Perceptual Uniform Simulation for Tang Tomb Mural Inapinting by Camera Array

Meng Wu[1,2,*] , Huiqin Wang [2] and Wenzong Yang [3]

[1]*School of Management*, Xi'an University of Architecture and Technology, Xi'an, Shaanxi, China, 710055
[2]*School of Information and Control Engineering*, Xi'an University of Architecture and Technology, Xi'an, Shaanxi, China, 710055
[3]Shaanxi History Museum, Xi'an, Shaanxi, China, 710061

***Abstract* — Image inpainting is an effective restoration technology for damaged images used to fill the lost or deteriorated parts of art treasures. Tang tomb mural uses camera array to get high resolution digital images. It is colorful and has plenty of construction information, so it is hard to make a perceptual uniform simulation. In order to simulate the process of filling the damaged pixels as the restorers do, this paper studies an exemplar based inpainting technique. There are some difficulties to inpaint directly: i) the original exemplar-based image inpainting algorithm relied on a global traversal of all pixels to find the best matching exemplar, it is a big time wasting process; ii) the source of the exemplar using only a single lens capturing image, there is a limit on the exemplars to get the final best effects; iii) the mural is colorful, but the previous algorithm always used RGB color model to in-paint the missing patch individually in three channels which experimentally can easily make a mistake in color display. To solve these problems, in this paper the exemplars source are chosen from camera array, and reduce redundancy aim to save processing time. In order to simulate a visual perceptual uniform process, it takes the mural's color information into account by adding Lab color parameter to the data term. This helps to calculate the priority value and change the order of the filling strategy. The simulation result shows that the improved algorithm can quickly restore the Tang tomb mural better and reduce the error accumulation.**

Keywords - Inpainting, Mura, camera array, priority

I. INTRODUCTION

Tang dynasty play great role in Chinese history. Tang tomb murals which are from the imperial tombs give so many information to help audience to know the scene 2000 years ago [1]. There are approximately 500 pieces of murals collected in Shaanxi History Museum. Most of them are damaged by the underground water, the bacterium, the sedimentation etc. so they have some cracked, flaked, faded, disrupted, detached, powdered, mildewed disease [2]. Image inpainting is a novel technique which imitates the mural restorations by filling the damaged parts according to the remaining parts based on PDE (Partial Differential Equation) or Texture synthetic algorithm. This technology has received more and more attentions in digitalized relics protection and virtual restoration. There are some novelty progresses on ancient murals in recent years.

In 2004, Pei et al. [3] studied on Chinese ancient paintings and murals' color restoration by modeling with Markov random field model to estimate the stains, cracks, and artificial damage of the image. In 2008, in order to obtain more correlation of adjacent scale wavelet coefficients, George Papandreou et al. [4] added the hidden Markov tree model of image sparse representation model which can adjust the multi-dimension correlation of wavelet coefficient to improve the accuracy of image reconstruction. They use this method to repair Greece prehistoric mural. In 2012, Purkait et al. [5] developed an exemplar based coherent texture synthesis techniques combined with a novel high-frequency generating technique that can enhance line or brush strokes. In 2013, Ghorai et al. [6] propose a novel algorithm by detecting straight and curve line to enhance the deteriorated mural images. In 2014, Kumar et al. [7] proposed an integrated algorithm to virtually enhance the mural images by taking the weighted average of original image with the mean image. In China Lu dongming's team in Zhejiang university and Wang Shuwen's team in northwest university for nationalities [8~11] their research focuses on Dunhuang grottoes murals mural restoration. However, Dunhuang murals are exposed in the open environment while Tang tomb murals are all underground. They have different eroded models. Dunhuang grottoes murals is under the blazing sun for quite a long time, so the color fading mode is research focus point. The Tang tomb mural is underground, for 2000 years the left information is valid and colorful, it can be the exemplars source to fill the cracked parts using the exemplar-based inpainting technology.

The Tang tomb mural original digital images are collected by Swiss Sinar P2 large format cameras with digital back sinar 75 LV. By using camera array to catch lots of multi-lens HD digital pictures as the exemplars source to inpaint the mural image. In order to get a both efficiency and effectiveness result, this paper firstly, expand the exemplar source from one single picture to the camera array picture; secondly, reduce the redundancy by counting the similarity between the exemplars; finally, improve the priority formula by adding the Lab color parameters that can make a perceptual uniform Tang tomb mural inpainted result.

II. KEY OBSERVATIONS ON EXEMPLAR-BASED IMAGE INPAINTING

Exemplar-based image inpainting algorithm is proposed by Criminisi [12] in 2004. It can rebuild the missing information both textures and structures simultaneously. It can imitate the steps how the ancient painter draw the mural. It is processing the mural image which is left by using texture synthesis methods along the bright isophote. So the filling order which exemplar should inpainted first and the filling object which exemplar is most similar to the missing part are very important to the results.

The essential model is:

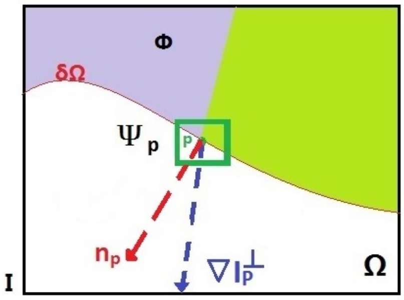


Figure 1. The image of essential inpainting model

$\left|\Psi_{\hat{p}}\right|$ is the area of $\Psi_{\hat{p}}$, and n_p is a unit vector orthogonal to the front $\delta\Omega$ in the point p. The priority is computed for every exemplar on the boundary, with distinct exemplars for each pixel on the boundary of the target region. We compute directional similarity between the normal component of intensity gradient $\nabla I_p^{\perp}$, where the superscript represents the normal component, and normal vector n_p at pixel p.

The program steps are:

1) To find the exemplar that has the highest priority in the edge of damaged area.

There are two main parameters in the priority $P(p)$: one is the confidence term $C(p)$ and the other is the data term $D(p)$, and they are defined as follows:

$$P(p) = C(p) \cdot D(p) \tag{1}$$

$$C(p) = \frac{\sum_{q \in \psi_p \cap (I-\Omega)} C(q)}{\left|\psi_p\right|} \tag{2}$$

$$D(p) = \frac{\left|\nabla I_p^{\perp} \cdot n_p\right|}{\beta} \tag{3}$$

2) To find the best matching exemplar in the source region and fill it to the corresponding positions where to be inpainted.

Assumed that $\Psi_{\hat{p}}$ is the highest priority exemplar that needs to be inpainted, and find the best matching exemplar $\Psi_{\hat{q}}$ from the exemplars source region. Where the distance $d(\Psi_{\hat{p}}, \Psi_{\hat{q}})$ between two generic exemplars $\Psi_{\hat{p}}$ and $\Psi_{\hat{q}}$ is simply defined as the sum of squared differences (SSD) of the already filled pixels in the two exemplars.

$$\Psi_{\hat{q}} = \arg \min_{\Psi_q \in \Phi} d(\Psi_{\hat{p}}, \Psi_{\hat{q}}) \tag{4}$$

Having found the source exemplar $\Psi_{\hat{q}}$, p' is copied from its corresponding position from the area of $\Psi_{\hat{q}}$.

3) To update the confidence term

After filling the exemplar, the new filled pixels become the known region from unknown region, so we need to update all the confidence of each pixel on the edge in the inpainting exemplar.

$$C(\hat{p}') = C(\hat{q}), p' \in \Psi_{\hat{p}} \cap \Omega \tag{5}$$

4) Repeat the above steps until the entire image restoration is complete.

From the model we noticed that:

1) The essential model just uses the gray isophote as the structures data. The Tang tomb mural is underground and not affected by ultraviolet, so it has plenty color when they were excavated. If using the model inpaint the color image directly it maybe not suitable. It needs to add some color information to the priority $P(p)$ formula. This paper uses different color models to separate the color channel. And below are the inpainting experiment use RGB and Lab model.

(a) Damaged image (b)RGB inpainted (c)Lab inpainted
Figure 2. The results of inpainted in different color channel

Picture (a) is damaged image whose missing region includes four different colors. Picture (b) is Red, Green, and Blue (RGB) color model to fill the missing part in three channels individually [13]. But RGB three channels have weak correlation, so there be some pixels get the wrong color results. Picture (c) choose L for lightness and a and b for the color-opponent dimensions (Lab) color model to fill the region in three channels individually. Lab color model can insure the exemplars to get color information correct [14]. But if just inpainted Lab in three channels, there will be loose some construction information wrong such as the figure (c). So it is necessary to add the Lab parameters into the priority computational process to make a perceptual uniform result.

2) The single lens just catches a part of the mural image. The whole mural image needs a camera array to get the all of the information. There is a contradiction between the efficiency and effect. If the exemplar source is just from one

DOI 10.5013/IJSSST.a.17.47.05 ISSN: 1473-804x online, 1473-8031 print

single lens, it limits to offer a fitful $\Psi_{\hat{q}}$ to instead of $\Psi_{\hat{p}}$; if the exemplar source is from the entire camera array, there may be a running time waste. So it is needed to find a suitable exemplar source to get a good balance between the efficiency and effect.

III. MURAL NOVEL INPAINTING BY CAMERA ARRAY

A. Expand exemplar source

Usually the inpainting model uses the left exemplars that just from one lens to imitate the missing part. But the Tang tomb mural is bigger than normal options. For example, the "Polo Play Paint" is three meters high and seven meters long.

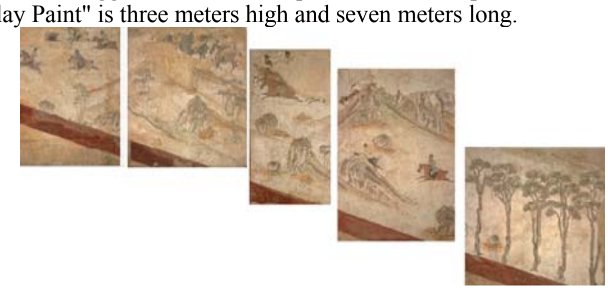


Figure 3. The Tang tomb mural Polo Play Paint

It was collected by camera array to the get high definition image by taking the two adjacent pictures overlap 40% -50%. So the total camera array makes a big data size, as follows.

TABLE I. THE CAMERA ARRAY DATA SIZE

Blocks	**B-1**	**B-2**	**B-3**	**B-4**	**B-5**
cameras	240	270	160	220	280
Data(G)	4.5	5	3.7	4.2	5.2

The table I shows exemplar-based image inpainting algorithm is a global traversals-based optimization model which gives the computer CPU busy tasks if it stich the pictures at first. It will make the CPU running out, so this paper use the method that inapint the image by separate lens but the exemplars source come from the camera array.

Figure 4. The camera array pictures of HD Tang tomb mural

In order to reduce the redundancy and the running time, this paper use to. It defines the similarity between the exemplars use the mean square error (Mean Squared Error, MSE). If distributional difference between the adjacent pixel exemplar is small, then MSE (0 ~ 255) will approach to zero. When the MSE between the exemplar in a continuous region are close to zero, the search processing in the region will have a greater redundancy, as in the figure below.

Figure 5. The redundancy in continuous exemplars

The image discretized with the 5×5 exemplar exemplares, and we define two adjacent exemplars that set i , j as the center for the exemplar $\Psi_{i,j}$ and set i_1, j_1 as the center for the exemplar Ψ_{i_1,j_1} , i_2, j_2 as the center for the adjacent exemplar Ψ_{i_2,j_2} respectively, the mean square error between them is defined by the following formula:

$$\sum_{n-1}^{N}\sum_{n-1}^{N}(\Psi_{i_1,j_1}(n)-\Psi_{i_2,j_2}(n))^2/N^2>\delta \tag{6}$$

In this paper, chose $\delta=7$, it is according to the experience of heritage restoration standard, which is suitable for texture effects of Tang tomb murals, and the redundant is controlled within reasonable limits.

The inpainting process is as follows:

It discrete all the camera array images of tomb murals as I_1 , I_2 , …, I_m and set all exemplars 5 × 5 $\Psi_{i,j}$ ($\Psi_{i,j} \in I_1$, I_2, …, I_m) to make a exemplarss library.

1) To detect the damaged region edges $\delta\Omega$ from the I_1 which is just from one camera capture picture;

2) To calculate the priorities of each point $P(p)$, $(p \in \delta\Omega)$.

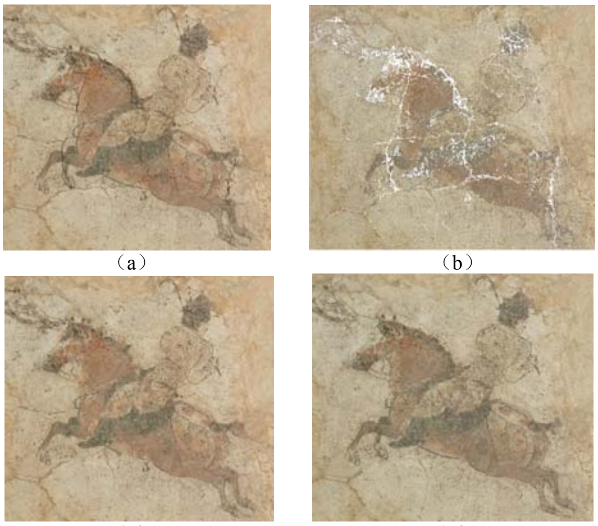
3) To find the highest priority exemplar $\Psi_{\hat{p}}$ from the original image I_1 ;

4) To discretize the original image I_1 and the other camera array images I_2 , I_3 , …, I_m , and find the best suitable exemplar $\Psi_{\hat{q}}$ to match $\Psi_{\hat{p}}$ from the obtained exemplars library whose MSE is large than δ , and filled it into position $\Psi_{\hat{p}}$;

5) Updated the confidence term $C(\hat{p}')$;

6) Repeat the above steps until the entire image inpaiting is complete.

Experiment results are shown as below:



（a）（b）（c）（d）

Figure 6. Inpainting results by camera array

The picture (a) is the spliced damaged mural image; the picture (b) is the marked damaged mural image; the picture (c)is the spliced inpainted mural image; the picture (d)is the inpainted mural image with camera array. The picture (d) shows that inpainting by camera array restores the mural in single lens one by one, and uses the camera array source to fill the marked regions, then spliced the inpainted pictures later. It shows a better result than (c) which spliced the pictures first and inpainted later.

The improved algorithm can effectively solve the problem between the less information in a single photo can't get enough exemplars and spliced the multi-lens pictures together in the traversal model cause a heavy time waste. So overall, it makes a better inpainted effect and obviously shortened processing time. We choose four different inpainting methods to test the process time consuming. They are as follows:

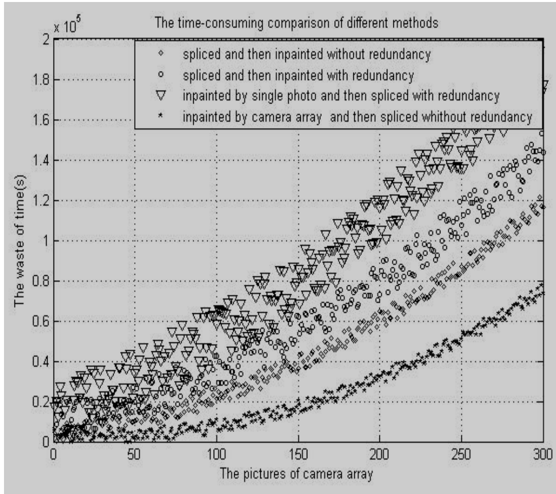
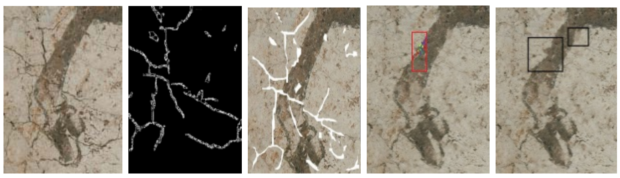


Figure 7. The time-consuming comparison

There are four different methods to inpaint the same mural 'Tang polo'. '▽' shows the time when we inpaint each single-lens photos individually and spliced all the pictures finally; 'ο' shows the time when we spliced the pictures first and then inpaint the whole mural; '◇'shows the time when we spliced the pictures first and then inpaint the whole mural without redundancy; '☆' shows the time when we inpaint each single-lens photos but the exemplars from the all of the camera array pictures without redundancy. So just change the exemplars source it will ensure the effect and save the running time.

B. *Optimize the priority by adding color parameter*

However, there are some exemplars which are not suitable to express the construction information in local parts. It's because that the essential exemplar-based image inpainting model just use gray-gradient to calculate the highest priority in different channels for color image inpainting. In this paper part two figure 2, it shows that the inpainted results by three channels individually in Lab color space is better than in RGB color space. This is some local details as bellows:



（a）（b）（c）（d）（e）

Figure 8. Inpainting in different color space.

Picture (a) is the damaged local image, picture (b) is the mask image, picture (c) is the marked local image, (d) the RGB three channels inpained result[13], picture (e)is the Lab three channels inpained result[14]. It shows that choose Lab color space can keep the color consistent better than

DOI 10.5013/IJSSST.a.17.47.05

ISSN: 1473-804x online, 1473-8031 print

RGB space, but there are some construction error in (e).

The main two reasons for this phenomenon as following:

1) The priority is decided by the result of confidence term and data term. If one of them is very small or near to 0, the exemplar can be filled incorrect. If inpainting is in different channels individually, the filling process may be chosen different exemplars in different channels. It made a worse result when the different channel reconstructed.

2) The confidence term in the texture part is less stable than data term, when the low frequency texture regions have lower priority than it. That makes the image inpainting will along with the direction of lower texture exemplars and lead to the error accumulation.

In [15] it shows when the inpainting goes on and on, there are few original pixels in the exemplar $\Psi_{\hat{p}}$, the exemplar's confidence value will be reduced quickly lead the priority value decent along with it as follows:

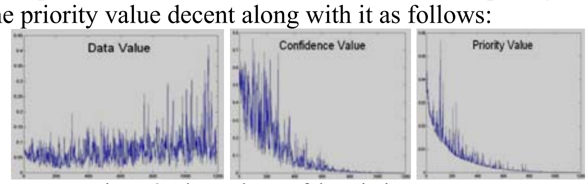


Figure 9. The tendency of the priority parameters

It means if a data value is very small, the exemplar can't be timely filling no matter how much confidence value is, even if the patch window is only a few pixels is unknown. So we should increase the proportion of stable data term. For the mural images, image structure information is very complex, and the image generally has continuous exemplars of similar color. Exemplars in the objects edge lead the construction continuity, so they should get the bigger priorities. So the value of $D(p)$ in these exemplars is more importance. In this paper it refine the priority computation formula, and adds the Lab color parameter into the data term directly instead of inpainting L,a,b three channels separately, and changes the priority algorithm formula as flows:

$$P(p) = \alpha C(p) + \beta W(p) \tag{7}$$

$$W(p) = D(p) + S(p) \tag{8}$$

$$\sigma = \sigma(L) + \sigma(a) + \sigma(b) \tag{9}$$

$$S(p) = \frac{\mu_{|\psi_p|}}{\sigma} \tag{10}$$

$C(p)$ is the confidence term, $W(p)$ is the data term, it include the original data term $D(p)$ and the color term $S(p)$, α and β is the adjusting parameter .The σ is the mean-square, it include L,a,b three elements instead of using Lab space channel individually; $S(p)$ is the normalize color distribution in ψ_p, $\mu_{|\psi_p|}$ is the expectation of exemplars in ψ_p.

It adaptively changed when $C(p) \geq 0.7 \,\&\, \sigma \leq 60$, then $\alpha = 1$, $\beta = 0$; when $C(p) \leq 0.2 \| \sigma \geq 360$, then $\alpha = 0$, $\beta = 1$; other circumstances, when $C(p) \neq 0$ $\&\sigma \neq 0$, $\alpha = 0.617$, $\beta = 0.383$. It means that when the data term is small or approach to 0, the exemplars whose color changes slowly and confidence is bigger will be inpainted firstly; But when the confidence term is small or approach to 0, it will make the exemplar's priority quickly reduce to 0, then the exemplars will be later repaired. Between these two situations it can chose the golden section point, so that make a good balance on both $C(p)$ and $D(p)$ in Lab space. The optimized priority formula takes the mural color elements into full consideration and instead of using three channel images to inpaint the color mural individually.

C. Redefining filling strategy

In the exemplar-based inpainting priority update model in[15], update the filling edge once after inpainting each damaged exemplar in the front region repeatedly by the priority value formula, until the all of the exemplars on it inpainted then go to the next layer, it named "peeling onion skins". In this method, we noticed that the high texture areas along the construction direction may inpainted on and on, cause the error accumulation caused "garbage exemplars". Meanwhile the other parts of the fronts have not changed anymore in this repeating of updating. So in this paper we propose a new updating method that not update until all exemplars on the filling edge are inpainted, it inpaints all of the filling edge exemplars one by one, then update once. It can greatly reduce the running time of mural inpianting obviously, and can fill the exemplars in a ring filling order from the outside to the inside; we called it "peel a boiled egg". It efficiently de duce the "garbage exempalrs" and save considerable running time.

IV. THE EXPERIMENTAL RESULTS

The experiments is on the Windows platform seven and the demo use Microsoft Visual C++ open-source computer vision library in 2010 (Open Source Computer Vision Library,OpenCV2.3.1).The processor is Inter (R) Xeon (R) X5670@2.93GHz, and the memory is 64G. In order to see the details of the efficiency of the Tang tomb mural experiments, we choose one single picture inpainted effects to compare the different among Aujol's algorithm [13] and Suny's algorithm [14]，Sai's algorithm [15] . The results are shown as follows:

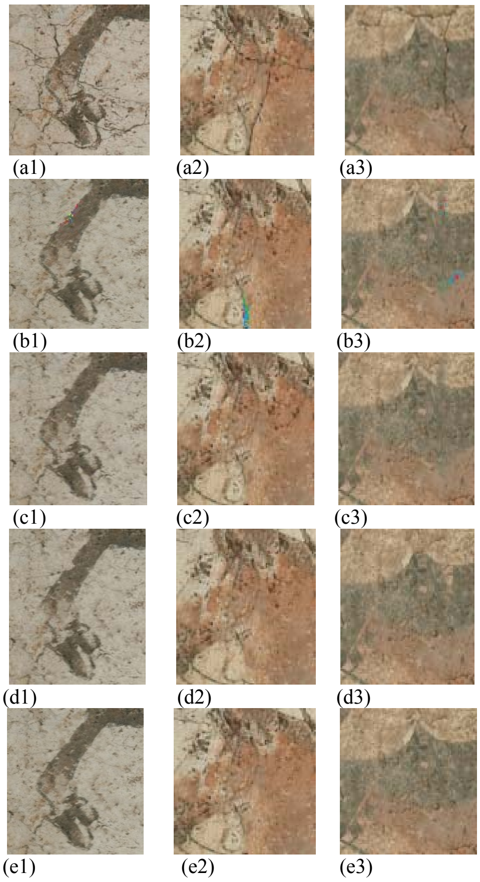


Figure 10. Tang tomb mural inpainting details comparison

Picture (a1~a3) is the original mural; picture (b1~b3)) is results of the algorithm mentioned in [13]; picture (c1~c3)) is the results of algorithm mentioned in [14]; picture (d1~d3)) is the results of algorithm mentioned in [15]; picture (e1~e3)) is the results of our algorithm.

TABLE II. THE TIME CONSUMING(S)

Methods	**[13]**	**[14]**	**[15]**	**Our**
a	362	343	226	187
b	412	387	274	231
c	323	301	185	146

The table II shows that our algorithm uses the shortest time consuming to make the damaged region be inpainted. The exemplars source expanding and color parameter adding ensure the better effect, and the similar exemplar redundancy and the filling strategy ensure the efficiency.

V. CONCLUSION

This paper proposes a novel image inpainting algorithm, whose aim is to solve the problem that Tang tomb mural is too large to inpaint entirely. We take three strategies to improve the exemplar-based algorithm, and it makes the inpianting process could be implemented and reduce the running time with a better effect. First we expand the exemplars source from camera array instead of one photo, and reduce the redundancy by counting the similarity of all the exemplars, that means we increase the efficient exemplars; second we add Lab color factor to the priority formula to avoid the confidence value descending quickly and the essential formula just include gray factor, that means we increase the color information of murals; at last we change the priority update strategy in the filling edge, that decrease the times of updating and ensure the inpainting effect. This method is proper to HD multi-lens Tang tomb mural image which capture by camera array. Inpainting in each photos using plenty of camera array source then spliced all the photos later can ensure the whole Tang tomb mural be efficient inpainted and the improvement of priority method can make the perceptual uniform effect in both color and construction.

When we do the experiments in this research, we noticed that there are something should be improved in future. It is needed to build an exemplars library including all the disease which make the information missing. So the Tang tomb mural can be inpainted by different scale in different missing style.

ACKNOWLEDGMENT

This paper is supported by Scientific Research Foundation for Returned Scholars, Ministry of Education of China (K05055), Natural Science Foundation of Shaanxi Province of China (2017JM6435), Special fund of the Education Department of Shaanxi Province (17JK1426), Science and Technology Program of Beilin District (GX1605).

REFERENCES

[1] Zhou Manxing. The status of the tomb murals in the art history of China [J]. Shaanxi education (high version). 2012(09):31-33

[2] Duan Ping. Tang tomb murals preserved protection and restoration by the current situation and methods [J]. China's cultural relics scientific research. 2007(04),56-59

[3] S. C. Pei, Y. C. Zeng, C. H. Chang. Virtual restoration of ancient Chinese paintings using color contrast enhancement and lacuna texture synthesis [J]. Image Processing, IEEE Transactions on,2004,13（3）:416-429

[4] George Papandreou, Petros Maragos. Image Inpainting with A wavelet Domain Hideen Markov Tree Model [J].Acoustics, Speech and Signal Processing, 2008.IEEE International Conference.: 773-776

[5] Purkait, Pulak. Digital restoration of damaged mural images[C].ACM International Conference Proceeding Series, 8th Indian Conference on Computer Vision, Graphics and Image Processing, ICVGIP 2012, December 16, 2012:33-38

[6] Ghorai, M. Kolkata. A robust faint line detection and enhancement algorithm for mural images [C]: Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), 2013 Fourth National Conference on, 2013:1-4

[7] Kumar, K., Mayank. Digital restoration of deteriorated mural images[C] Digital restoration of deteriorated mural images. ICSIP 2014, 5th International Conference on Signal and Image Processing, 2014: 36-41.

[8] Yuan, Qingshu, Lu, Dongming; Wu, Qi; Liu, Gang. Large area

interactive browsing for high resolution digitized Dunhuang murals [J].Lecture Notes in Computer Science, v 5940 LNCS, 2009: 166-176

[9] Yang Xiaoping, Wang Shuwen. Based on markov sampling of dunhuang fresco restoration [J]. Journal of computer applications, 2010,(07):1835-1840

[10] Yang Xiaoping, Wang Shuwen. Improved algorithm based on priority of dunhuang murals complex damaged area repair [J]. Journal of computer-aided design and graphics, 2011,23(2):284-289

[11] Wang Shuwen Yang Xiao equality. Dunhuang mural image restoration method based on image decomposition [J]. Journal of shandong university,2010(02):11-17

[12] A.Criminisi,P.Perez,K.Toyama.Region filling and Object removal by exemplar-based image inpainting[J].IEEE Transactions on Image Processing,2004,13(9):1220-1212

[13] Aujol J F, Ladjal S, Masnou S. Exemplar-based inpainting from a variational point of view [J]. SIAM Journal on Mathematical Analysis, 2010, 42(3): 1246-1285.

[14] Suny A H, Mithila N H. A shadow detection and removal from a single image using lab color space [J]. IJCSI International Journal of Computer Science Issues, 2013, 10(4).

[15] Sai Hareesh, A. Chandrasekaran, V. A fast and simple gradient function guided filling order prioritization for exemplar-based color image Inpainting[C]. 2010 IEEE International Conference on Image Processing, ICIP. 2010: 409-41