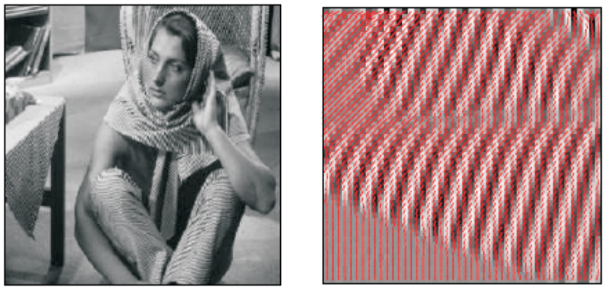
There are mainly three categories of approaches for this problem: interpolation based methods, reconstruction based methods, and learning based methods. The most common methods used in practice are the interpolation methods, such as bilinear and bicubic interpolation [2] [3], require only a small amount of computation. However, because they are based on an oversimplified slow varying image model, these simple methods often produce images with various problems along object boundaries, including aliasing, blurring, and zigzagging edges. The reconstruction based methods [4] [5] enforce a reconstruction constraint which requires that the smoothed and down-sampled version of the high resolution (HR) image should be close to the LR image. The learning based methods [6] [7] "hallucinate" high frequency details from a training set of HR/LR image pairs. The learning based approach highly relies on the similarity between the training set and the test set. It is still unclear how many training examples are sufficient for the generic images.

Meanwhile, various algorithms have been proposed to improve the interpolation-based approaches and reduce edge artifacts, aiming at obtaining images with regularity (i.e. smoothness) along edges. In one of the earliest papers on the subject, Jensen and Anastassiou [8] propose to estimate the orientation of each edge in the image by using projections onto an orthonormal basis and the interpolation process is modified to avoid interpolating across the edge. Allebach and Wong [9] propose to use an estimate of the high-resolution edge map to iteratively correct the interpolated pixels. Instead of explicitly estimating edges, Li and Orchard [2] propose a statistical estimation method that tunes interpolation coefficients according to local edge structures. While this method produces superior results, its computational complexity is prohibitive due to the large window size used to estimate local covariances. Improved interpolation methods have also been cast as a non-linear partial differential equation PDE problem, [10] where the algorithm attempts to satisfy smoothness and orientation constraints. Other methods have been proposed which perform interpolation in a transform (e.g. wavelet) domain [11] [12]. These algorithms assume the low-resolution image to be the lowpass output of the wavelet transform and utilize dependence across wavelet scales to predict the "missing" coefficients in the more detailed scales.

The above listed SR methods have been designed to increase the resolution of a single channel (monochromatic) image. To date, there is very little work addressing the problem of color SR. The typical solution involves applying monochromatic SR algorithms to each of the color channels independently [13] [14], while using the color information to improve the accuracy. Another approach is transforming the problem to a different color space, where chrominance layers are separated from luminance, and SR is applied only to the luminance channel [15]. Both of these methods are sub-optimal as they do not fully exploit the correlation across the color bands. Other methods using learning based techniques have been proposed for color image interpolation [16], yet results still depend on the training phase and the used dataset.

In this paper, we propose a novel variational color image interpolation algorithm based on the new grouplet transform [1] which provides an efficient multiscale geometric representation for natural images. The grouplet transform was proposed by Mallat as a directional multiresolution transform that can efficiently capture and represent boundaries and textures in natural images. Furthermore, it allows to define a geometrical flow that can be used to orient our interpolation technique. Having well represented the geometry of each color channel by using geometrical grouplets, we propose a grouplet-based structure tensor whose role is to couple the geometrical information of the different image color components. Then, a functional is defined on the multispectral geometry defined by this

This work was supported by the French National Research Agency (ANR) under the QuIAVU project.



(a) (b)

Figure 1: (a) Original image, (b) a zoom on the association field of the barbara image

structure tensor. The minimization of this functional insures the synthesize of the SR image.
The rest of the paper is organized as follows. Section 2 presents the grouplet transform and provides motivation for its use in our algorithm. In Section 3, we present our variational super-resolution algorithm. We report the results of our experiments in Section 4 and conclude the paper in Section 5.

2. GEOMETRICAL GROUPLETS

Geometrical grouplets have been recently introduced by Mallat in [1]. They are constructed with association fields that group points to take advantage of geometrical image regularities. We only present here a brief review of the Grouplet transform. The reader can refer to [1] for a full detailed description of the Grouplet transform.
Grouplet transform uses a multiscale association field in order to group together wavelet coefficients in the direction specified by the flow [1]. These recursive groupings allow to take into account junctions and long range regularities of images.
The geometrical grouplet transform is first computed by performing group matching on the 2D wavelet transform of the image in order to obtain the association field. The role of this field is to group together points that have similar neighborhoods in order to exploit the geometry of the image. The computation of the association field is performed as follows: First the image grid Ω is divided into two subgrids Ω_{even} (even columns) and Ω_{odd} (odd columns) then, each point in the odd subgrid is associated to a point in the even subgrid according to a block matching criteria (refer to [1]for more details). Then, a weighted Haar lifting is applied successively to points that are grouped by the association field. This iterative process decomposes the original image in an orthogonal basis called grouping basis. Consequently, at each step, the image is decomposed into a detail and an approximation image. An example of an association field computed on the Barbara image is shown in figure 1.
Compared to other geometrical representation, such as bandelet or curvelet transforms, the grouplet transform is more flexible since the association fields can deviate from the integral lines in order to converge to singularity points such as junction or crossings. Fine image structures are consequently well represented. Therefore, the interpolation of the represented information in the "missing" (or to be synthesized) pixels of the SR image following the directions of the association field yields to a precise synthesis of the SR image. We present in the following section this interpolation technique.

3. GROUPLET-BASED SUPER-RESOLUTION TECHNIQUE

Given that the image geometry is efficiently represented and characterized by the multiscale association field, we present in this section an interpolation method oriented by the captured geometry. First, we present our grouplet-based structure tensor and then, we describe our interpolation technique.

3.1 Grouplet-based structure tensor

Extending differential-based operations to color or multi-valued images is hindered by the multi-channel nature of color images. The derivatives in different channels can point in opposite directions, hence cancelation might occur by simple addition. The solution to this problem is given by the structure tensor for which opposing vectors reinforce each other.
In [17] Di Zenzo pointed out that the correct method to combine the first order derivative structure is by using a local tensor. Analysis of the shape of the tensor leads to an orientation and a gradient norm estimate. For a multichannel image $I = \left(I^1, I^2, \ldots\ldots, I^n\right)^T$ the structure tensor is given by

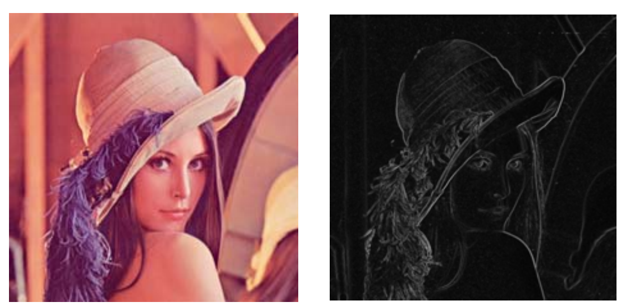
$$M = \begin{pmatrix} I_x^T I_x & I_x^T I_y \\ I_y^T I_x & I_y^T I_y \end{pmatrix} \quad (1)$$

where I_x and I_y are the horizontal and vertical derivatives respectively.

The multichannel structure tensor describes the 2D first order differential structure at a certain point in the image.
The motivation of this work is to make the interpolation oriented by the optimal geometry direction captured by the grouplet transform in order to synthesize fine structures for the SR image. For that purpose, a multiscale multistructure grouplet-oriented tensor for an m-valued ($m = 3$ for color images and $m = 1$ for gray images) image is defined by:

$$G^j = \begin{bmatrix} \sum_{i=1}^{m} \left(\frac{\partial}{\partial x} g_i^j \cos\theta_i\right)^2 & \sum_{i=1}^{m} \frac{\partial}{\partial x} g_i^j \cos\theta_i \frac{\partial}{\partial y} g_i^j \sin\theta_i \\ \sum_{i=1}^{m} \frac{\partial}{\partial x} g_i^j \cos\theta_i \frac{\partial}{\partial y} g_i^j \sin\theta_i & \sum_{i=1}^{m} \left(\frac{\partial}{\partial y} g_i^j \sin\theta_i\right)^2 \end{bmatrix}$$
$$for \quad i = 1, 2, \ldots.. m \quad (2)$$

The norm of G^j is defined in terms of its eigenvalues λ_+ and λ_-, $||G^j|| = \sqrt{\lambda_+ + \lambda_-}$. The angle θ_i represents the angle of the direction of the grouplet association field. j is the scale of the grouplet transform. g_i^j is the corresponding grouplet coefficient. i designates the image channel ($i = 1, 2, \ldots, m$). Figure 2 shows the norm of the grouplet-based structure tensor defined in (2) of the 'Lenna' image.



(a) Lenna Image (b) Norm of the structure tensor defined in (2)

Figure 2: Norm of the grouplet-based structure tensor

Until now, we have characterized edges and the geometrical flow (the association field) of the image. We present in the following subsection our super-resolution variational approach that is oriented by these two geometric features.

3.2 Super-Resolution

We formulate our interpolation approach as the following variational problem,

$$\tilde{I}_i = \min_{I_i} \left(\int_x \int_y \left(\left\| \tilde{\nabla} I_i(x,y) \right\| + \left\| \tilde{\nabla} G^j(x,y) \right\| + \lambda \left\| G^j(x,y) \right\| \right) dxdy \right) \tag{3}$$

subjected to the following constraints,

$$I_i(ms\Delta, ns\Delta) = I_i'(m,n) \qquad \begin{array}{l} 0 \le m \le \left\lfloor \frac{w}{s\Delta} \right\rfloor \\ 0 \le n \le \left\lfloor \frac{h}{s\Delta} \right\rfloor \end{array} \tag{4}$$

where $I_i'(m,n)$ is the original image before interpolation, Δ is the grid size of the upsampled image, w and h are the width and the hight of the image respectively and s is the scaling factor.
$\tilde{\nabla}$ is the directional gradient with respect to the grouplet geometric direction θ and λ is a constant.
The Euler equation of (3) is

$$\tilde{\nabla} \cdot \left(\frac{\tilde{\nabla} I_i(x,y)}{\left\| \tilde{\nabla} I_i(x,y) \right\|} + \frac{\tilde{\nabla} \left\| G^j(x,y) \right\|}{\left\| \tilde{\nabla} I_i(x,y) \right\|} \right) + \lambda \left\| G^j(x,y) \right\| \tag{5}$$

By expanding (5) we obtain after simplification,

$$\begin{aligned} & I_{i_{xx}} \cos^2\theta + I_{i_{yy}} \sin^2\theta - \left(I_{i_{xy}} + I_{i_{yx}} \right) \cos\theta \sin\theta + \\ & \quad \left\| G^j(x,y) \right\|_{xx} \cos^2\theta + \left\| G^j(x,y) \right\|_{yy} \sin^2\theta + \lambda \left\| G^j(x,y) \right\| = 0 \end{aligned} \tag{6}$$

where $\left\| G^j(x,y) \right\|_x$ and $\left\| G^j(x,y) \right\|_y$ are, respectively, the horizontal and vertical derivatives of the norm matrix $\left\| G^j(x,y) \right\|$ computed at a scale j to extract the horizontal and vertical details of the color image.
Equation (6), which yields to a factor-of-two interpolation scheme, is applied to each color band i and it can be easily discretized by using finite differences. By using equation (6) and solving for $I(m\Delta, n\Delta)$ (λ is set equal to 4), we obtain the final interpolating scheme on the upsampled grid (for simplicity $I(m,n)$ is used to denote $I(m\Delta, n\Delta)$):

$$\begin{aligned} I_i(x,y) = {} & \tfrac{1}{4} \left[I_i(x-1,y) + I_i(x+1,y) \right] \cos^2\theta + \\ & \tfrac{1}{4} \left[I_i(x,y-1) + I_i(x,y+1) \right] \sin^2\theta \; - \\ & \tfrac{1}{8} \left[I_i(x+1,y+1) + I_i(x-1,y-1) \right. \\ & \quad \left. - I_i(x-1,y+1) - I_i(x+1,y-1) \right] \cos\theta \sin\theta + \\ & \tfrac{1}{4} \left[\left\| G^j(x-1,y) \right\| + \left\| G^j(x+1,y) \right\| \right] \; \cos^2\theta + \\ & \tfrac{1}{4} \left[\left\| G^j(x,y-1) \right\| + \left\| G^j(x,y+1) \right\| \right] \; \sin^2\theta \end{aligned} \tag{7}$$

The process can be iterated with the resolution increased by a factor of two on each iteration. We represent in the following section some experimental results.

4. EXPERIMENTAL RESULTS

We perform experiments to validate our interpolation algorithm and compare it with existing ones. To achieve this, we compare our approach with the ones proposed by Li et al. in [2], Mueller et al. in [18] and Zhang et al. in [19]. These approaches are marginally applied to the color images.
We used several standard test images of size 512×512, including Lena, Peppers, Barbara and the opera house of Lyon (Fig.3). Due to the copyrights, we are unable to use digital cinema materials as an example in this paper. To show the true power of the interpolation algorithms, we first downsampled each image by a factor of four and then interpolated the result back to its original size. This provides a better comparison than a factor of two interpolation, and is well justified if one compares the ratio of NTSC scan lines (240 per frame) to state-of-the-art HDTV (1080 per frame), which is a factor of 4.5.

Figure 3: Image of the opera house of Lyon

We show in Figures 4, 5 and 6 the zoom-in comparisons of different algorithms on the test images. We can see that our algorithm outperforms the other interpolation schemes in every test image. Particularly, our algorithm is clearly superior to other super-resolution techniques, as it is able to better reconstruct the details of the image without distorting the smooth regions.

The quality of the SR images is also evaluated using $CIEDE2000$ color difference equations [20] [21]. The $CIEDE2000$ evolved from traditional colorimetry and color difference calculations is tested using several psychophysical datasets. The color differences between the original images and each of the SR images obtained using different interpolation schemes are shown in figures 7, 8 and 9 for Opera, Barbara and Lenna images respectively. Our grouplet-based approach showed the lowest color difference and therefore it approaches the original image more than the other interpolation techniques. Therefore, it respects the colorimetric characteristics of the original image.

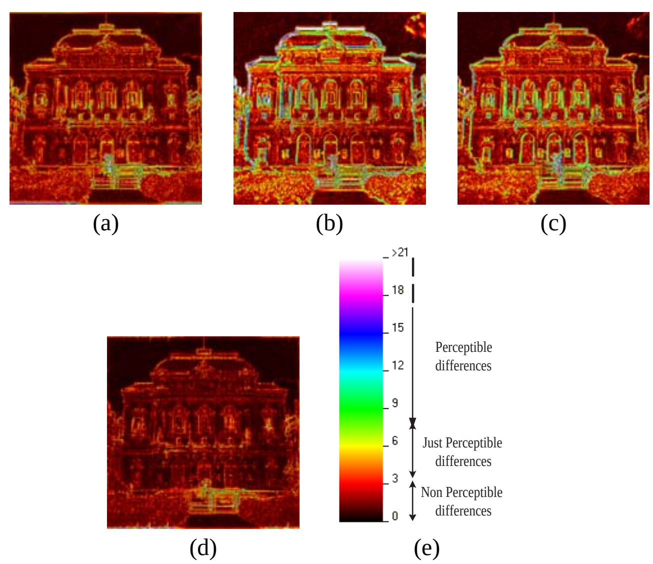


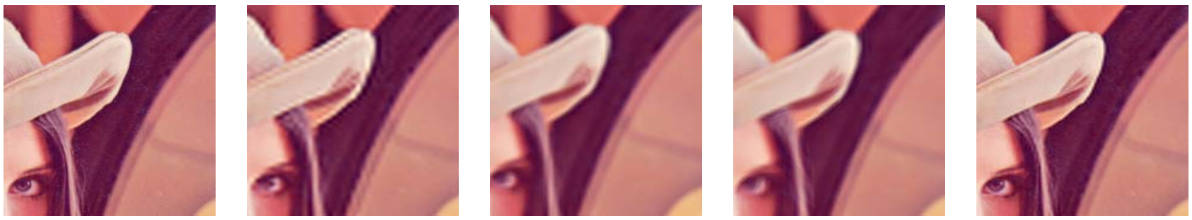
Figure 7: Color differences between the original image and the result obtained by using the method of (a) Mueller et al. [18], (b) Zhang et al. [19], (c) Li et al. [2] and (d) our approach

5. CONCLUSION

In this work, a grouplet-oriented color image interpolation technique is presented. First, the geometrical flow of the image is computed by using the grouplet transform. Then, a grouplet-based structure tensor is defined to couple geometric information of the

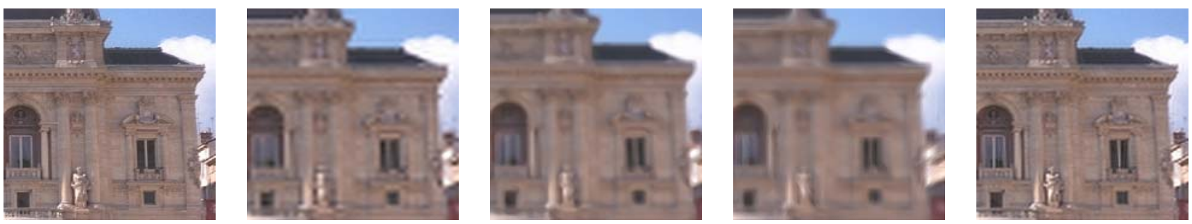
(a) (b) (c) (d) (e)

Figure 4: (a) original image, results obtained by using the methods proposed by: (b) Mueller et al. [18], (c) Zhang et al. [19], (d) Li et al. [2] and (e) our approach



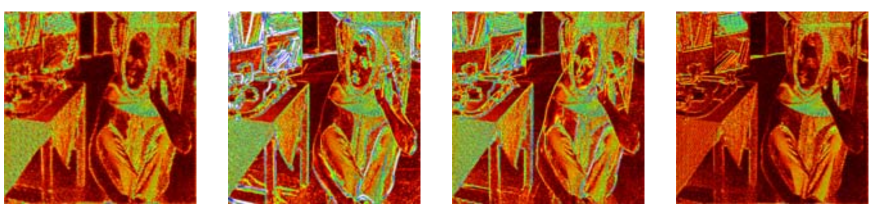
(a) (b) (c) (d) (e)

Figure 5: (a) original image, results obtained by using the methods proposed by: (b) Mueller et al. [18], (c) Zhang et al. [19], (d) Li et al. [2] and (e) our approach



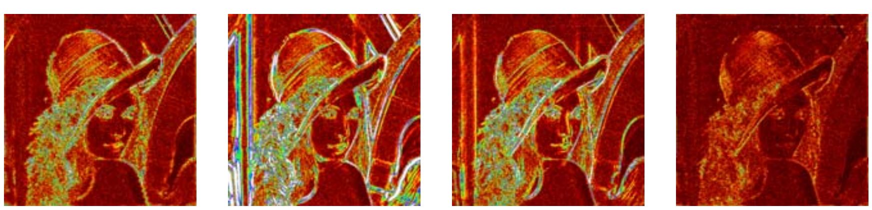
(a) (b) (c) (d) (e)

Figure 6: (a) original image, results obtained by using the methods proposed by: (b) Mueller et al. [18], (c) Zhang et al. [19], (d) Li et al. [2] and (e) our approach



(a) (b) (c) (d)

Figure 8: Color differences between the original image and the result obtained by using the method of (a) Mueller et al. [18], (b) Zhang et al. [19], (c) Li et al. [2] and (d) our approach



(a) (b) (c) (d)

Figure 9: Color differences between the original image and the result obtained by using the method of (a) Mueller et al. [18], (b) Zhang et al. [19], (c) Li et al. [2] and (d) our approach

different color channels of the image. A variational approach is finally defined on the captured geometry. The minimization of the proposed functional ensures the synthesize of the SR image. We have shown improvement over existing geometrically driven interpolation techniques on a subjective scale, and in many cases with an improvement in color difference. In a future work, we intend to subjectively assess the quality of our SR technique.

REFERENCES

[1] Stephane Mallat, "Geometrical grouplets," *Applied and Computational Harmonic Analysis*, 2008.

[2] X. Li and M. T. Orchard, "New edge-directed interpolation," *IEEE transactions on Image Processing*, 10, 10, pp. 1521-1527, 2001.

[3] P. Thevenaz, T. Blu, and M. Unser, *Image Interpolation and Resampling*. Handbook of Medical Imaging, Processing and Analysis, Academic Press, San Diego, USA, 2000.

[4] S. Baker and T. Kanade, "Limits on super-resolution and how to break them," *IEEE Trans. on PAMI*, 24, 9, pp. 1167-1183, 2002.

[5] M. Ben-Ezra, Z. C. Lin, and B. Wilburn, "Penrose pixels: Superresolution in the detector layout domain," in *Proc. ICCV 2007*, 2007.

[6] C. Liu, H. Y. Shum, and W. T. Freeman, "Face hallucination: Theory and practice," *International Journal of Computer Vision*, 75, 1, pp. 115-134, 2007.

[7] Q. Wang, X. Tang, and H. Y. Shum, "Patch based blind image super resolution," in *Proc. ICCV 2005*, 1, pp. 709-716, 2005.

[8] K. Jensen and D. Anastassiou, "Subpixel edge localization and the interpolation of still images," *IEEE transactions on Image Processing*, 4, pp. 285-295, 1995.

[9] J. Allebach and P. W. Wong, "Edge-Directed interpolation," in *Proc. IEEE Int. Conf. on Image Proc.*, 1996.

[10] H. Jiang and C. Moloney, "A new direction adaptive scheme for image interpolation," in *Proc. IEEE Int. Conf. on Image Proc.*, pp. 369-372, 2002.

[11] W. K. Carey, D. B. Chang, and S. S. Hermami, "Regularity-preserving image interpolation," in *Proc. IEEE Int. Conf. on Image Proc.*, pp. 1293-1297, 1999.

[12] D. D. Muresan and T. W. Parks, "Prediction of image detail," in *Proc. IEEE Int. Conf. on Image Proc.*, pp. 323-326, 2000.

[13] N. R. Shah and A. Zakhor, "Resolution enhancement of color video sequence," *IEEE transactions on Image Processing*, 6, 8, pp. 879-885, 1999.

[14] B. C. Tom and A. Katsaggelos, "Resolution enhancement of monochrome and color video using motion compensation," *IEEE transactions on Image Processing*, 2, 10, pp. 278-287, 2001.

[15] M. Irani and S. Peleg, "Improving resolution by image registration," in *CVGIP:Graph. Models Image Process.*, 53, pp. 231-239, 1991.

[16] Karl S. Ni, Truong Q. Nguyen, "Color Image Superesolution Based on a Stochastic Combinational Classification-Regression Algorithm," in *Proc. IEEE Int. Conf. on Image Proc.*, pp. 89-92, 2007.

[17] DiZenzo S., "A note on the gradient of multi images," *Computer Vision Graphics and Image processing*, vol. 33 (1), pp. 116–125, 1986.

[18] Mueller Nickolaus, Lu Yue, Do Minh N., "Image interpolation using multiscale geometric representations, " in *Proceedings of the SPIE, Computational Imaging V*, vol. 6498, pp 64980A, 2007.

[19] L. Zhang and X. Wu, "An edge guided image interpolation algorithm via directional filtering and data fusion", *IEEE transactions on Image Processing*, 15, pp 2226-2238, 2006.

[20] G. M. Johnson and M. D. Fairchild, "A top down description of S-CIELAB and CIEDE2000," *Color Res. Appl.*, vol. 27, 2002.

[21] G. Sharma, W. Wu and E. D. Dalal, "The CIEDE2000 color difference formula: Implementations notes, supplementary test data and mathematical observations," *Color Res. Appl.*, 2004.