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Image completion based on views of large displacement

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Abstract This paper presents an algorithm for image completion based on the views of large displacement. A distinct from most existing image completion methods, which exploit only the target image's own information to complete the damaged regions, our algorithm makes full use of a large displacement view (LDV) of the same scene, which introduces enough information to resolve the original ill-posed problem. To eliminate any perspective distortion during the warping of the LDV image, we first decompose the target image and the LDV one into several corresponding planar scene regions (PSRs) and transform the candidate PSRs on the LDV image onto their correspondences on the target image. Then using the transformed PSRs, we develop a new image repairing algorithm, coupled with graph cut based image stitching, texture synthesis based image inpainting, and image fusion based hole filling, to complete the missing regions seamlessly. Finally, the ghost effect between the repaired region and its surroundings is eliminated by Poisson image blending. Our algorithm effectively preserves the structure information on the missing area of the target image and produces a repaired result comparable to its original appearance. Experiments show the effectiveness of our method.

Keywords Image completion · Large displacement view · Image stitching · Texture synthesis

1 Introduction

Image completion is the task of filling in the missing or damaged regions of an image with the available information from the same or another image to generate a perceptually satisfactory result. Due to the wide applications in photo editing, rig removal and special effects production [6], image completion has received great attention in the past decade. Many methods have been brought forward so far [22], but most of them are mainly focused on single image based techniques.

Few methods address image completion based on views of large displacement. In fact, this provides a feasible way for image completion in our lives. For instance, when we take photos at some famous resorts, an undesired person may run into the view of our camera. The problem is, therefore, how to generate a visually pleasing result after removal of the intruder from the image. It would be difficult to complete the target image by itself, especially for missing regions with complex structures. On the other hand, if we have another view of the same scene with a large displacement that reveals the previously occluded regions, we can faithfully restore the occluded regions on the target image.

Image completion based on views of large displacement is different from traditional image completion. Traditional methods only make use of the surrounding known pixels on the target image to solve its unknown regions, which is in nature an ill-posed problem [21]. However, video completion bears a certain similarity to our problem in adopting other frames to repair the current frame, but it normally exploits the adjacent frames to fulfil the task, taking no account of those frames with LDVs.

In this paper, we explore the problem of image completion based on the view of large displacement. The first challenge is how to convert the visible regions on the LDV image into usable information for repair. Images taken from different views may present great distortion for the same scene. Thus, it is unfeasible to repair the damaged regions on the target image by globally warping the LDV image. Since the LDV image contains components with different scene depths, we first need to segment it as well as the target image into several corresponding planar scene regions (PSRs). We then transform the candidate PSRs on the LDV image onto their counterparts on the target image by image matching and warping.

After the transformation of the candidate PSRs on the LDV image, another challenge is how to repair the target image. Overlappings and gaps may occur between the warped PSRs, as they are independently warped with different homographies. Moreover, the missing regions on the target image may consist of multiple PSRs. Thus, for each pixel in the missing region, several candidate pixels or none may exist in the warped PSRs. No previous image completion methods have addressed such a repairing problem. We here propose a new image repairing algorithm to tackle it. Coupled with graph cut based image stitching [25], texture synthesis based image inpainting and image fusion based hole filling, the algorithm adaptively repairs the different parts in the missing regions with different schemes. In addition, due to luminance difference between the target image and the LDV image, a ghost effect may appear on the repaired result. To eliminate it, we further adopt Poisson image blending [20] to generate a seamless result.

Our main contribution lies in that we describe a novel idea for image completion, i.e. completing the target image using the available information on the LDV image. We also propose for the first time a preliminary framework for effectively dealing with such a problem.

The rest of the paper is organized as follows. Section 2 reviews related work. Section 3 describes our approach of image completion in detail based on the view of large displacement. Experimental results and analysis are given in Sect. 4. Section 5 concludes the whole paper and highlights future work.

2 Related work

Here we mainly review the relevant techniques on image and video completion.

2.1 Image completion

Since Bertalmio et al. [3] presented their work on image inpainting for the first time in 2000, many methods have been brought forward. Nevertheless, most of them are single image based and can be classified as partial differential equations (PDEs) based methods, texture synthesis based methods, and statistics based ones.

PDE based methods regard image completion as PDE solving [3] or variational problems [1, 5] by specifying the known pixels around the damaged regions as boundary conditions. The image repairing process is, therefore, the diffusion of the known pixels into the missing regions. Such methods work well for small regions, but may fail for highly textured regions.

Texture synthesis based methods select the known regions on the target image as texture swatches, then perform texture synthesis with these swatches to generate new image fragments for the missing regions [8, 9, 13, 15]. These methods produce satisfactory results for the textured regions, but cannot recover the precise structure information in large missing regions. Under the guidance of specified structure curves in the blank regions, remarkable repairing results are generated in [19, 24]. However, this demands complicated user interaction for scenes with complex structures.

Statistics based methods solve the problem of image completion by statistical analysis. Levin [17] obtained global statistical distribution based on the available part of the image by statistical learning and found the most probable image by loopy belief propagation. The EM based method [10] treats the problem as the estimation of the missing or damaged regions and adopts an expectation maximization (EM) algorithm for ML estimation based on sparse representation of image completion.

To the best of our knowledge, few methods focus on image completion based on views of large displacement.

2.2 Video completion

Bertalmio et al. [2] extended fluid dynamics based image completion to video sequences. This method is capable of filling small textureless holes on each video frame, but is unsuitable for completing large holes. Regarding video completion as a global optimization problem on texture synthesis, the methods in [26] and [23] recover the missing information by directly sampling spatio-temporal patches of local structures or motion. Jia et al.'s method [14] searches for the optimal matched fragments in the video sequences to fill the hole boundary with the highest priority and imposes constraints on the selected patches to maintain temporal consistency. Motion periodicity is also utilized for texture synthesis based video repairing [12].

As can be seen, most video completion techniques assume small camera motion between adjacent frames. They just fetch the information in the adjacent frames for repairing. However, for the problem discussed in this paper, we cannot directly use the information on the LDV image because of the severe distortion of the same scene under different views.

3 Image completion based on views of large displacement

In this paper, we explore two key issues regarding image completion based on the view of large displacement, i.e., how to transform the visible parts on the LDV image to the target image with less distortion and how to use the transformed pieces to repair the missing regions on the target image.

We define a local region of a bounding box on the target image, which encloses the missing area. We refer to this local region as the repairing window. Then, we decompose the two images into several corresponding PSRs and refer to the PSRs on the LDV image whose projection on the target image covers or partially covers the missing area as the candidate PSRs. We warp the candidate PSRs on the LDV image to their counterparts on the target image through image matching and warping. Thus the visible information encoded in the warped PSRs can be directly adopted for repairing the target image. For the second issue, by defining appropriate repairing and fusion priority functions, a new image repairing algorithm combining image stitching, texture synthesis and image fusion is proposed to restore the missing regions with the warped PSRs. We further adopt Poisson image blending to eliminate ghost effects and generate a seamless result. The pipeline of our method is illustrated in Fig. 1, and the completion process is shown in Fig. 2.

The following sections will elaborate on the individual stages and provide the details of our approach.

3.1 Transformation of the visible information in LDV

We perform the following steps:

(1) *Image segmentation into PSRs.* Interactive segmentation of the scene into accurate PSRs by the user is difficult. We use a mean shift algorithm [7] to segment the target image and the LDV image initially into a set of image patches. Then we merge those patches belonging to the same PSR interactively, and finally specify the counterparts between the PSRs on the LDV and the target image. This is the only step involving user interaction in our algorithm.

(2) *Feature extraction and matching.* A robust feature extraction method, i.e., the scale invariant feature transform (*SIFT*) feature detector [18], is adopted to obtain enough matched feature points for each corresponding PSRs pair.

(3) *Homography solving and image warping.* There may exist some outliers among the matched feature points under the influence of image noises. We reject those outliers by the RANSAC algorithm and the Levenberg–Marquardt algorithm [11], and obtain the homography H for each corresponding PSRs pair by solving

$$X = HX', \quad i.e.\ \lambda \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{bmatrix} h_0 & h_1 & h_2 \\ h_3 & h_4 & h_5 \\ h_6 & h_7 & 1 \end{bmatrix} \begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix},$$

where X and X' are the homogeneous coordinates of the matched feature points. λ is a homogeneous constant, and $h_0, \ldots, h_7$ are the unknown parameters of H.

By now, the candidate PSRs on the LDV image can be transformed into their counterparts on the view of the target image to serve for repairing as shown in Fig. 3.

3.2 A new image repairing algorithm

The repairing window on the target image may be covered by the projection of more than one warped candidate PSR, and overlappings and gaps may exist among the warped PSRs as illustrated in Fig. 3.

We present a new image repairing algorithm as shown in Fig. 4. Let the missing region on the target image be $\boldsymbol{\Omega}$. After transformation, the warped candidate PSRs fall onto the repairing window $\hat{\boldsymbol{\Omega}}$ in Fig. 4a. Some parts cover the

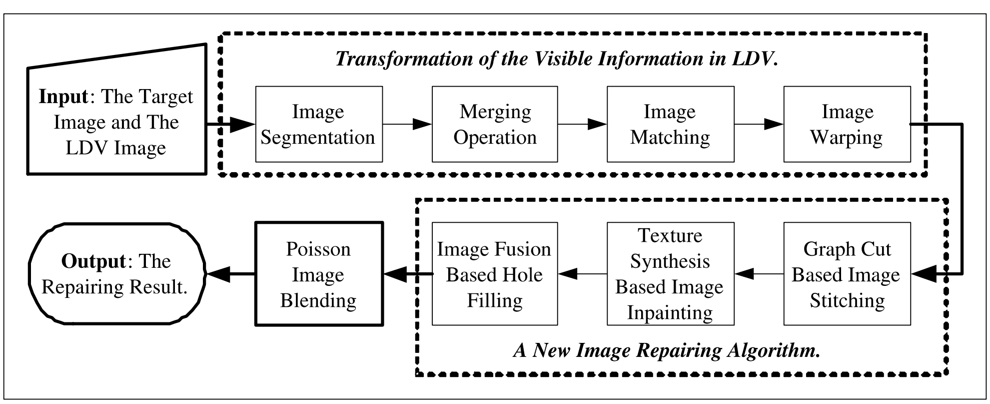


Fig. 1. The pipeline of our method

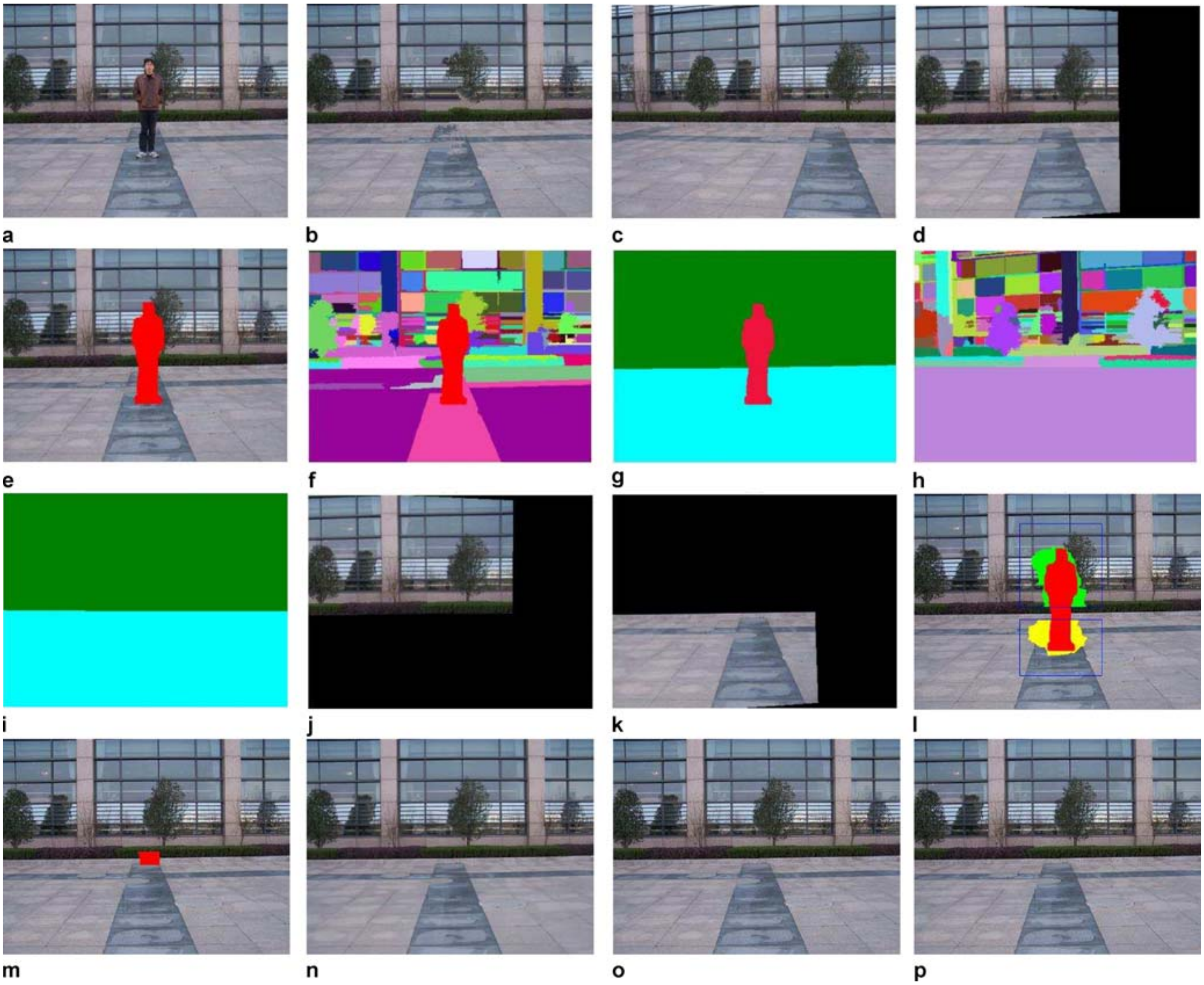


Fig. 2a–p. Profile of the library. **a** The target image, **b** Repairing result obtained by a texture synthesis based method [8], **c** The LDV image. **d** The warped LDV image. **e** Removing the person from the target image. **f** Initial segmentation of the target image. **g** PSRs on the target image. **h** Initial segmentation of the LDV image. **i** PSRs on the LDV image. **j**,**k** Warped PSRs from the LDV image. **l** Optimal seam lines (contours of the *green* and *yellow regions*). **m** Intermediate repairing result by graph cut based image stitching. **n** Repairing result after texture synthesis based image inpainting with the residual missing pixels in *red*. **o** The final repairing result. **p** The original scene

missing area, filling in the blank pixels; some parts overlap with the known pixels of the target image within $\hat{\boldsymbol{\Omega}}$. As stated above, the warped PSRs may overlap with each other generating overlappings $\boldsymbol{\Omega}_b^o$ along the common boundary L_{sb}, or disconnect leaving gaps $\boldsymbol{\Omega}_c^o$ between them. Except for $\boldsymbol{\Omega}_b^o$ and $\boldsymbol{\Omega}_c^o$, the rest of the missing pixels $\boldsymbol{\Omega}_a^o$ hold one–one correspondency in the warped PSRs.

Our algorithm divides the missing region $\boldsymbol{\Omega}$ on the target image into three parts and repairs them with different schemes as illustrated in Fig. 4b. Since the common boundary L_{sb} of the PSRs usually contains significant features, to ensure faithful restoration of these feature lines in $\boldsymbol{\Omega}$, we define a region of band $\boldsymbol{\Omega}'$ along L_{sb}. Let $\boldsymbol{\Omega}_a$ denote the area outside the band within the repairing window, i.e., $\boldsymbol{\Omega}_a = \boldsymbol{\Omega} \cap \tilde{\boldsymbol{\Omega}}'$. $\boldsymbol{\Omega}_a$ is restored by graph cut based image stitching. Let $\boldsymbol{\Omega}_b$ denote the missing area inside the band and covered by the warped PSRs. $\boldsymbol{\Omega}_b$ is recovered by texture synthesis based image inpainting. Note that there might be a few pixels in $\boldsymbol{\Omega}'$ that fail to be filled by texture synthesis due to the match constraints. We refer to these pixels as $\boldsymbol{\Omega}_c$, which is finally filled by fusing the nearby known pixels on the target image.

Our image repairing process can be briefly described as follows:

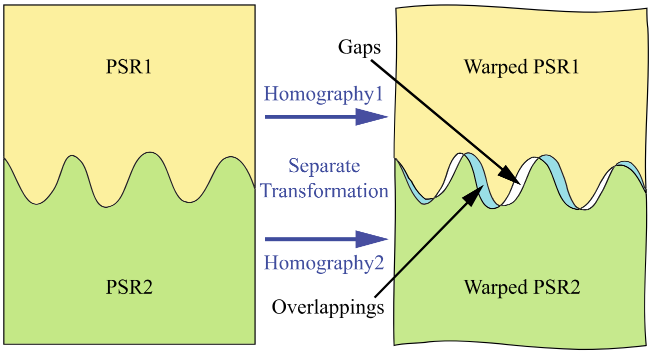
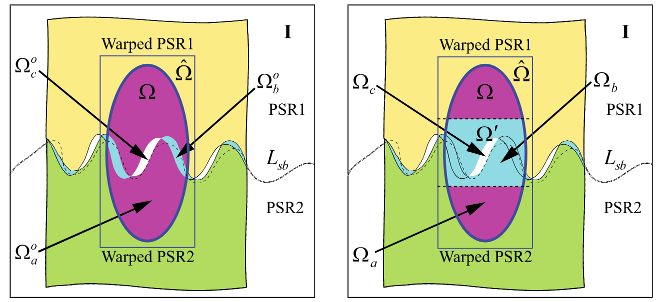


Fig. 3. Transformation of the visible information on the LDV image. The candidate PSRs on the LDV image are independently warped onto their counterparts on the target image, hence several overlappings and gaps appear among the warped candidate PSRs



a The target region **b** The practical strategy

Fig. 4a,b. Our image repairing algorithm. The target image $\boldsymbol{I}$ consists of two PSRs with their common boundary L_{sb}. The warped PSRs fall onto the repairing window $\hat{\boldsymbol{\Omega}}$, which encloses the missing region $\boldsymbol{\Omega}$ on $\boldsymbol{I}$. **a** Circled by the *blue lines*, $\boldsymbol{\Omega}$ contains three parts, i.e., the missing pixels under the overlappings $\boldsymbol{\Omega}_b^o$, the gaps $\boldsymbol{\Omega}_c^o$ and the remainder $\boldsymbol{\Omega}_a^o$. **b** Our algorithm divides $\boldsymbol{\Omega}$ into three parts and repairs these with different schemes. The missing pixels in $\boldsymbol{\Omega}_a$ outside the region of band $\boldsymbol{\Omega}'$ are first recovered by graph cut based image stitching. Then those in $\boldsymbol{\Omega}_b$ are restored by texture synthesis based image inpainting. Finally, those in $\boldsymbol{\Omega}_c$ are completed by image fusion based hole filling

– *Graph cut based image stitching* stitches the warped candidate PSRs onto $\boldsymbol{\Omega}_a$.
– *Texture synthesis based image inpainting* samples the warped PSRs to synthesize $\boldsymbol{\Omega}_b$ in terms of a defined repairing priority function.
– *Image fusion based hole filling* fuses the nearby known pixels to fill the gaps $\boldsymbol{\Omega}_c$ under the control of a defined fusion priority function.

We now discuss the details of our repairing algorithm.

3.2.1 Graph cut based image stitching

In order to stitch the warped candidate PSRs onto $\boldsymbol{\Omega}_a$ seamlessly, we use a graph cut algorithm [4] to discover the optimal seam lines in the overlapping regions of the warped PSRs and the known area on the target image within $\hat{\boldsymbol{\Omega}}$. The graph cut algorithm works by expressing the problem as finding the min-cut in a weighted graph and minimizing the color gradient differences across the seaminess. This has already been used in texture synthesis [16] and image stitching [25], and is well suited for this purpose.

After finding the optimal seaminess, the warped PSRs are stitched onto the target image along the seaminess to fill the remaining pixels in $\boldsymbol{\Omega}_a$.

3.2.2 Texture synthesis based image inpainting

The remaining missing pixels in $\boldsymbol{\Omega}_b$ are filled one by one with texture synthesis based image inpainting. It begins with a pixel on the boundary of $\boldsymbol{\Omega}'$, i.e., $\partial\boldsymbol{\Omega}'$, and iteratively selects the next pixel with the highest priority to proceed. For each pixel p to be filled, we define a 3×3 patch centered at p. The existent pixels in the patch are used as the constraints for finding the best match m according to the SSD metric (the sum of squared differences between the colors of their surrounding pixels). The candidate matches for p are confined to the surrounding pixels of the corresponding 3×3 patch in the warped candidate PSRs. The whole process is terminated when a certain condition is satisfied.

To ensure a faithful restoration of the potential feature lines along the common boundary L_{sb}, it is important to select a good seed pixel to start the texture synthesis process. An appropriate repairing priority function needs to be defined. For a boundary pixel p in the missing region, we define its repairing priority as $P_I(p)=C_I(p)*S_I(p)$, where

$$C_I(p)=\sum_{i=1}^{8} w(p_i)/8$$

is the confidence term that represents the reliable information contained in p's 8-neighborhood, thereinto $w(p_i)$ is the reliability weight of p's 8-neighborhood pixel p_i. In implementation, we set a threshold $\tau=3/8$ for $C_I(p)$ to qualify the boundary pixels with enough known neighbors and control the repairing process from the boundary pixels to the interior of $\boldsymbol{\Omega}'$ progressively.

$$S_I(p)=(l/L)*(\nabla I_p^{\perp}\cdot n_p/\alpha)$$

is the structure term, in which l is the number of PSRs referred to by pixels in p's 8-neighborhood. L is the number of warped PSRs projecting into the repairing window. l/L can endow the pixels near L_{sb} with high repairing priority. ∇I_p represents the color gradient at p, $\perp$ denotes the orthogonal operator, n_p is the unit normal of p on $\partial\boldsymbol{\Omega}'$ and α

is a normalization factor. $\nabla I_p^{\perp} \cdot n_p/\alpha$ represents the interaction strength of the image structure with the boundary of the missing region and boosts the priority of a patch where the structural interaction takes place [8].

Table 1 illustrates our inpainting algorithm based on texture synthesis. In the algorithm, two termination conditions are provided. If $\partial\boldsymbol{\Omega}'$ is empty, which indicates that all pixels in the missing region are repaired, the image repairing process terminates. Or else, if the highest repairing priority is 0 and the repairing cycle fails to repair any pixels, which means that none of the remaining pixels can be matched with a pixel in the warped PSRs, the algorithm also terminates this inpainting process. The remaining missing pixels, if any, are filled by the following hole filling process.

3.2.3 Image fusion based hole filling

After texture synthesis based image inpainting, some still missing pixels in $\boldsymbol{\Omega}_c$ remain unrepaired. Normally, only a few of them exist as shown in Fig. 5. We therefore take the pixel-wise fusion operation to deal with such pixels. The basic idea is to fill in the residual pixels with the color fused by those of its known neighbors.

To make the result more reasonable, fusion operation should start from the residual pixel with more known pixels and less PSRs in its neighborhood. For the pixel p, we define the fusion priority function $P_F(p)$ as

$$P_F(p) = C_F(p) * S_F(p).$$

Here $C_F(p) = n/4$ is the confidence term and $S_F(p) = 1/l$ is the support term. $C_F(p)$ sets high priority for the residual pixel with more known pixels in its 4-neighborhood, n is the number of its known neighbors. $S_F(p)$ sets high priority for the pixel with less PSRs in its 4-neighborhood and l is the number of PSRs covering $\boldsymbol{\Omega}$.

With the above definition, all residual pixels are first sorted according to their fusion priorities. Then, the one with the highest priority is filled with the average color of its 4 neighbors, and the priorities of relevant residual pixels are refreshed thereafter. The above process is repeated until all residual pixels are filled.

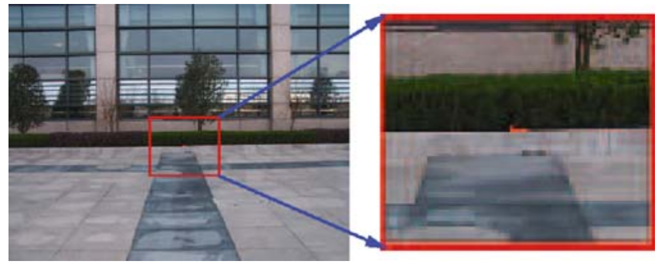


Fig. 5. The intermediate repairing result (from Fig. 2n) after texture synthesis based image inpainting. The *red pixels* within the zoom-in rectangle are those residual missing pixels in $\boldsymbol{\Omega}_c$ that hold no matched pixels in the warped PSRs during texture synthesis based image inpainting process

Table 1. Texture synthesis based image inpainting

1. Initialization.
Initialize $\partial\boldsymbol{\Omega}'$ and $\boldsymbol{\Omega}'$.

2. Weight setup.
If $p_i \in \boldsymbol{\Omega}'$, $w(p_i) = 0$; else $w(p_i) = 1$. $\forall p_i \in \boldsymbol{I}$.

3. Priority computation.
- Compute $C_I(p)$, $\forall p \in \partial\boldsymbol{\Omega}'$. If $C_I(p) < \tau$, $P_I(p) = 0$.
- Else, search for m in the warped PSRs.
- If $m = \emptyset$, $P_I(p) = 0$; else compute $S_I(p)$ and $P_I(p)$.

4. Copying and filling.
Repair $p_m = \arg\max_{p\in\partial\boldsymbol{\Omega}'} [P_I(p) > 0]$ with $m(p_m)$, $w(p_m) = 0$.

5. Update $\partial\boldsymbol{\Omega}'$ and $\boldsymbol{\Omega}'$.

6. Repairing cycles and termination conditions.
- *Cycle 1.* Repeat steps 4 and 5 until no more pixel is repaired in two successive iterations. If $\partial\boldsymbol{\Omega}' = \emptyset$, exit.
- *Cycle 2.* Repeat steps 2 ∼ 5 until no more pixel is repaired in two successive cycles.
If $\partial\boldsymbol{\Omega}' \neq \emptyset$ && $\max_{p\in\partial\boldsymbol{\Omega}'} P_I(p) = 0$,
go to the following hole filling process.

3.3 Poisson image blending

Due to the luminance difference between the LDV image and the target image, ghost effects may appear on the repaired result as shown in Figs. 6j and 7f. We tackle this issue by Poisson image blending [20].

Let S be the domain of the target image. $\boldsymbol{\Omega}$ represents the repaired region in S with boundary $\partial\boldsymbol{\Omega} = \{p \in S \setminus \boldsymbol{\Omega} : N_p \cap \boldsymbol{\Omega} \neq \emptyset\}$, in which N_p denotes p's 4-neighborhood. Supposing that f^* is the known color of all pixels in $\partial\boldsymbol{\Omega}$, we obtain the fusion color f of all pixels in $\boldsymbol{\Omega}$ by solving the following linear equations:

$$|N_p| f_p - \sum_{q\in N_p\cap\boldsymbol{\Omega}} f_q = \sum_{q\in N_p\cap\partial\boldsymbol{\Omega}} f_q^* + \sum_{q\in N_p\cap\boldsymbol{\Omega}} g_{pq},$$

where $p \in \boldsymbol{\Omega}$. $g_{pq} = c_p - c_q$ is the color gradient between the repaired pixels p and q in $\boldsymbol{\Omega}$. We can solve the above large-scale sparse linear equations efficiently with the conjugate gradient method.

4 Results and discussion

We implemented the proposed algorithm on an Intel Pentium IV 1.6 GHz PC with 256 MB main memory under the Windows XP operating system. Figures 2, 6 and 7 demonstrate the experimental results.

Figure 2a presents the target image. We first adopt the traditional texture synthesis based image completion method [8] to repair the occluded area and get Fig. 2b. Obviously, the missing part of the tree cannot be well re-

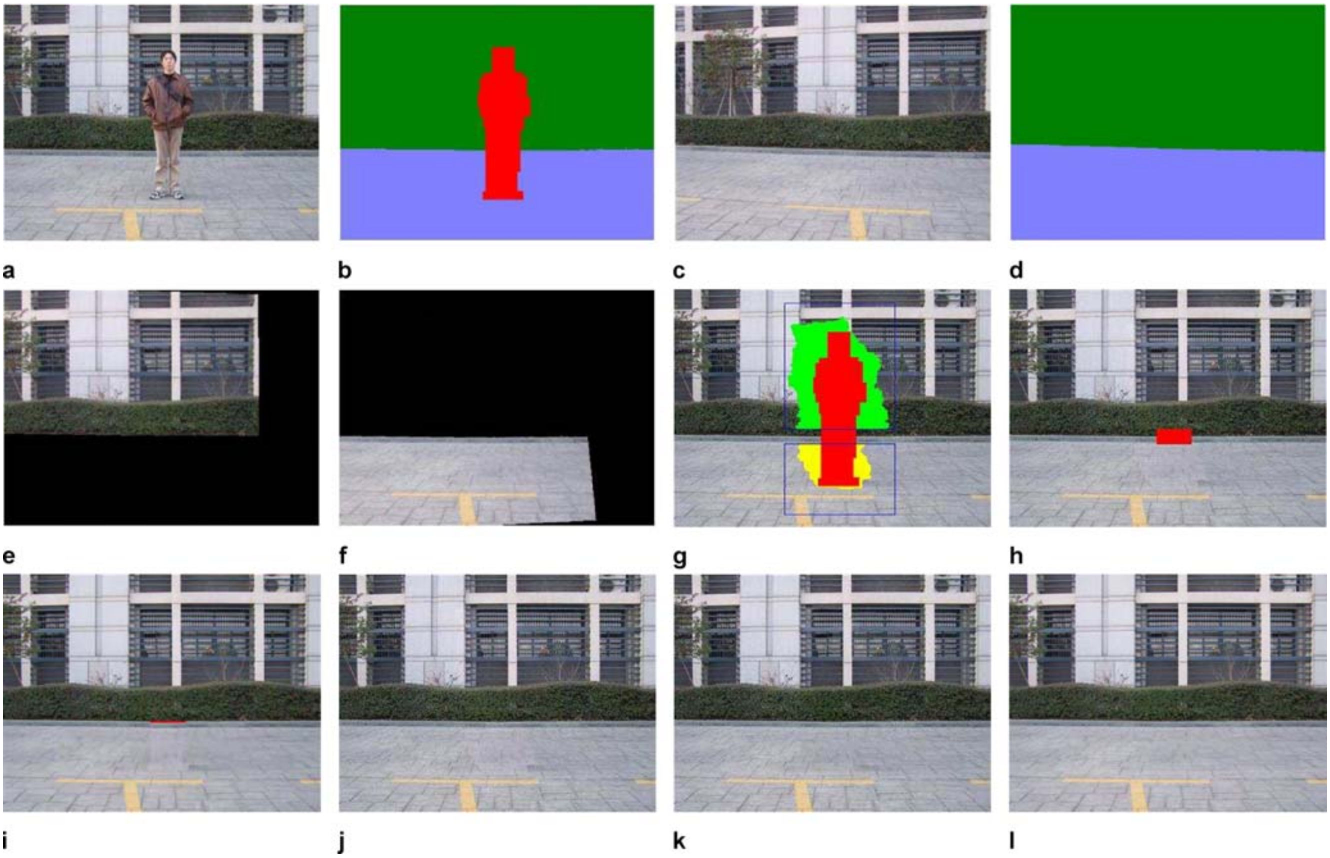


Fig. 6a–l. A corner of a building. **a** Target image. **b** PSRs on the target image. **c** LDV image. **d** PSRs on the LDV image. **e**,**f** Warped PSRs from the LDV image. **g** Optimal seam lines produced by graph cut (contours of the *green* and *yellow* areas). **h** Intermediate repairing result by graph cut based image stitching. **i** Repairing result after texture synthesis based image inpainting with the residual missing pixels in *red*. **j** Repairing result without Poisson image blending. **k** The final repairing result. **l** The original scene

constructed due to its insufficient condition [21]. Sun et al.'s method [24] can achieve remarkable image repairing results for the missing regions with strong structure information. However, their method requires that structure curves be carefully specified, which is impossible for a missing area with such a complex structure in our case. By exploiting the information from an LDV image of the same scene, our method can obtain the more natural repairing result as shown in Fig. 2o.

Figure 2c is an LDV image, and Fig. 2d is its globally warped image with respect to Fig. 2a. Compared with Fig. 2a, distinct distortion is exhibited in the wall of Fig. 2d. Repairing the occluded region with Fig. 2d directly will lead to a poor result.

Figures 2e–o illustrate the process of our algorithm. The red mask in Fig. 2e is the specified target region. Figure 2f presents the initial segmentation of the target image with mean shift, and Fig. 2g shows its PSRs after interactively merging the fragments that belong to the same scene plane. Similarly, Fig. 2h presents the initial segmentation of the LDV image, and Fig. 2i shows its PSRs. Figures 2j and k are the warped candidate PSRs on their counterparts on the target image. We then carry out graph cut based image stitching. Figure 2l shows the optimal seam lines produced by graph cut. Figure 2m is the result of image stitching along the optimal seam lines. Figure 2n is the intermediate repairing result after texture synthesis based image inpainting. We obtain the final repairing result Fig. 2o after image fusion based hole filling on the residual missing pixels (shown in red in Fig. 2n). It took less than 1 min to repair about 10 000 missing pixels on the target image with a size of 461×361 besides the time for interaction.

Figures 6 and 7 demonstrate the other two experiments. Figures 6j and 7f show the repairing result without Poisson image blending. An obvious ghost effect exists due to the illuminance difference between the target image and the LDV image. In comparison, Figs. 6k and 7g show the seamless repairing results with Poisson image blending, which are comparable to the original scene in Figs. 6l and 7h. As can be seen, our algorithm works well even for large missing regions with complex structure information.

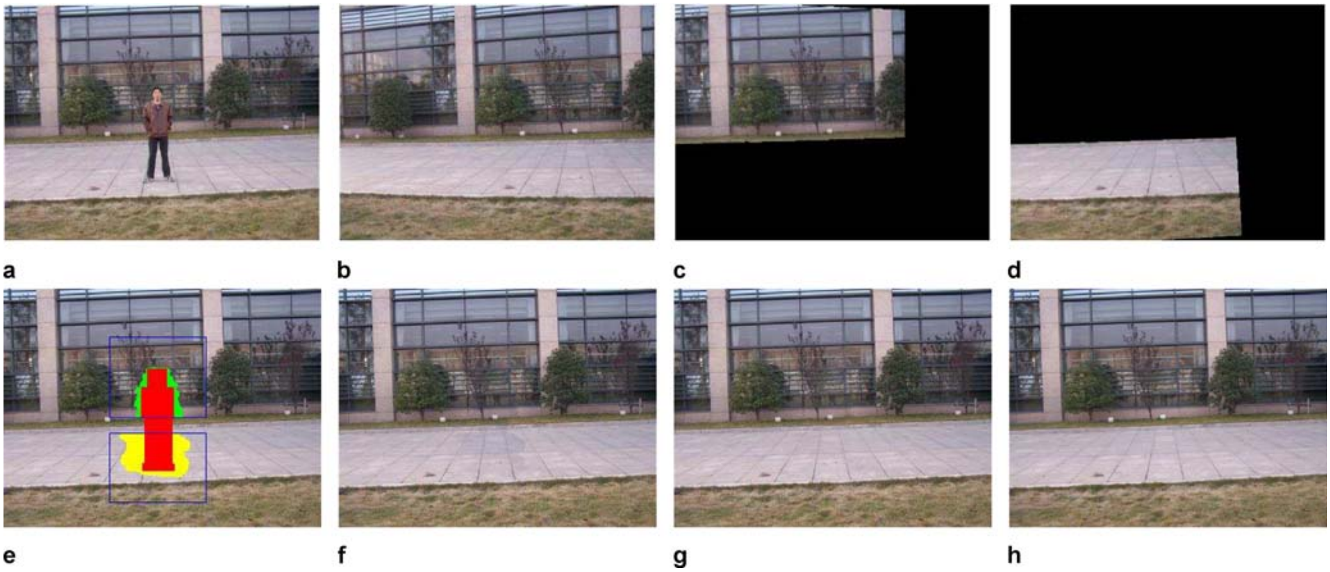


Fig. 7a–h. Profile of a teaching building. **a** Target image. **b** LDV image. **c**,**d** Warped PSRs from the LDV image. **e** Optimal seam lines shown as the contours of the *green* and *yellow regions*. **f** Repairing result without Poisson image blending. **g** The final repairing result. **h** The original scene

5 Conclusion and future work

Image completion based on views of large displacement fills in occluded or damaged regions of a target image exploiting the visible information of the LDV images. In this paper, we propose an effective solution for this problem. By employing the techniques of image segmentation and image matching, we transform the LDV image into usable information, and then repair the missing region with a new image repairing algorithm. Experiments show that our method works well even for large missing regions with complex structure, and achieves superior repairing results to previous image completion techniques.

The following topics are to be investigated in future:

– PSRs on the target image and the LDV image one as well as their counterparts are currently specified by user interaction, which is time-consuming. We wish to employ the information of color distribution and relative location of the initially segmented image patches to automatize this process.
– At present, we only verify our method with a single LDV image. However, image completion from multiple images with different views will be more useful for photo editing and completion. We shall further test the cases of several LDV images with complex occlusions.

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