Stitching Line and Deformation Propagation for Seamless Image Stitching

Chunxiao Bian, Chuangbai Xiao, Huiqin Xi, Yi Liu
College of Computer Science and Technology, Beijing University of Technology
Beijing, 100124, China
bianchunxiao1@163.com, cbxiao@bjut.edu.cn,
liuyiwin@gmail.com

ABSTRACT

This paper presents an approach to determine the optimal stitching line and propagate deformation in irregular overlap for image stitching. First, determine the optimal stitching line that has the lowest cost of some candidate lines in the irregular region; second, detect and match the features in the neighborhood of the optimal stitching line and calculate deformation vectors; finally, spread the deformation vectors to the whole of image region by Poisson equation and constitute the image gradient field that can reconstruct seamless mosaic. This method has no limitation to the shape of the overlapping area so can reduce the juncture of structure and color in the stitching images. Compared with other methods this method can achieve better visual results both in structure and color.

Categories and Subject Descriptors

I.4. [**Image Processing and Computer Vision**]: Scene Analysis – *sensor fusion*

General Terms

Algorithms

Keywords

Main direction; optimal stitching line; deformation propagation; gradient filed

1. INTRODUCTION

Recently image stitching being a research focus in the field of computer view is widely used in satellite photos, expanding the camera resolution and vision, video compression and retrieval, and image repair. The purpose of the image stitching is to form a visually acceptable panoramic image and naturally transit in structure and color. Image stitching including two main seams: one is color seam, the difference of brightness or color caused by shooting time and light; the other is structure seam that due to the structure misalignment or fracture.

To generate a satisfactory stitching image, a natural transition in color and structure between two images is required. In recent years, some scholars and research institutions put forward lots of methods to eliminate color seam. Szeliski and Shum [1] based on feather through using distance to average the weight. Uyttendaele [2] added interpolating function to reduce the difference of color. According to feather, Wood [3] introduced Vornoi graph to determine the pixels in the stitching region should be selected from which image. Although feather can decrease the contrast at the same time it can easily cause fuzzy and ghost. Multi-resolution spline blending can also solve color seam such as: Burt [4] putting forward Laplacian pyramid to blend color, Su[5]using wavelet domain to blend, Sevcencoa [6] proposing haar wavelet to reduce color difference.

Optimal seam [7] is also applied to stitch image; the ideal of this method is to look for a stitching line that can make the difference of color minimum in the overlapping region. Some methods used to get the line, as following: Efros [8] using dynamic programming to search the least gray difference, Kwatra [9] coming up to graph cut to determine the optimal seam.

Currently the mainstream method of image stitching is to process global image in gradient domain. Perez [10] provided Poisson blending that has better effect to color seam, but cannot handle structure misalignment. Morel [11] put Fourier transform and Poisson editor together to fusion image. Jia [12,13] and Ge [14] used the information of gradient domain to deform in structure and color, while this method has a high demand on the accuracy of feature points near the stitching line. Levin [15] proposed an effective method using the gradient strength in the overlapping region, however this method is suitable for the difference on color not structure. Han et al [16] proposed a smooth image pyramid from images which have been stitched at some scales to hide unnatural transitions when enlarge the images. This method converses the color and structure of the two images, so it need images have similar content at different levels to produce plausible results.

Our work is similar to the approach of Jia et al [12]. They aimed at searching the stitching line at the regular overlapping region and matching feature points in the stitching line, without taking the irregular region and matching points off the stitching line into consideration. We have solved these limitations. First stitching line can obtain in any shape of overlapping region, second the feature points are matched at the neighboring of the stitching line. And another improvement to Jia method is using the information of edge to propagate the deformation to make the edge and color can smoothly transfer. The rest of the paper is organized as follow: section 2 introduces how to get the optimal stitching line; section 3 is deformation propagation and image construction; in section 4 results and comparisons with other methods are given. Conclude this paper in section 5.

IVCNZ '12, November 26 - 28 2012, Dunedin, New Zealand.

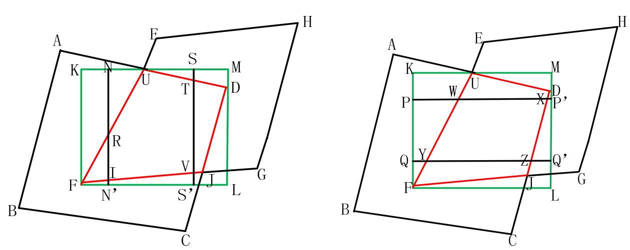
2. THE OPTIMAL STITCHING LINE

Using stitching line to stitch images first proposed by Jia [12], then some improvements were put forward by Jia [13] and Ge [14]. However these methods should make sure that the overlapping region is rectangular, while the overlapping region is almost irregular after matching two images. So this paper proposes a method to get the optimal stitching line in any shape of the overlapping region. Using three steps to get the line: determine the direction of the main cut line, search the initial points and choose the optimal stitching line.

2.1 The Main Direction of Line

The main direction of overlapping region is either vertical or horizontal. The source image is I_s and the target image is I_t, $I = I_s + I_t$, using the Sobel masks S_1, S_2(1) to calculate the gradient of vertical and horizontal direction. In Figure 1(a) the overlapping quadrangle of the two images is UFDJ, the smallest rectangle covering the UFDJ is KFLM, the middle part of the rectangle KFLM is $NN'S'S$ with $NS = \frac{2}{3}KM$, the common region of the overlapping and $NN'S'S$ is quadrangle UVIRT, label $\bigtriangledown_x I^a$ and $\bigtriangledown_y I^a$ as the horizontal and vertical gradient value in quadrangle UVIRT of Figure 1(a). Almost the same with Figure 1(a), $\bigtriangledown_x I^b$ and $\bigtriangledown_y I^b$ are the horizontal and vertical gradient in quadrangle WYZJX of Figure 1(b). Then by setting threshold T, define N_x^AandN_y^A, $A \in \{a\ , b\}$ to be the number of the pixel whose gradient values are larger than T. If $N_x^a < N_y^a$ and $N_x^b < N_y^b$, the main direction of stitching line is horizontal, as Figure 1(a); if $N_x^a > N_y^a$ and $N_x^b > N_y^b$, the main direction is vertical, as Figure 1(b); if the two above cases cannot be satisfied, comparing $\frac{N_x^a}{N_x^a+N_y^a}$and $\frac{N_y^b}{N_x^b+N_y^b}$, if $\frac{N_x^a}{N_x^a+N_y^a} \geqslant \frac{N_y^b}{N_x^b+N_y^b}$ the main direction is horizontal, otherwise the main direction is vertical.

$$S_1 = \begin{bmatrix} 1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \quad S_2 = \begin{bmatrix} 1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{1}$$

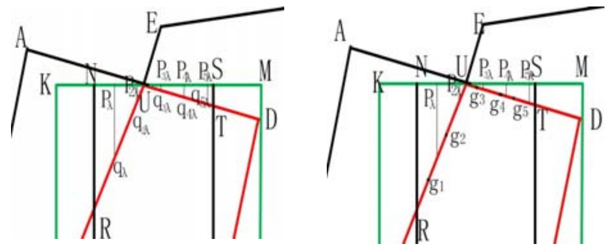


(a) the vertical main line **(b)the horizontal main line**

Figure 1.the main direction of stitching line

2.2 The Initial Points of Stitching Line

In order to get the optimal stitching line Jia and Ge applied dynamic programming and shortest path, which led to large calculation amount. To save calculation time and get the optimal stitching line in any shape of overlapping region, this paper proposes a new method: first looking for a group of initial points, then growing a group of lines based on these points, last choosing the optimal line from these lines. Determine five points as the initial points on the top of the edge (in Figure 1 the top edge is UT and UR). We label the coordinate of S, N, U as (X_s, Y_s),(X_n, Y_n) and (X_u, Y_u) and we know from Figure 1 the three points have the same y-coordinate. Define $\lambda = round(\frac{X_s - X_n}{10})$ and denote the coordinate of P_n on the edge of NS as (X_{pn}, Y_{pn}), $X_{pn} = X_n + 2\lambda + n$, $n = 0 - 5\lambda$, $Y_{pn} = Y_n$. The point with coordinate (X_{qn}, Y_{qn}) is the projection of p_n on the edge of UR and UT, as show in Figure 2(a) (Figure 2 is local enlargement of Figure 1). Then we define the



(a)map to overlapping region **(b) five initial points**

Figure 2. Enlargement view of Fig. 1

gradient alignment cost of $q_n$as:

$$C(q_n) = (1-\beta)C_g(q_n) + \beta C_d(q_n), 0 \leqslant \beta \leqslant 1 \tag{2}$$

β is a weight used to balance the relative influence of the two cost setting to be 0.3; $C_g(q_n)$, $C_d(q_n)$ measure the gradient smoothness and similarity. $C_g(q_n)$and $C_d(q_n)$ can be calculated as follow:

$$\begin{aligned} C_g(q_n) &= \sum_{i=-1}^{i=1}\sum_{j=-1}^{j=1} \bigtriangledown I_s(X_{qn}+i, Y_{qn}+j) + \sum_{i=-1}^{i=1}\sum_{j=-1}^{j=1} \bigtriangledown I_t(X_{qn}+i, Y_{qn}+j) \\ &= \sum_{i=-1}^{i=1}\sum_{j=-1}^{j=1} \sqrt{\sum_{p=1}^{p=2} |I_s(X_{qn}+i, Y_{qn}+j) * S_p|^2} \\ &+ \sum_{i=-1}^{i=1}\sum_{j=-1}^{j=1} \sqrt{\sum_{p=1}^{p=2} |I_t(X_{qn}+i, Y_{qn}+j) * S_p|^2} \end{aligned} \tag{3}$$

$$\begin{aligned} C_g(q_n) &= \sum_{i=-1}^{i=1}\sum_{j=-1}^{j=1} \|(I_s(X_{qn}+i, Y_{qn}+j) - I_t(X_{qn}+i, Y_{qn}+j)) * S_1\| \\ &+ \sum_{i=-1}^{i=1}\sum_{j=-1}^{j=1} \|(I_s(X_{qn}+i, Y_{qn}+j) - I_t(X_{qn}+i, Y_{qn}+j)) * S_2\| \end{aligned} \tag{4}$$

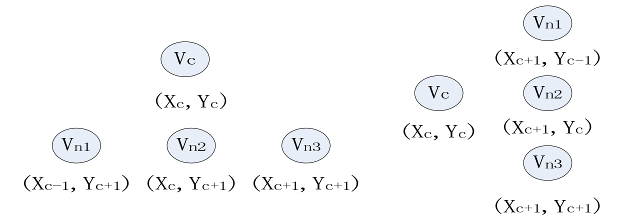
When it is a color image, we should deal with R, G, B three channels respectively.

The final aim is to determine five initial points, so we set all points into five groups based on (5), $m = 1 - 5$. The initial point g_m is the minimum cost of each group, so we get five points $(g_1, g_2, g_3, g_4, g_5)$ as show in Figure 2(b).

$$\varphi_m = \{q_n, n = (m-1)\lambda + 1, (m-1)\lambda + 2, \cdots, m\lambda\} \tag{5}$$

2.3 Confirm Optimal Stitching Line

Firstly grow five lines based on the five initial points, then choose a line with the minimum cost value as the optimal stitching line. The five lines start from five points g_1, g_2, g_3, g_4, g_5 in Figure 2(b). The current point is V_c with coordinate(X_c, Y_c), the next point isV_n with coordinate(X_n, Y_n), V_n chosen fromV_{n1}, V_{n2}, V_{n3}. If the main direction is vertical the candidateV_{n1},V_{n2},V_{n3} with coordinate $(X_c - 1, Y_c + 1)$, $(X_c, Y_c + 1)$, $(X_c + 1, Y_c + 1)$ shown in Figure 3(a). The Figure 3(b) shows the horizontal candidate. Determining the next point V_n requests to calculate the gradient alignment cost of V_{n1}, V_{n2}, V_{n3}, respectively denoted as $A(V_1), A(V_2)$ and $A(V_3)$ by using the equation of (6). $C(V_{ej})$ can be calculated by use of (2)and $j = 1 - 9$ are the neighboring of the three candidates



(a)main direction is vertical (b)main direction is horizontal

Figure 3. Next point to grow

V_{n1}, V_{n2}, V_{n3} as shown in Figure 4. The V_{e4}, V_{e5}, V_{e6} in Figure 4 are equal to the points V_{n1}, V_{n2}, V_{n3} in Figure 3(a). The coordinate of the points V_{ej} in Figure 4 is $(X_c - 4 + j, Y_c + 1)$. Which point should be chosen as next point is determined by (7). V_n should have the minimum gradient cost, if two points having the same value, the priority of point selected is V_{n2},V_{n1} and V_{n3}.

$$A(V_1) = \sum_{j=1}^{j=7} C(V_{ej}); A(V_2) = \sum_{j=2}^{j=8} C(V_{ej}) \quad (6)$$

$$A(V_3) = \sum_{j=3}^{j=9} C(V_{ej})$$

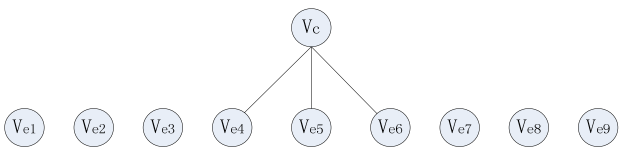


Figure 4. Evaluate of accumulates costs of next points

$$V_n = \begin{cases} V_{n2} & \mathrm{A(V}_{n2}) \leqslant \min\{A(V_{n1}), A(V_{n3})\} \\ V_{n3} & \mathrm{A(V}_{n3}) < \min\{A(V_{n1}), A(V_{n2})\} \\ V_{n1} & \text{otherwise} \end{cases} \quad (7)$$

Now five lines have been calculated by an iterative operator; next we should choose the optimal one according to (8). $m = 1 - 5$ on behalf of five stitching lines ,J_m is the total number of pixels in the mth stitching line,$V_n(m, j)$denoting the jth points in the mth stitching line.

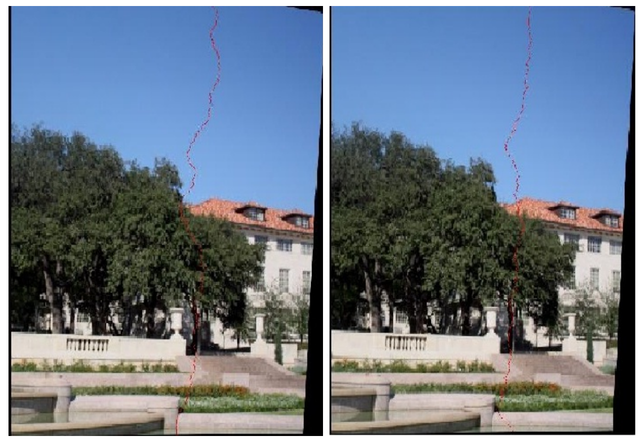
$$L(m) = \frac{\sum_{j=1}^{j=j_m} A(V_n(m, j))}{j_m} \quad (8)$$

The line with the minimum $L(m)$ is the optimal one. As neighboring pixels of the points are involved when calculates the stitching line, which makes the stitching line through the smooth region of the image as far as possible, and lays foundation for image fusion. The stitching line in Figure 5(a) is calculated by our method, Figure 5(b) is the result of Jia. In calculation of the gradient alignment, the two methods both consider smoothness and similarity of the gradient, but our method involves more neighborhood information, so it can more smoothly cross the region. The average search stitching line time of our method is 1.03ms; Jia using shortest path time is 2.24ms; Ge using dynamic programming time is 2.07ms, the size of the image 1058×799.

3. DEFORMATION PROPAGATION AND IMAGE CONSTRUCTION

3.1 Detecting and Matching Feature Points

Although the matching has been done when getting the overlapping region of the two images, the transform matrix cannot reflect the local deformation of the image. So if the two images directly stitched, some structural dislocation, fussy and fracture will be generated in the stitching edge. Based on the above problems, Jia and Ge detected and matched feature points on the



(a)our method's line (b)Jia method's line

Figure 5. Contrast of the two methods

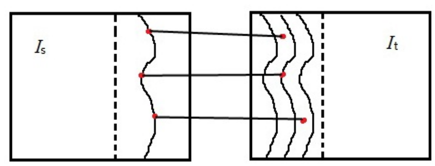


Figure 6. Feature detection and matching

stitching line, while our method is different in source image $I_s$and target image I_t. We detect feature points on the stitching line in source image I_s, while detect feature points on the ε neighboring of stitching line in target image I_t as show in Figure 6 The set $\{p_s^1, p_s^2, p_s^3, \cdots, p_s^n\}$ and $\{p_t^1, p_t^2, p_t^3, \cdots, p_t^m\}$ denote the features detected from I_s and I_t. This paper uses SURF to describe the feature and matches the feature with neighboring detection and second nearest neighbor distances. The specific method as follow:

(1) Calculate the SURF feature description for every point..

(2) Define the point p_s^iin set of $\{p_s^1, p_s^2, p_s^3, \cdots, p_s^n\}$ to be the centre of circle, denoting the neighboring of radius r as $O(P_s^i)$, and search the point from the set of $\{p_t^1, p_t^2, p_t^3, \cdots, p_t^m\}$ which locate in $O(P_s^i)$ as one of points consisting the set of $\{P_t^i\}$.

(3) Calculation the Euclidean distance of the point P_s^i and every point of $\{P_t^i\}$denote as $dis(P_s^i, P_t^j)$; $Ratio(P_s^i, P_t^j)$ is the ratio of the minimum distance and the second smallest distance. If $Ratio(P_s^i, P_t^j) \leqslant Thre$, points P_s^i and P_t^j are matching points. Delete P_s^i and P_t^j from corresponding sets.

(4) Repeat 1-3, until the set $\{p_s^1, p_s^2, p_s^3, \cdots, p_s^n\}$ is empty.

3.2 Get and Propagate Deformation Vector

3.2.1 Deformation vector

To make the structure and color smoothly transit from I_s to I_t, every pixel in I_t need a deformation vector denoting the deformation of structure and color. Suppose the matching points $(P_s^i, P_t^j)$the deformation vector as:

$$V(P_t^j) = \{V_x(P_t^j), V_y(P_t^j), V_{\bigtriangledown x}(P_t^j), V_{\bigtriangledown y}(P_t^j)\} \qquad (9)$$

V_x and V_y are the change value of x and y components from I_s to I_t in the image space as show in Figure 7 $V_{\bigtriangledown x}$ and $V_{\bigtriangledown y}$ are the difference of the gradient value between P_s^i and P_t^j, and are calculated as:

$$V_{\bigtriangledown h} = \bigtriangledown_h I_s(P_s^i) - \bigtriangledown_h I_s(P_s^i), h \in \{x, y\} \qquad (10)$$

Gradient approximates use the forward difference method. When they are color images, three channels have the same calculation way, so $V(P_t^j)$ is an eight dimension vector.

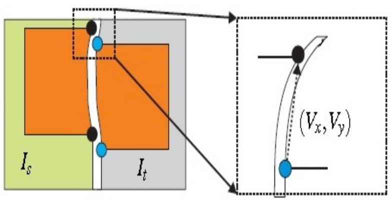


Figure 7 Structure deformation

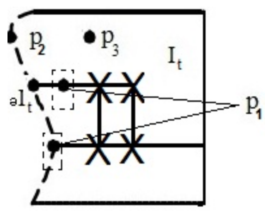


Figure 8 Deformation propagation

3.2.2 Deformation Propagation

After getting the deformation vector of the feature point, we need smoothly spread it to the rest of the target image region. Compared with color, human are more sensitive to the smooth of an edge, so choose edge as the structure feature. We use JSEG [17] to get the obvious feature and make sure that every matching point should associate with only one edge. In order to determine the associated edge, we should track the edge from matching point p. When faced with the curve crossing point, we should check the next point of the crossing, select the point with smallest change in curvature as the next point and track block the points with other directions shown in Figure 8 '×'. As show in Figure 8, I_t being the target region, ∂I_t denoting the inner of the edge (in Figure 8 the dotted line),$p \in I_t$, we consider the deformation vector under the following three situations:

(1) p is the matching feature point or the associated edge (P_1 in Fig. 8). The deformation vector has been calculated by (9*)*

(2) P is not the matching feature point in the inner edge (P_2 in Fig. 8), using Neumann edge condition:$\bigtriangledown V(P) = 0$.

(3) P is inside of I_t, the deformation vector unknown, so the deformation propagation is needed.

Therefore, in order to smoothly propagate the deformation vector to the rest of pixels in the image I_t, we should make sure the (11) has the minimum value.

$$V^* = argmin \iint_{p \in I_t} \|\bigtriangledown V\|^2 \, dp \qquad (11)$$

The gradient value $\bigtriangledown$ should be calculated for the every component of vector V, (11) equality of Laplace equation:

$$\triangle V = 0, \forall p \in I_t, with V|_{\partial I_t} = V^*|_{\partial I_t} \qquad (12)$$

The Laplace equation is the special situation of Poisson equation, so we can use the over relaxation iteration method with Chebyshev accelerated to reduce the calculation time. Now we can get the deformation vector for every pixel in image I_t, then use the deformation vector perform an inverse mapping with the nearest interpolation to get the gradient G_t of image I_t.

3.3 Image Reconstruction

Reconstruction image I_t using gradient G_t, the method is similar to[10]. The minimum value of   is the minimum of the color in image I_t (if the image is color, we should have the same way to three channels).

$$V^* = argmin \iint_{p \in I_t} \|\bigtriangledown I_t - G_t\|^2 \, dp \qquad (13)$$

Equal to Poisson equation:

$$\triangle I_t = \bigtriangledown G_t, \forall p \in I_t \qquad (14)$$

$\bigtriangledown G_t = \frac{\partial u_t}{\partial x} + \frac{\partial v_t}{\partial y}$ is the divergence of gradient $G_t = (u_t, v_t)$. We also can use the over relaxation iteration method with Chebyshev accelerated to get the result.

4. EXPERIMENTAL RESULTS

There are three improvements between our method and Jia: first the optimal stitching line can more smoothly cross the image, second using SURF to detect and match feature points, third using JSEG to propagate deformation We use two groups of experiments to demonstrate the effectiveness of our method. The first group shows in Figure 9(a),(b) we choose two images with great difference in color. (c) (d) (e) (f) are the local of the result. (c) is the optimal seam[7] result where exists obvious stitching seam in structure and color. The edge of pool and tree have large structure misalignment (as shown in red rectangle), at the same time the color has little transition between two images. (d) is the result obtained by feathering [1]where the structure misalignment has been reduced, while producing some fuzzy in stitching image and some ghost appearing in branch (in red rectangle). The GIST1 [15]result is shown in (e). The difference of color has a great improvement, while there are still some structure dislocation for example the dislocation in edge of pool and building (shown in red rectangle). (f) shows the result of Jia [12]where the color fusion is very good. As the matching points are not very accurate and the principle of deformation propagation, so there still exists some little structure misalignment in pool and building (shown in red rectangle). (g) is the result of our method. Both the structure and the color have better results and the transition is very natural in the neighboring of the stitching line.

Our method can also deal with some unconventional image stitching with arbitrary overlapping region. We compare our method to some other methods using two images from Jia. Only an input image is used in Figure 10(a), and the lower brush need to align with the upper one, having the mask drawn with yellow region in Figure 10(b). (c) is the optimal seam. Not only the structure but the color is not alignment. (d) is the result of feathering, structure dislocation can be found. (e) is the result of GIST1 where some misalignment exists in structure.(f) is the result of passion blending. (g) shows the result of Jia where the color can get better fusion, while the unnatural transition still exists in structure. (h) is the result of our method that comparing with Jia, the transition in structure is more natural.

5. CONCLUSIONS

This paper gives a method of obtaining the optimal stitching line in irregular overlapping region and propagating the deformation to generate a visually acceptable image. This method can avoid the feature detection and eliminate the stitching seam in structure and color. This paper has three innovations. First, proposes a method to obtain the optimal stitching line in irregular overlapping region. Second, enlarge the range from stitching line to its neighboring to detect the feature, and use the SURF and ratio of the second nearest distances to determine the matching points. Third, presents associated edge to make more points have the initial deformation, so the propagating is more fast and accurate. We can conclude from some experiments that our method has a better result in structure and color, and running time also has a great improvement.

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

(e) **(f)** **(g)**

Figure 9 Building

The Figure 9 (a) and (b) are two input images. (c) is the result of optimal seam[7] used to stitch image. (d) is the result of [1], using feather to reduce the difference of color. (e) the result of GIST1 [15], the color difference has great improvement compare with (c) and (d). (f) is the result of Jia's [12], where the color stitching is visual acceptable. (g) is result of our method, having good result in structure and color.

6. REFERENCES

[1] R. Szeliski and S. Heung-Yeung, Creating full view panoramic image mosaics and environment maps. *in Proceedings of 24th International Conference on Computer Graphics and Interactive Techniques, 3-8 Aug. 1997,* New York, NY, USA, 1997, pp. 251-8.

[2] M. Uyttendaele, A. Eden and R. Skeliski, "Eliminating ghosting and exposure artifacts in image mosaics," in *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001, 8-14 Dec. 2001,* Los Alamitos, CA, USA, 2001, pp. 509-16

[3] D. N. Wood, A. Finkelstein, J. F. Hughes, C. E. Thayer, and D. H. Salesin, "Multiperspective panoramas for cel animation," in *Proceedings of 24th International Conference on Computer Graphics and Interactive Techniques, 3-8 Aug. 1997*, New York, NY, USA, 1997, pp. 243-50.

[4] P. J. Burt and E. H. Adelson, "A multiresolution spline with application to image mosaics," *ACM Transactions on Graphics,* vol. 2, pp. 217-36, 1983.

[5] S. Ming-Shing, H. Wen-Liang and C. Kuo-Young, "Analysis on multiresolution mosaic images," *IEEE Transactions on Image Processing,* vol. 13, pp. 952-9, 2004.

[6] I. S. Sevcenco, P. J. Hampton and P. Agathoklis, "Seamless stitching of images based on a Haar wavelet 2D integration method," in *2011 17th International Conference on Digital Signal Processing (DSP 2011), 6-8 July 2011*, Piscataway, NJ, USA, 2011, p. 6 pp.

[7] J. Davis, "Mosaics of scenes with moving objects," in *Proceedings 1998 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 23-25 June 1998*, Los Alamitos, CA, USA, 1998, pp. 354-60

[8] A. A. Efros and W. T. "Freeman, Image quilting for texture synthesis and transfer" in *Computer Graphics Annual Conference (SIGGRAPH 2001), August 12, 2001 - August 17, 2001,* Los Angeles, CA, United states, 2001, pp. 341-346.

[9] V. Kwatra, A. Schodl, I. Essa, G. Turk, and A. Bobick, "Graphcut textures: image and video synthesis using graph cuts," *in ACM Transactions on Graphics ACM SIGGRAPH 2003, 27-31 July* 2003, USA, 2003, pp. 277-86

[10] P. Perez, M. Gangnet and A. Blake, "Poisson image editing," *in ACM SIGGRAPH 2003, July 27, 2003 - July 31,* San Diego, CA, United states, 2003, pp. 313-318.

[11] J. M. Morel, A. B. Petro and C. Sbert, "Fourier implementation of Poisson image editing," *Pattern Recognition Letters, vol. 33,* pp. 342-348, 2012.

[12] J. Jia and C. Tang, "Eliminating structure and intensity misalignment in image stitching," *in Proceedings - 10th IEEE International Conference on Computer Vision, ICCV 2005, October 17, 2005 - October 20,* 2005, Beijing, China, 2005, pp. 1651-1658.

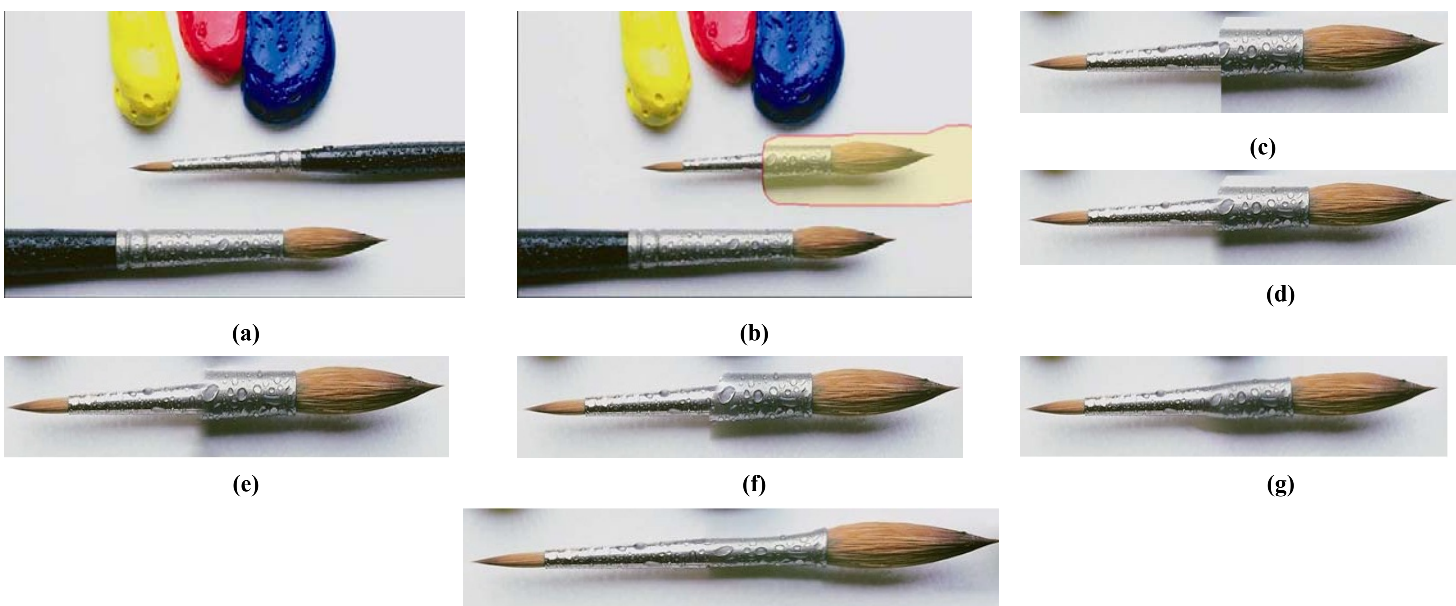
[13] J. Jia and C. Tang, "Image stitching using structure deformation," *IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30,* pp. 617-631, 2008.

[14] Ge Shi-ming, Cheng Yi-min,Zeng Dan and He Bing-bing. "Sparse Feature Matching and Deformation Propagation for Seamless Image Stitching," *Journal of Electronics & Information technology,* pp. 2795-2799, 2007.

[15] A. Zomet, A. Levin, S. Peleg, and Y. Weiss, "Seamless image stitching by minimizing false edges," *IEEE Transactions on Image Processing, vol. 15,* pp. 969-77, 2006.

[16] C. Han and H. Hoppe, "Optimizing continuity in multiscale imagery," *in ACM SIGGRAPH Asia 2010, SIGGRAPH Asia 2010, December 15, 2010 - December 18,* 2010, Seoul, Korea, Republic of, 2010, p. Disney Research; Microsoft Asia; Autodesk.

[17] Y. Deng and B. S. Manjunath, "Unsupervised segmentation of color-texture regions in images and video," *IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23,* pp. 800-10, 2001



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 10 Brush

(a) is the input image, and (b) copy the lower brush to the upper one. (c) optimal seam result. (d) feather result .(e) is the result of GIST1. (f) Poisson blending (g) shows the result of Jia's method. (h) is the result of our.