Neurocomputing 123 (2014) 150–155

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Letters

Robust object removal with an exemplar-based image inpainting approach

Jing Wang [a,d], Ke Lu [a,*], Daru Pan [a], Ning He [b], Bing-kun Bao [c]

[a] College of Computing & Communication Engineering, Graduate University of Chinese Academy of Science, Beijing 100049, China
[b] School of Information, Beijing Union University, Beijing 100101, China
[c] Institute of Automation, Chinese Academy of Sciences, China
[d] College of Computer Science and Technology, Henan Polytechnic University, Jiaozuo 454000, China

ARTICLE INFO

Article history:
Received 27 November 2012
Received in revised form
31 May 2013
Accepted 3 June 2013
Communicated by M. Wang
Available online 29 July 2013

Keywords:
Object removal
Image inpainting
Exemplar
Filling priority
Similarity

ABSTRACT

Object removal can be accomplished by an image inpainting process which obtains a visually plausible image interpolation of an occluded or damaged region. There are two key components in an exemplar-based image inpainting approach: computing filling priority of patches in the missing region and searching for the best matching patch. In this paper, we present a robust exemplar-based method. In the improved model, a regularized factor is introduced to adjust the patch priority function. A modified sum of squared differences (SSD) and normalized cross correlation (NCC) are combined to search for the best matching patch. We evaluate the proposed method by applying it to real-life photos and testing the removal of large objects. The results demonstrate the effectiveness of the approach.

1. Introduction

Object removal is the recovery of missing parts of an image in a given region so that the restored image looks natural. Image inpainting is a typical method to accomplish this object removal task. The term inpainting was first emerged in the art realm with the meaning of repairing the ancient paintings [1]. It has become a standard tool in digital photography for image restoring. Intensive research is under way to generalize the image inpainting to a key tool for video and 3D movie post-production [2,17,18]. Besides its applications on images and videos, the inpainting problem involves the analysis of structural and texture patterns, which makes an impact in other image processing fields from the theoretical view.

The basic notations of image inpainting are shown in Fig. 1. Here I is the original image, Λ denotes the undestroyed or fixed region, and Ω is the region to be inpainted. The goal of image inpainting is to repair the missing region Ω with the undamaged region Λ and restore the original image I. As one of the representative researches on image inpainting, exemplar-based method [3] tries to find a correspondence map that assigns regions in Ω corresponding regions in Λ. Then, some well-founded heuristics follow this basic idea to accomplish the inpainting task. The key aspects are to determine the filling priority and to search for the best matching candidates. However, the priority model proposed in [3] is problematic because of the large dropping confidence value when the filling proceeds. Also, the method in [3] does not consider the condition that numerically close candidates are found in the stage of the best matching searching.

In this paper, we propose an improved exemplar-based inpainting aiming at solving the problems mentioned above. We first introduce a regularized factor in the priority model. We then combine the strength of a modified sum of squared differences (SSD) and the normalized cross correlation (NCC) to search for the best matching patch. This would enhance the robustness of the inpainting model, especially for the large removal regions. The rest of the paper is organized as follows. Section 2 introduces the related work. In Section 3, we describe the current exemplar-based image inpainting algorithm. Based on this, we point out the weakness in original exemplar-based inpainting algorithm and introduce our improved method in Section 4. Experiments are introduced in Section 5, followed with a conclusion in Section 6.

2. Related work

As a type of image restoration problem, image inpainting involves a number of theories and approaches in image completion [10], texture synthesis [7,9], image replacement [8], image

* Corresponding author. Tel.: +86 13661152700.
E-mail addresses: luke71@126.com, wjasmine@hpu.edu.cn (K. Lu).

0925-2312/$ - see front matter © 2013 Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.neucom.2013.06.022

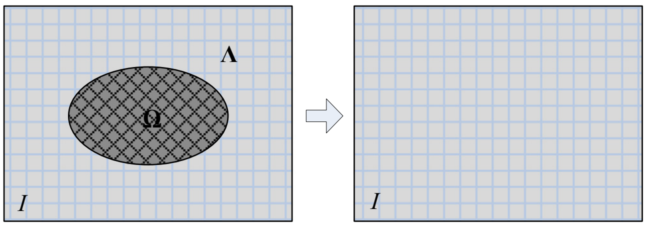

Fig. 1. A schematic illustration of image inpainting which is to repair the missing region **Ω** with the undamaged region **Λ**.

interpolation [15], image deblurring [16], image search [19], etc. The research on image inpainting technology mainly includes three directions. The first direction is inpainting based on the variational partial difference equations (PDEs) for repairing some small image scratches. The second direction is inpainting based on the texture synthesis technology for filling some large image regions, and the third one is the combination of the methods.

For the first direction, researchers pay attention to the structure inpainting in images. Inspired by the partial difference equations of physical heat flow, Bertalmio et al. [4] propose a novel image inpainting algorithm that replicates the basic techniques used by professional restorators. This algorithm restores small regions in image by propagating information from the surrounding areas in the isophotes direction. Later, Chan and Shen [5] develop general mathematical models for inpainting involving the recovery of edges, and the total variation (TV) model is built for local non-texture image inpaintings. Although the TV inpainting model can keep the image edges and compute efficiency, it destroys the connection principle in human disocclusion process. Thus, Chan and Shen [6] present the curvature-driven diffusions (CDD) inpainting model that modifies the conductivity coefficient with the curvature of the isophotes.

For the second direction, texture synthesis technique is the main research foundation. Based on Heeger and Bergen's work [7], Igehy and Pereira [8] present an image replacement technique by integrating composition into the texture synthesis algorithm. Then, Harrison [9] synthesizes an image by using a given input image as the texture mask. This method could replace an object in image even if the background is non-homogeneous. Drori et al. [10] propose a fragment-based image completion algorithm that iteratively approximates the unknown region and fills in the image by adaptive fragments. The input image is completed by a composition of fragments under the combinations of spatial transformations. Under constraint inpainting conditions, these two class algorithms could do an impressive work for repairing structure or texture regions in image.

In recent years, researchers try to explore new image inpainting techniques that could repair structure and texture regions simultaneously [11]. At the beginning, Bertalmio et al. [12] proposed an algorithm for the filling of texture and structure in the regions of missing image information. The basic idea is to first decompose the image into the sum of two functions with different basic characteristics and then reconstruct each one of these functions separately with structure and texture fill-in algorithms. The shortage is the blur effect at the edge of the inpainted region. Combined the advantages of structure and texture inpaintings, Criminisi and Toyama [3] first present an exemplar-based inpainting algorithm for removing large region objects. This approach computes the fill order of patches in missing region by using the confidence value and image isophotes of pixels on the boundary of missing region, then finds the best match patch in the remaining regions to fill in the missing regions. For exemplar-based inpainting, Xu and Sun [13] use the sparsity of natural image patches to lead patch propagation that the two concepts of sparsity at the patch level are proposed for modeling the patch priority and patch representation.

3. Exemplar-based inpainting

According to Criminisi's model [3], an image is divided into two parts: Λ represents the undestroyed image region which called source region, and Ω represents the damaged image region called the target region (see Fig. 1). The boundary of Ω is denoted by $\delta\Omega$. The original exemplar-based inpainting algorithm contains three main steps as follows.

3.1. Compute the filling priority

This step determines the filling order of patches in target region. After computing the filling priority of all the pixels along the boundary of target region, the pixel p with the highest priority is used as the center pixel to choose the target patch Ψ_p to be inpainted. The filling priority equation can be described as follows:

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

where $C(p)$ denotes the confidence term and $D(p)$ denotes the data term. More specifically, $C(p)$ and $D(p)$ are computed by the following:

$$C(p) = \frac{\sum_{q \in \Psi_p \cap \Lambda} C(q)}{|\Psi_p|}, \quad 0 \le C(p) \le 1 \tag{2}$$

$$D(p) = \frac{|\nabla I_p^{\perp} \cdot n_p|}{\alpha}, \quad 0 \le D(p) \le 1 \tag{3}$$

Given a pixel p on the boundary of target region, its confidence $C(p)$ equals to the ratio between the confidence sum of pixels in $\Psi_p \cap \Lambda$ and the total number of pixels in Ψ_p. Considering the structure feature around p, $D(p)$ equals to the product of the unit normal vector n_p of p and the isophotes vector $\nabla I_p^{\perp}$, and α is the normalization factor.

3.2. Search for the best matching patch

In this step, the algorithm searches for the best matching patch $\Psi_{\hat{q}}$ for the target patch Ψ_p in source region. The SSD distance $d(\Psi_p, \Psi_q)$ is introduced to compute the similarity between each patch Ψ_q in source region and the target patch Ψ_p:

$$\Psi_{\hat{q}} = \underset{\Psi_q \in \Lambda}{\arg\min}\, d(\Psi_p, \Psi_q) \tag{4}$$

$$d_{SSD}(\Psi_p, \Psi_q) = \sum[(R_{\Psi_p} - R_{\Psi_q})^2 + (G_{\Psi_p} - G_{\Psi_q})^2 + (B_{\Psi_p} - B_{\Psi_q})^2] \tag{5}$$

In Eq. (5), R, G and B denote the values of intensity of each color channel.

3.3. Copy the best matching patch information and refresh the boundary of target region

In this step, the algorithm fills the region corresponding to $\Psi_p \cap \Omega$ by replicating the corresponding region in the best matching patch $\Psi_{\hat{q}}$ to the target patch Ψ_p. Besides, the boundary of the target region $\delta\Omega$ has to be renewed.

The above steps are implemented iteratively until the removal region is fully inpainted.

4. Improved inpainting model

4.1. Regularizer term ω

For the target patch with the highest filling priority, the original exemplar-based inpainting algorithm fills in the target region by the best matching patch selected in source region. Taking both the structure and the texture information into consideration simultaneously, the exemplar algorithm is supposed to repair images with a large target area. However, the algorithm still has some weaknesses as shown in Fig. 2. According to this instance, it is clear that the original exemplar-based algorithm in [3] has imperfect inpainting result. It can be attributed to the improper modeling on the confidence value. As shown in Fig. 3(a) and (b), the descending effect on $C(p)$ accumulates along with the filling. As a result, the priority value also takes on a rapid descending fashion. This is called “dropping effect” [14] and it largely undermines the central inpainting regions.

To solve the problem, we introduce a regularized factor in the confidence term:

$$R_C(p) = (1-\omega)C(p) + \omega \tag{6}$$

Here ω denotes the regularize factor to control the smoothness of confidence curve and $\omega = 0.7$.

In priority model, the confidence term $C(p)$ reflects the consistency of texture features around the pixel p, which is used as an indicator for measuring the filling priority. Generally speaking, the texture feature might be consistent in different areas in image, and the texture feature might be inconsistent in same area in image. However, Eq. (6) uses the fixed regularized factor ω to compute the confidence value of the patches to be inpainted. It does not consider the above problems. With an empirical study, we find that ω could better reflect the texture features in various images with flexible values. So, ω is set to an adjustable value interval $[0.1, 0.7]$. Specifically, the filling priority equation is updated as

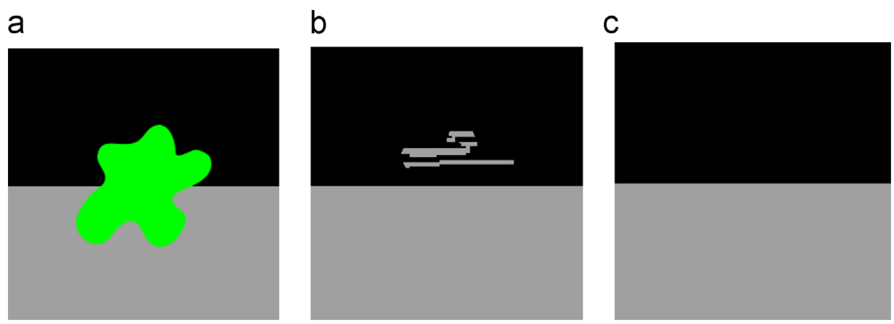

Fig. 2. (a) Image to be inpainted, (b) inpainted result by original exemplar-based algorithm, and (c) expected inpainted result.

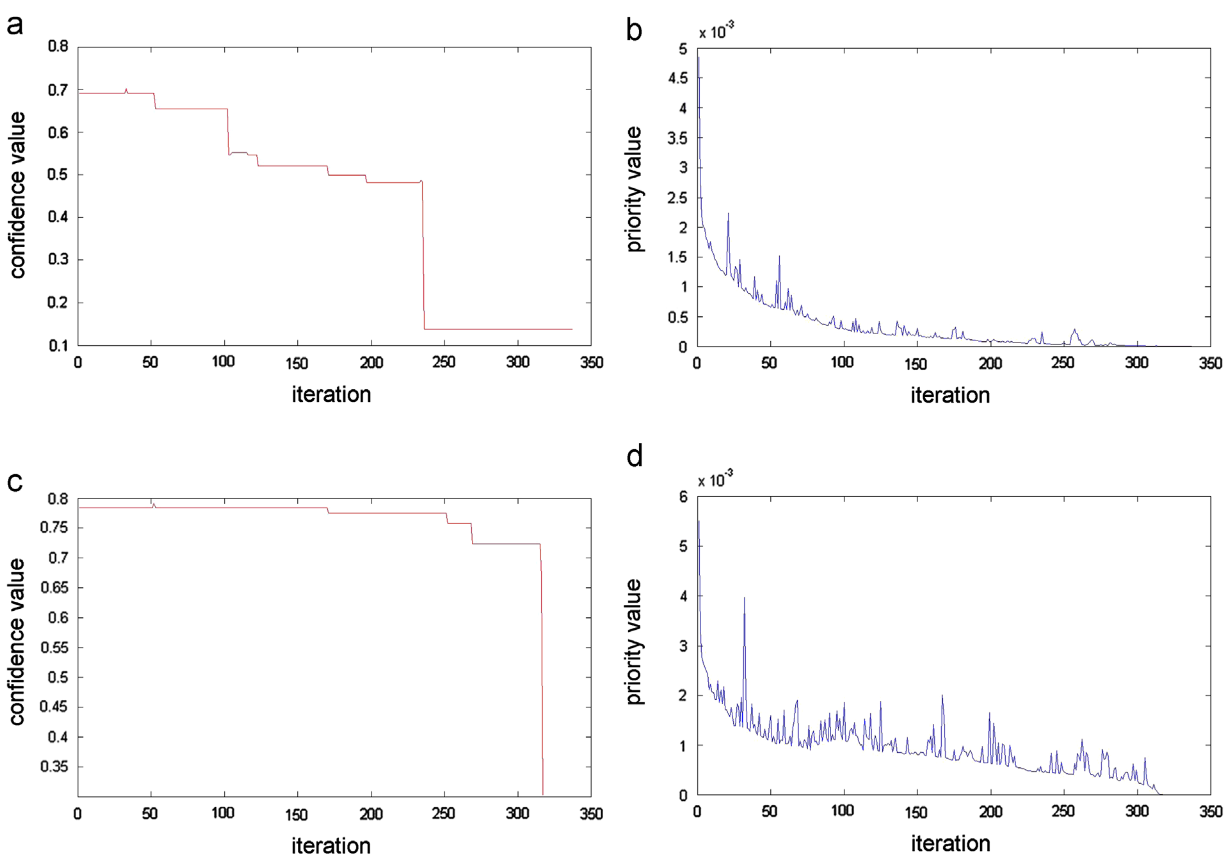

Fig. 3. An analysis of “dropping effect”. As shown in (a) and (b), the descending effect on $C(p)$ accumulates along with the filling. From (c) and (d) we can see that the effect is suppressed by using our strategy.

follows:

$$P(p) = R_C(p)D(p) \quad (7)$$

In this way, the confidence value and priority value are changed as shown in Fig. 3(c) and (d). With the flexible values of ω, it is clear that the "dropping effect" in confidence curve is suppressed significantly.

4.2. Two-round search

We also propose a strategy on the best matching patch searching. We observe that the original model does not consider the condition when multiple candidates, of which the SSD are numerically close, are found. The candidate with the lowest SSD value is not necessarily the most visually compatible one. So we propose a two-round search to address this problem.

We first propose to use the mean SSD distance to replace the original intensity of each color channel. To some extent, the mean SSD could better reflect the average similarity of patches. The new SSD is described as follows:

$$\overline{d}_{SSD}(\Psi_p, \Psi_q) = \sum[(\overline{R}_{\Psi_p} - \overline{R}_{\Psi_q})^2 + (\overline{G}_{\Psi_p} - \overline{G}_{\Psi_q})^2 + (\overline{B}_{\Psi_p} - \overline{B}_{\Psi_q})^2] \quad (8)$$

where $\overline{R}$, $\overline{G}$, and $\overline{B}$ denote the mean values of intensity of each color channel. In addition, we introduce the NCC distance as the second match condition to measure the similarity of patches.

$$d_{NCC}(\Psi_p, \Psi_q) = \frac{\left[\sum G_{\Psi_p} \cdot G_{\Psi_q}\right]^2}{\sum[G_{\Psi_p}]^2 \cdot \sum[G_{\Psi_q}]^2} \quad (9)$$

where G denotes the grayscale values of image. NCC provides a different measuring criterion on the similarity between different patches. With these two measures, a two-round search can be made: a few candidate patches are firstly selected according to the mean SSD and they are re-ranked with the NCC measure as the second round searching.

5. Experimental results

The improved inpainting algorithm is tested on a few real-life images with various background. The comparisons with the original exemplar-based inpainting algorithm are shown in Fig. 4. Column (a) shows four original images to be edited. The removal regions are designedly selected as the regions across the common border between scenes (like the water and the shore). The inpainted results by original method have some improper fillings in the target regions. For example, the shoreline in the first two images in column (c) is poorly reconstructed. As for the third image, there are some texture residuals of the hat and the pants left in the reconstructed region. We note that these improper inpaintings all stay in the central target regions. This is due to the rapid decay of the confidence value and the simplest searching strategy in the original exemplar-based method. In contrast, the proposed algorithm obtains better inpainted results as shown in column (b). The shorelines look much more natural and the residuals generally disappear. These results demonstrate the effectiveness of the introduced regularized factor and the search for the best matching patches based on the combined measures.

The area of the target regions selected in Fig. 4 is relatively small. To further demonstrate the robustness of the proposed

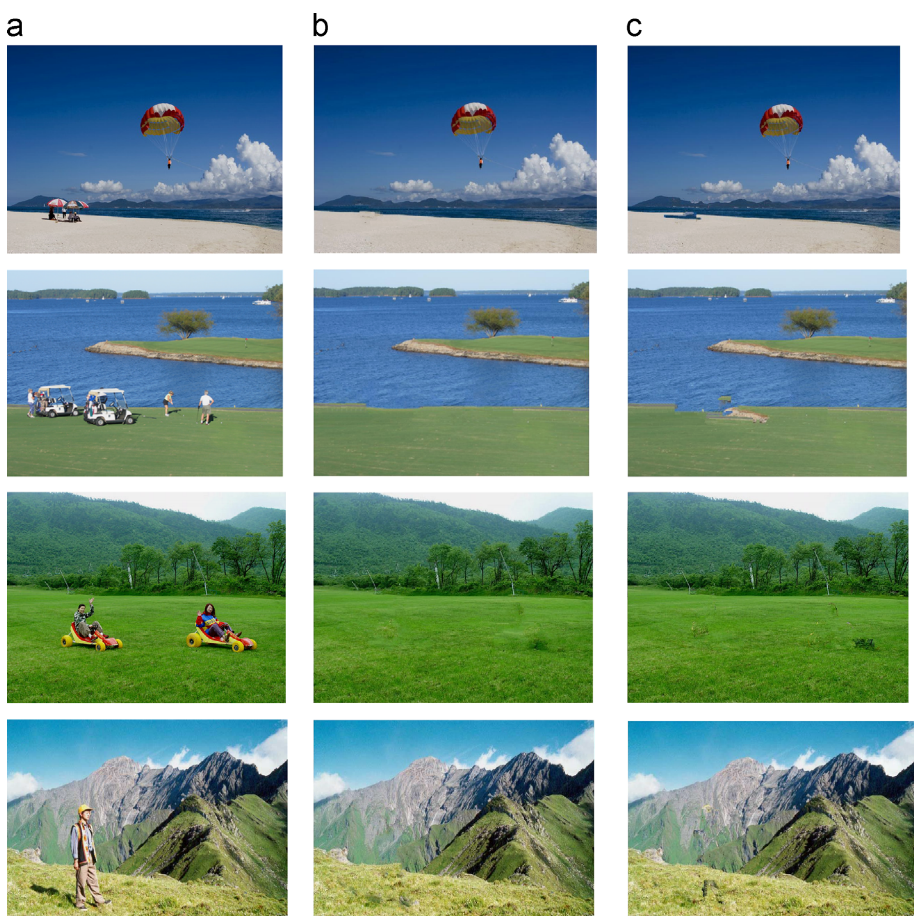

Fig. 4. Comparison with the original exemplar-based inpainting algorithm [3]. Column (a), original images; column (b), results with our method; column (c), results with the original exemplar-based inpainting algorithm.

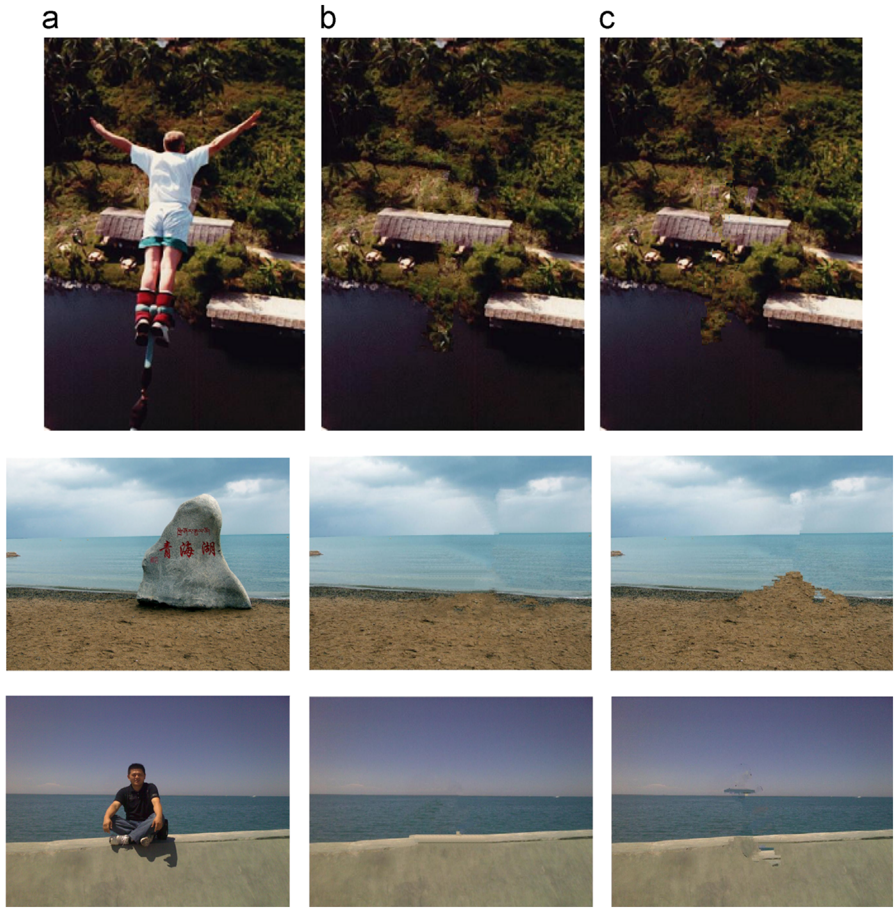

Fig. 5. Object removal with large areas. Column (a), the original images; column (b), results with an unwanted objects removed; column (c), results with the original exemplar-based inpainting algorithm.

algorithm, we test our method on some real-life images with larger removal area. As shown in Fig. 5, compared with the object removal results in column (c) by original exemplar-based inpainting algorithm, the unwanted objects in column (a) are replaced with plausible inpaintings which generally look natural (column (b)).

6. Conclusions

We propose an improved exemplar-based image inpainting method for removing objects in digital images. We introduce a regularized factor, which adjusts the curve of the patch priority function, in computing the filling order. To find the best matching patch, we use a modified SSD distance as the measure in the first-round search. Then, we extract the best patch among the top candidates using a NCC measure for the second-round search. These improvements actually make the inpainting more robust to images with the large removal regions. However, there is a room for the improvement with regard to the proposed inpainting model, such as the computation of filling priority. In our future work, we will focus on the improvement of filling priority and generalize the method to video editing.

Acknowledgments

This work was supported by the China Special Fund for Meteorological-Scientific Research in the Public Interest (GYHY201106044), NSFC (Grant nos. 61103130, 61070120, and 61141014), National Program on Key Basic Research Project (973 Programs) (Grant nos. 2010CB731804-1 and 2011CB706901-4).

References

[1] G. Sapiro, Image inpainting, SIAM News 35 (4) (2002) 1–2.
[2] V. Caselles, Exemplar-based image inpainting and applications, SIAM News 44 (10) (2011) 1–3.
[3] A. Criminisi, P. Perez, K. Toyama, Region filling and object removal by exemplar-based image inpainting,, IEEE Transactions on Image Processing 13 (9) (2004) 1200–1212.
[4] M. Bertalmio, G. Sapiro, et al., Image inpainting, in: ACM SIGGRAPH 2000, 2000, pp. 417–424.
[5] T.F. Chan, J. Shen, Mathematical models for local non-texture inpaintings, SIAM Journal Application Mathematics 62 (3) (2001) 1019–1043.
[6] T.F. Chan, J. Shen, Non-texture inpainting by curvature-driven diffusions (CDD), Journal of Visual Communication and Image Representation 12 (4) (2001) 436–449.
[7] D. Heeger, J. Bergen, Pyramid-based texture analysis/synthesis, in: ACM SIGGRAPH 1995, vol. 29, 1995, pp. 229–238.
[8] H. Igehy, L. Pereira, Image replacement through texture synthesis, in: Proceedings of the 1997 IEEE International Conference on Image Processing, 1997.
[9] P. Harrison, A nonhierarchical procedure for resynthesis of complex texture, in: Proceedings of the International conference on Central Europe Computer Graphics, Visualization, and Computer Vision, 2001.
[10] I. Drori, C.O. Daniel, H. Yeshurun, Fragment-based image completion, ACM Transactions on Graphics 22 (3) (2003) 303–312.
[11] P. Arias, G. Facciolo, V. Caselles, G. Sapiro, A variational framework for exemplar-based image inpainting, International Journal of Computer Vision 93 (2011) 319–347.
[12] M. Bertalmio, et al., Simultaneous structure and texture image inpainting, IEEE Transactions on Image Processing 12 (8) (2003) 882–889.
[13] Z.B. Xu, J. Sun, Image inpainting by patch propagation using patch sparsity, IEEE Transactions on Image Processing 19 (5) (2010) 1153–1165.
[14] W.H. Cheng, et al., Robust algorithm for exemplar-based image inpainting, in: The International Conference on Computer Graphics, Imaging and Vision (CGIV 2005), 2005, pp. , 64–69.

[15] C. Ballester, M. Bertalmio, et al., Fill-in by joint interpolation of vector fields and gray-levels, IEEE Transactions on Image Processing 10 (2001) 1200–1211.
[16] J. Wang, K. Lu, N. He, Q. Wang, Total variant image deblurring based on split Bregman method, Chinese Journal of Electronics 40 (8) (2012) 1503–1508.
[17] M. Wang, R.C. Hong, X-T. Yuan, et al., Movie2Comics: towards a lively video content presentation, IEEE Transactions on Multimedia 14 (3) (2012) 858–870.
[18] M. Wang, B.B. Ni, X-S. Hua, et al., Assistive tagging: a survey of multimedia tagging with human–computer joint exploration, ACM Computing Surveys 44 (4) (2012).
[19] M. Wang, K.Y. Yang, X-S. Hua, et al., Towards a relevant and diverse search of social images, IEEE Transactions on Multimedia (8) (2010) 829–84212 (8) (2010) 829–842.

Jing Wang received the Ph.D. degree in computer application technology from Graduate University of Chinese Academy of Science, Beijing, China, in 2012. She is a lecturer at College of Computer Science and Technology, Henan Polytechnic University. Her research interests include digital image processing and intelligent algorithms.

Ke Lu was born in Ningxia on March 13, 1971. He received master degree and Ph.D. degree from the Department of Mathematics and Department of Computer Science at Northwest University in July 1998 and July 2003, respectively. He worked as a postdoctoral fellow in the Institute of Automation Chinese Academy of Sciences from July 2003 to April 2005. Currently he is a professor of the University of the Chinese Academy of Sciences. His current research areas focuses on curve matching, 3D image reconstruction and computer graphics.

Daru Pan received the B.S. degree and the M.S. degree from the Huazhong University of Science and Technology in 1995 and 1998, respectively, and his Ph.D. degree in communication and information system from the South China University of Science and Technology in 2005. He has been working in South China Normal University from 2005. Currently he is an associate professor in the College of Physics and Telecommunication. His current research interests include opportunistic network and multimedia transmission system.

Ning He was born in Panjin, Liaoning Province on July 29, 1970. She graduated from the Department of Mathematics at Ningxia University in July 1993. She received M.S. degree and Ph.D. degree in applied mathematics from the Northwest University and Capital Normal University in July 2003 and July 2009, respectively. Currently she is a vice professor of the Beijing Union University. Her research interests include image processing and computer graphics.

Bing-Kun Bao received the Ph.D. degree in control theory and control application from the Department of Automation, University of Science and Technology of China (USTC), China, in 2009. From 2009 to 2011, she continued researching in electrical and computer engineering at the National University of Singapore (NUS). She is currently a postdoctoral researcher in the Institute of Automation, Chinese Academy of Science, and a researcher in the China–Singapore Institute of Digital Media. She was the special session chair of MMM'13 and received the Best Paper Award from ICIMCS'09.