ORIGINAL ARTICLE

Content-aware copying and pasting in images

Meng Ding · Ruo-Feng Tong

Abstract We present a content-aware image copy-and-paste technique which combines ideas from both matting and gradient-based methods. We modify the diffusion process used in the gradient-based approach to use the alpha matte for the cloned area as a weight function to control intensity interpolation. This ensures that the color style of the significant parts of the selected region is preserved when pasting. We use a framework based on mean-value coordinates to implement our approach, allowing us to provide a parallel implementation suitable for use on a GPU. Experimental results show the advantages of our method.

Keywords Image pasting · Image cloning · Matting · Gradient domain · Laplace equation

1 Introduction

Image *composition* is an important task in image editing, which can be described as *copying* a manually selected source patch in one image and *pasting* it at a target location elsewhere (in another image or the same image), in such a way that the patch fits into the destination seamlessly and naturally. There are two kinds of techniques to perform image composition: *alpha blending* and *gradient domain* method. Alpha blending methods perform a simple and direct blending operation on intensities in the target image, while gradient domain methods reconstruct intensities

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in the pasted area by solving a partial differential equation (PDE) in the gradient domain.

In both of them, two separate subproblems must be considered: cutting and pasting. The former refers to extracting the patch to be copied from the source image, while the latter refers to inserting the patch into the target image. These are not necessarily straightforward problems. Firstly, it may be tedious and difficult for the user to exactly specify the source patch, and it may be desirable for the user to give general guidance as to its location, which is then algorithmically refined. Secondly, when pasting, the user may wish to modify the patch, or the surrounding image, or both, so that they match better in appearance in the final result. The pasting problem is the main concern of this paper.

Cutting plays a very important role in *alpha blending* method, since foreground pixels are superposed on background pixels with their opacities (alpha matte). Usually, user manually determines this alpha matte with interactive tools. However, using such tools requires skill and experience, and in many cases, making a clean and exact selection needs prolonged and intensive interaction. Therefore, some indirect cutting approaches are proposed for matting, in which the selection is no longer determined directly by user interaction. Instead, the alpha matte for the cut region is provided by some automatic refinement mechanism based on the user indicating certain areas as definitely belonging to the background, others as definitely foreground. Such approaches allow relatively lightweight user interaction, but they rely on the assumption that foreground and background colors vary smoothly, and so they do not always work well for natural images.

Unlike alpha blending methods which perform a simple and direct blending operation on intensities in the target image, gradient domain methods reconstruct intensities in the pasted area by solving a PDE in the gradient domain, so an

exact selection is no longer necessary which means that user control here is very simple: the user selects a region (cutting) in the source image and pastes it at a location in the target image. Although such methods have the ability to accomplish seamless image compositions, as pointed out in [5], they only work well when the textures in both the source and target images are sufficiently similar near the pasting boundary. Furthermore, since the essence of these methods is to construct a harmonic interpolant that diffuses intensity differences between background and pasted area across the seam boundary into the entire pasted area interior, and the construction of this interpolant is performed independently of the pasted patch's content. Consequentially, the resulting intensity changes in the pasted area may be unacceptable.

In this paper, we propose a content-aware image copy-and-paste technique which combines ideas from both matting and gradient-based methods. By *content-aware*, we mean that discrepancies of the color along the boundary are diffused in a way which depends on the pasted patch's contents. More specifically, we modify the diffusion process used in the gradient-based approach to use the alpha matte for the cloned area as a weight function. This controls intensity interpolation determined by a PDE for each pixel of the pasted region. The benefits of this hybrid approach, compared to previous image composite method, are twofold. Firstly, since a gradient-based approach is used, it is unnecessary to extract an accurate matte, which allows user interaction to be much less precise. Secondly, the main subject of the pasted region preserves its original color appearance due to the use of the alpha matte as a weight function.

The rest of the paper is organized as follows. After briefly summarizing related work in Sect. 2, we discuss our content-aware cloning method and various implementation issues in Sect. 3. Experimental results and further discussion are given in Sects. 4 and 5, and conclusions in Sect. 6.

2 Related work

As explained, alpha blending and gradient-based methods are two approaches for performing image composition. While the former approaches concentrate on the cutting (selection) techniques, the latter is more concerned with the details of the pasting method. We briefly review each in this section.

In alpha blending, the composite image I can be expressed by the following blending equation:

$$I = \alpha F + (1 - \alpha)B \tag{1}$$

where B is a background image, F is a foreground image F and α is a alpha matte which is used to represent selection.

Clearly, to achieve good results, determination of the alpha matte is important. Direct cutting tools, such as the *selection tool* in Adobe Photoshop [1] needs the user to manually select a patch through interaction, which requires skill and is labor intensive. Thus, recent work has considered algorithmic approaches to assisting the cutting process, producing either a hard cutting result (with binary, 0 or 1 alpha values) [2, 13, 14, 16] or a soft cutting result (allowing other alpha values) [4, 11, 17–19, 21]. Given an image in which a selection is to be made, the common idea of these methods is for the user to *scribble* to indicate some areas which are definitely to be selected, and some which are definitely not to be selected. This results in a pixel trimap (to be selected, not to be selected, undecided). An automatic refinement mechanism is used to yield the final selection. The former group obtains a binary alpha matte by solving a min-cut problem, which usually works well when the foreground and the other part have significant color differences. The latter group determines a fractional alpha matte by solving (1), where the values of F and B for each pixel in the undecided region are estimated in different ways. Although such approaches allow relatively lightweight user interaction, they do not always work well for natural images. Further detail is given in the comprehensive survey by Sun [20]. Our method makes the use of an alpha matte, but since this matte is not used to determine image intensities directly, an accurate alpha matte is unnecessary. Thus, the dependence on user selection in traditional alpha blending methods can be relaxed.

Gradient domain approaches have recently been devised to provide seamless pasting. They take advantage of the psychologists' observation that the human visual system is much more sensitive to local contrast than to absolute luminance or to slow changes in luminance [5, 10]. The essence of these methods is to construct a harmonic interpolant that diffuses the differences in intensity along the seam boundary between the source and target image into the entire image patch interior. For example, [15] constructs the pasted patch from a given gradient field (usually taken from the source image) by solving a Poisson equation with Dirichlet boundary conditions defined by the intensities of the target image along the boundary of the pasted region, while [7] uses a similar approach but solves a bi-Laplace equation. Jia et al. [8] further improves Poisson method by optimizing the blending boundary. More recently, [5] achieves similar composition results using mean-value coordinates. Chen et al. [3] propose a hybrid image composition method where the result is computed by combining Poisson method and alpha blending. Our method is also based on the gradient domain approach. However, unlike previous work of this kind, we introduce a weight function in the Poisson method so that the constructed harmonic interpolant is content-aware.

3 Content-aware image copying and pasting

We now introduce our content-aware image copying and pasting method. In our approach, an imprecise selection of the patch to be pasted is needed as well as an rough alpha matte (an accurate one is unnecessary). The user interface and how to get the alpha matte will be discussed later.

The main idea of our method is that, we introduce a weight function to control the construction of the harmonic interpolant in the original Poisson method. Figure 1 illustrates the notation: let $S \subset \mathbb{R}^2$ and $T \subset \mathbb{R}^2$ be the source and target image domains, respectively. Let $g : S \to \mathbb{R}$ and $f^* : T \to \mathbb{R}$ be intensities in the source and target images, and let $\Omega \subset \mathbb{R}^2$ be a closed subset of S with boundary $\partial\Omega$, which indicates the user selected patch.

3.1 Content-aware image copying and pasting

Given a target image and a source patch to be pasted, the standard Poisson method constructs the pasted image patch in such a way that the gradient field of the pasted patch is as close as possible to that of the source patch and the boundary intensity of the pasted patch agrees with that of the target image.

Mathematically, it is derived from finding the extremum of the functional J:

$$J[u(x, y)] = \iint_\Omega \|\nabla u - \mathbf{v}\|^2 \, d\Omega \quad \text{with } u|_{\partial\Omega} = f^*|_{\partial\Omega}, \quad (2)$$

where $\mathbf{v}(x, y)$ is a guidance vector field which is usually set to the gradient field of the source image and $u : \Omega \to \mathbb{R}$ is the desired output image patch whose value along the boundary $\partial\Omega$ equals to the value of corresponding pixel in the target image.

From the calculus of variations, when J reaches an extremum, $u(x, y)$ must satisfy the Ostrogradski equation: $F_u - \partial F_{u_x}/\partial x - \partial F_{u_y}/\partial y = 0$, which leads to the Poisson equation:

$$\Delta u|_\Omega = \text{div } \mathbf{v}|_\Omega \quad \text{with } u|_{\partial\Omega} = f^*|_{\partial\Omega}. \quad (3)$$

Now, if the guidance field $\mathbf{v}$ is a conservative field, which is true for the gradient of the source image g, this Poisson equation is equivalent to the following Laplace equation:
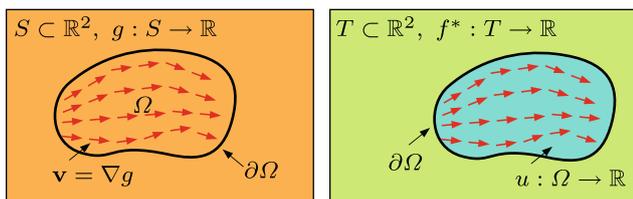
$$\Delta \tilde{u}|_\Omega = 0|_\Omega \quad \text{with } \tilde{u}|_{\partial\Omega} = (f^* - g)|_{\partial\Omega}, \quad (4)$$

where $\tilde{u} = u - g$. Thus, the desired output image can be simply expressed as $u = \tilde{u} + g$, which reveals that Poisson image cloning constructs a harmonic interpolant which diffuses the difference in intensity $(f^* - g)$ between the source and the target image away from the patch boundary into the entire patch region.

Note that this diffusion is independent of the source patch's content inside the boundary. In other words, given the boundary and the mismatch $(f^* - g)$ at this boundary, the additive correction $\tilde{u}$ is exactly the same for any source image, and can be called *content-free*.

However, it would be rather more useful to provide a *content-aware* interpolant so that the mismatch diffusion occurs in such a way as to take account of the content in the interior source image patch. See Fig. 4(c), the eclipse sun should be dark, but here, it is blue. Another example is given in Fig. 3(d) of the unsatisfactory results which can arise with the Poisson method. Note how the pasted woman appears darker than the original woman. However, the user would expect the pasted women to appear much more similar to the original woman, as they have the same illumination.

The unsatisfactory results in both of the above examples arise because the result has been constructed in a way such that the gradient field has minimal L^2-norm, but there is no perceptual reason for this to be the optimal solution. Indeed, as can be seen from these two examples, the output would be more acceptable if it better took into account the content of the patch being pasted. Thus, we propose an alternative with this in mind. We modify the kernel of the functional J by including a factor which depends on content (see (5)). For parts of the pasted region whose appearance should be preserved, a large factor value is used. Since the difference between the source patch and the constructed one in those parts will be emphasized by this large factor value, they will have a greater effect on the value of J. Conversely, by minimizing J, the colour of the constructed pixels in areas with high factor values will be forced to be closer to the corresponding pixel values in the source image, while pixels with low factor will on the other hand be allowed to exhibit greater differences.

In detail, then we introduce a weight function $\omega : \Omega \to (0, 1]$ into (2), and remembering that $\mathbf{v} = \nabla g$, we obtain a new functional

$$J'[u(x, y)]$$
$$= \iint_\Omega \left\| \nabla \left(\frac{u - g}{\omega} \right) \right\|^2 d\Omega \quad \text{with } u|_{\partial\Omega} = f^*|_{\partial\Omega}. \quad (5)$$

By defining $\tilde{u}' = (u - g)/\omega$, we obtain a similar Laplace equation to (4) but with different Dirichlet boundary condi-

Fig. 1 Notation for Poisson image cloning with guidance vector field $\mathbf{v} = \nabla g$. S, T are source and target images, with intensities g, f^* respectively. Ω is the patch to be cloned with boundary $\partial\Omega$, and u is the output patch

tions: $\tilde{u}'|_{\partial\Omega} = (f^* - g)/\omega|_{\partial\Omega}$. In this case, the final output image can be expressed as

$$u = \omega\tilde{u}' + g. \tag{6}$$

The effect of the additive correction term $\tilde{u}'$ is controlled by the weight map ω. We construct this content-aware weight map in such a way that, for important parts of the source patch whose original color appearance should be preserved, ω is set to zero or a very small value which implies that $1/\omega$ will be a large number, while for those parts that should be consistent with the target image, ω should be set to 1. This fits in well with a selection approach in which the user makes a loose selection around the source patch to be cut-and-pasted. The inner part of the source patch is the main object of interest, whose appearance should be preserved, so it is given a high weight. The outer part of the source patch is relatively unimportant, and is given a low weight: its appearance may change more significantly to allow a good match along the seam with the target image.

A natural way to generate this weight map is to use a matting technique. Given the source image selected by the user, matting gives an estimated alpha map $\alpha : S \rightarrow [0, 1]$. The α value represents the extent to which a given pixel can be regarded as being a foreground pixel, or an important pixel, in the terminology above. Thus, we can simply set the weight ω to

$$\omega = 1 - \alpha. \tag{7}$$

3.2 Implementation

Our user interface is simple, the user specifies a region to be cloned by drawing a boundary in the source image, then generates the content-aware weight map by making a few scribbles to indicate the important area, and finally, drags this region to somewhere in the target image.

Because the output image can be formulated by (6), and $\tilde{u}'$ is determined by a Laplace equation, we can use mean-value interpolation to construct a smooth interpolating membrane following the proposed approach in [5]. Given a region Ω with boundary $\partial\Omega = (\mathbf{p}_0, \mathbf{p}_1, \ldots, \mathbf{p}_n, \mathbf{p}_0)$, mean-value coordinates (MVCs) [6] for a point $\mathbf{x} \in \Omega$ can be calculated using

$$\lambda_i(\mathbf{x}) = \frac{w_i}{\sum_{j=0}^{n} w_j}, \quad i = 0, \ldots, n, \tag{8}$$

where

$$w_j = \frac{\tan(\alpha_{i-1}/2) + \tan(\alpha_i/2)}{\|\mathbf{p}_i - \mathbf{x}\|^2} \tag{9}$$

and α_i is the angle $\angle\mathbf{p}_{i-1}\mathbf{x}\mathbf{p}_i$ (see Fig. 2). Using these MVCs, the discrepancies $(f^* - g)$ at the boundary can be
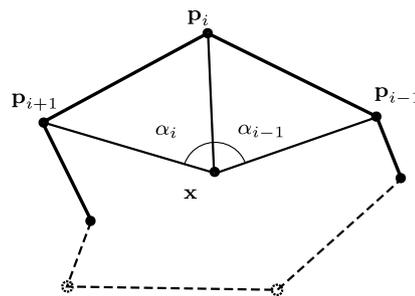
Fig. 2 Definitions for mean-value coordinates: $\mathbf{p}_i$ are boundary points ordered counter-clockwise

smoothly diffused to the entire region using

$$r(\mathbf{x}) = \sum_{i=0}^{n} \lambda_i(\mathbf{x})\big(f^*(\mathbf{p}_i) - g(\mathbf{p}_i)\big). \tag{10}$$

The final image patch is then given by $u = \omega r + g$.

A significant benefit of using mean-value coordinates is that the output value at each interior point can be interpolated totally independently of all other interior points, thus allowing a very efficient GPU implementation. Furthermore, the mean-value coordinates $\lambda_i(\mathbf{x})$ of a point $\mathbf{x}$ are only dependent on the boundary. Thus, once the user has specified the cutting boundary, all MVCs are determined, independently of where the patch is to be pasted: it is unnecessary to recalculate MVCs as the patch is dragged over the target image. This allows fast enough updates for the user to immediately see what the results of pasting will look like.

Alternative approaches may be used for producing the alpha matte. A simple approach is to use the *Elliptical Marquee Tool* and *Feather Tool* in Adobe Photoshop [1] to perform the selection. A more sophisticated approach is to use Levin's efficient matting method [12]. Note that, since we are not using it to extract foreground objects, an accurate alpha matte is unnecessary and user interaction need not be precise.

In our interface, the user can select the boundary by dragging the mouse with left-button down or by clicking on a few points which are then joined by straight lines. In the latter case, p_i are those clicked points, while in the former case, p_i are every pixel the boundary passes through.

4 Experimental results

We now present some results produced using our content-aware copying and pasting technique, and we compare the quality of these results to those obtained using the original Poisson method and Chen's method [3].

In Fig. 3, a manually selected patch is pasted into another location in the same image. Levin's method [12] was used to produce the matte; the α matte constructed is shown
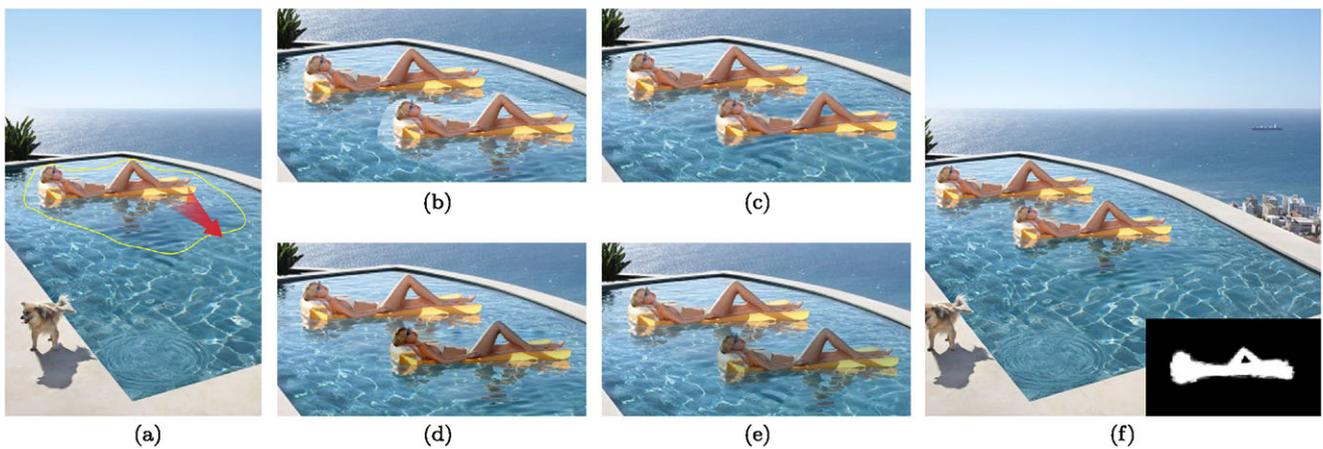
Fig. 3 A cloning example: (**a**) original image, and selected region, (**b**) result using direct cut-and-paste, (**c**) result using alpha blending, (**d**) result using Poisson method, (**e**) result using Chen's method [3], (**f**) result using our method (the used alpha matte is showed in *right-bottom corner*)
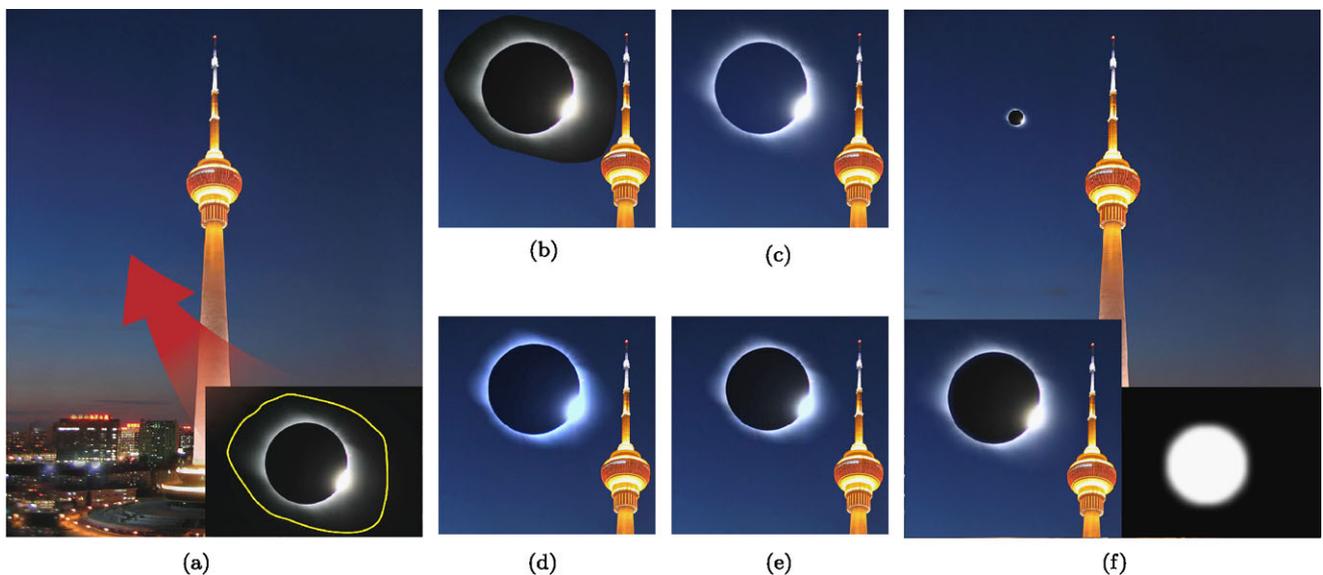
Fig. 4 Making a new image, by pasting the eclipsed sun into the target image (**a**); (**b**), (**c**), (**d**), (**e**): composite image using direct cut-and-paste, Poisson method, Chen's method [3] and Photo clip art [9]; (**f**) result using our method (the used alpha map is shown in the *right-bottom corner*, and for realistic purpose, we zoom the pasted sun out and the original size result is showed in the *left-bottom corner*)

in the right-bottom corner in Fig. 3(f). Direct cut-and-paste results in a very unsatisfactory composite image shown in Fig. 3(b), since an imprecise selection boundary is used, and there is an obvious seam between water in the pool and the pasted area. Naive alpha blending (the same α matte as used in our method) gives a unnatural composite image shown in Fig. 3(c), since the inverted reflection in water is omitted. Figure 3(d), (e) show the composite results obtained using the original Poisson method and Chen's method [3]. This time, no such visible seam exists. However, the color appearance of the main subject in the selection area (the woman) has changed. Since both women in the final result are the same, and are viewed under approximately identical illumi-

nation conditions, this appearance change is obviously undesirable. Figure 3(f) shows the result using our method, which has neither of the disadvantages of the other earlier results.

Figure 4 shows another example; this time, Adobe Photoshop tools were used to produce the matte. Here, the aim is to paste an image of the eclipsed suns into a target background image (Fig. 4(a)). Figure 4(b) shows the result using direct cut-and-paste. As can be seen, a visible seam exists and the cloned patch is not blended with the target image at all. Figure 4(c) shows the composite image generated using the original Poisson method. Almost perfect blending is achieved, as textures in source and tar-

Table 1 Performance for our method. "#Boundary" and "#Region" represents to the number of points in boundary and points inside the region, respectively, "MVC" represents to the time elapse in calculating mean-value coordinates and "paste" represents to the time elapse in pasting phrase

Exp. No.	#Boundary	#Region	GPU (ms)		CPU (ms)		Memory (Mb)
			MVC	paste	MVC	paste	
1	196	2,301	9	2	182	9	35.24
2	470	12,975	38	18	1,955	94	60.84
3	639	104,048	573	140	20,295	1,044	293.07
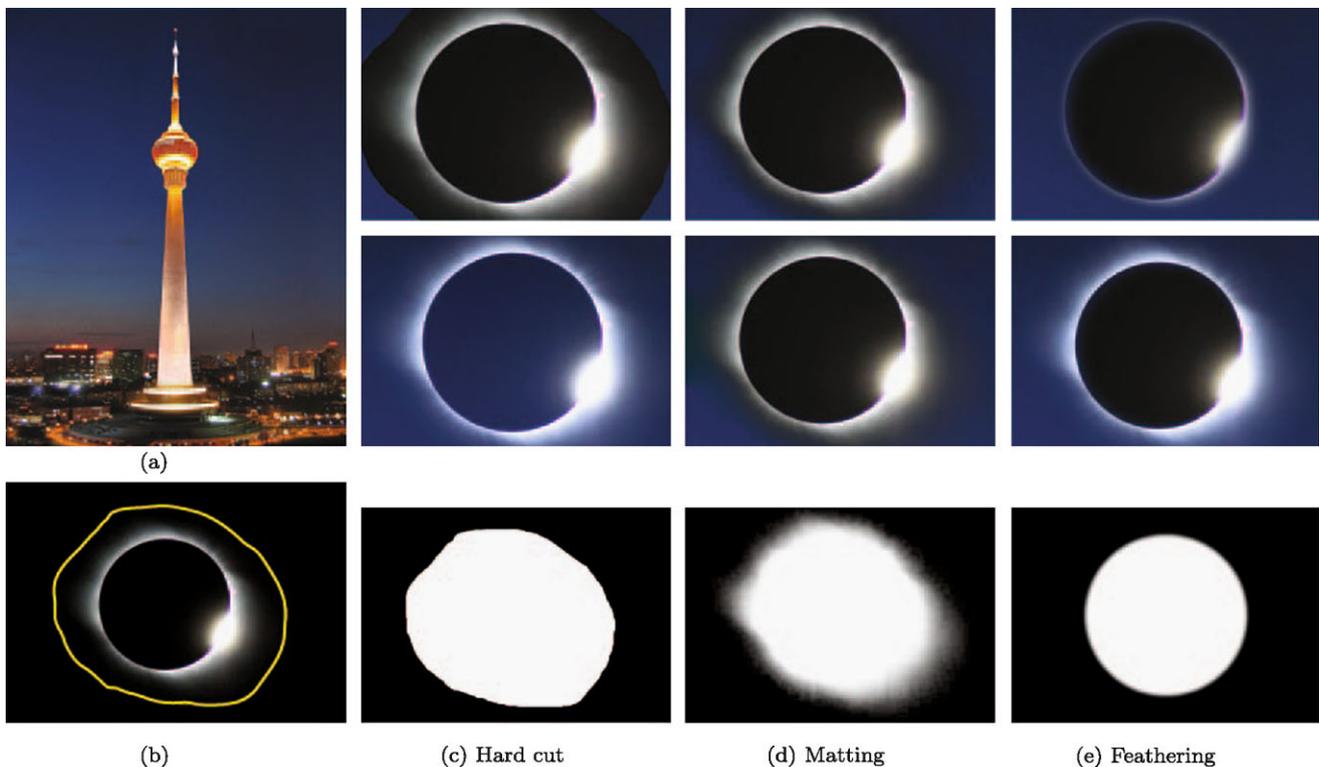
Fig. 5 Using different alpha mattes: (**a**) target image, (**b**) selection for pasting. The *right part* shows the results obtained using alpha blending (the *first row*) and our method (the *second row*) with the alpha mattes constructed in different way (the *third row*)

get images are sufficiently similar near the pasting boundary, and the color mismatch along the boundary is almost uniform. However, because the diffusion is done independently of the source patch's content, the moon's color is changed by this approach (in an eclipse, the moon is passing in front of the sun). We should see the dark side of the moon as black, but the Poisson approach results in it becoming dark blue like the sky. Figure 4(d), (e) show the result obtained using Chen's method [3] and Photo clip art [9], which reduce the discoloration in some degree but still suffer from it. Figure 4(f) shows the result using our method. Again, almost perfect blending is achieved, but this time, the moon has a much better color appearance. This is because the additive correction term $\tilde{u}'$ is weighted by ω,

and as a result, the sun itself is not influenced by diffusion.

Both time and space complexity of mean-value cloning are $O(nm)$, where n is the number of p_i points in the given boundary and m is the number of pixels in the region. We do not use any optimization strategy to performing mean-value cloning. Since the mean-value interpolant is very smooth away from the boundary of the pasted region, there is unnecessary to calculate the mean-value coordinates for every pixel inside the region. Thus, a more efficient version can be devised by using *adaptive mesh* [5]. Table 1 shows the performance of our implementation. Our experiments were carried out using an Intel Core2Duo 3.0 GHz PC with 4 GB memory and a NVIDIA GeForce 9600 GT graphics card.
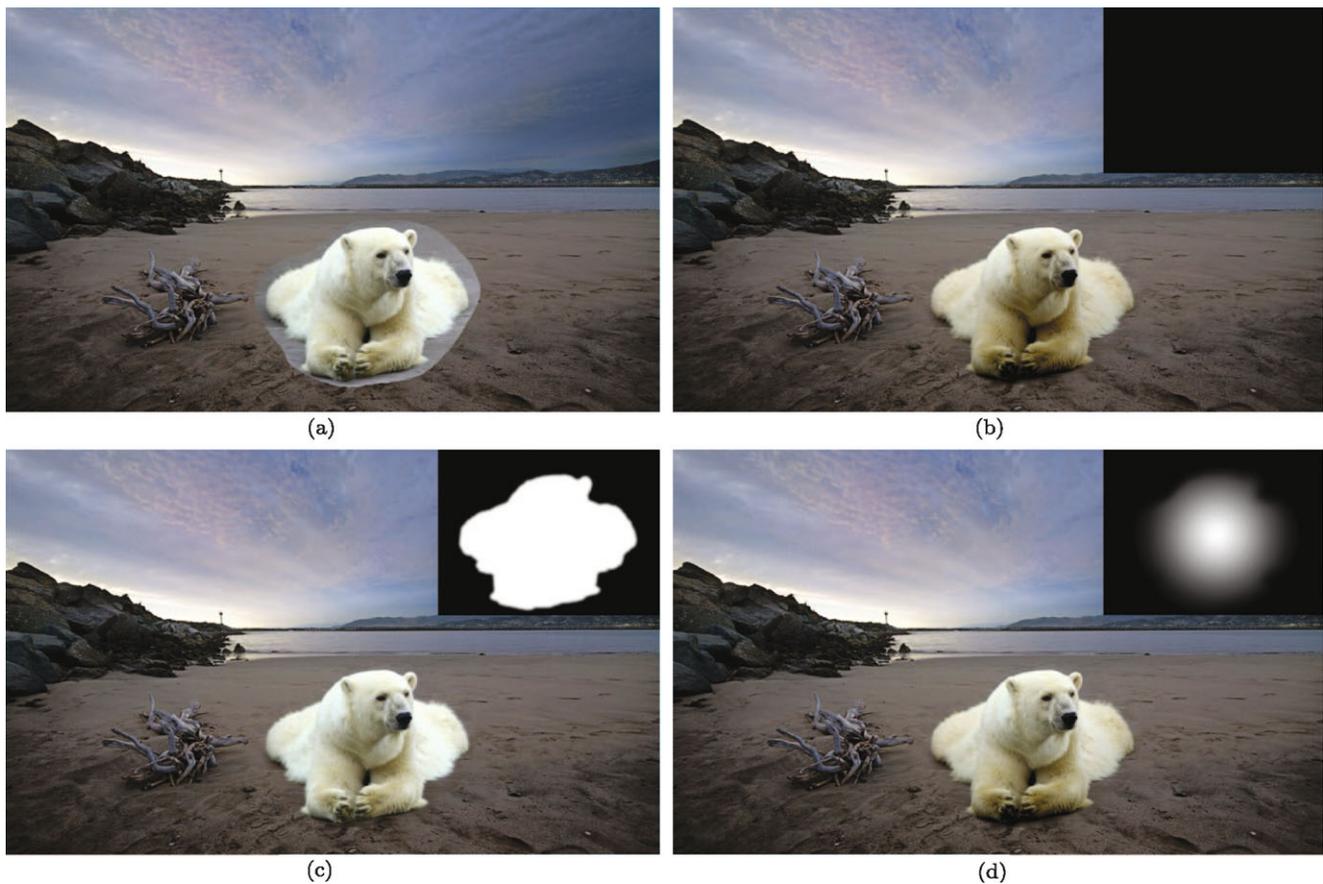
Fig. 6 Results using our framework and different alpha mattes manually created by various Adobe Photoshop tools; (**a**): source and target images; (**b**), (**c**), (**d**): results using alpha mattes shown in the top-right corner of each image

5 Discussion

In our technique, the pasted image patch can be constructed through the simple formula in (6), which can be regarded as a general framework: the user can choose different ω maps to get different composition results. In particular, if we set $\omega = 1$ everywhere, our method degenerates to the original Poisson method. As already mentioned, different approaches can be used for generating ω, such as interactive tools as used in the eclipsed sun example, to obtain the most desirable composite result. Figure 5 shows the results obtained using alpha blending (the first row of the right part of the figure) and our method (second row), with different alpha mattes (different columns, mattes shown in third row). In column (c), a binary alpha matte is used, and under this circumstance, our method corresponds to the original Poisson method. In column (d), a soft alpha matte created by Levin's method. The selection area is too large, resulting in part of the sky around the moon becoming black. In column (e), a soft alpha matte created by *Elliptical Marquee Tool* and *Feather Tool* in Adobe Photoshop [1] is used to give results where the moon is clearly black, yet the surrounding sky remains blue.

As noted previously, while the gradient field of the constructed region has minimal L^2-norm, there is no perceptual evidence to show that this construction is optimal. Indeed, different people will have different views about whether a final composite image is acceptable and appropriate; this also depends upon factors such as object geometry and lighting conditions. Because our method allows flexibility of approach in determining the alpha matte, this allows the user to provide varied effects appropriate to the images in question, as demonstrated by the previous examples. Figure 6 shows further results constructed using our framework, but different alpha mattes.

Our framework is not only useful for copy-and-paste, but also good for tidying up a "dirty" background when a photo has been taken against some different colored, but imperfect, background. Figure 7 shows the "tidy up" result. Here, the aim is to tidy up the background of the original photo, which is achieved by pasting the foreground patch to a pure black background. Figure 7(a) shows the original photo, the manually selected boundary and the used alpha matte created by Levin's method. Figures 7(c) and 7(d) shows the result obtained using alpha blending and our method respectively, a zoom-in view is given in Fig. 7(e). As can be seen,
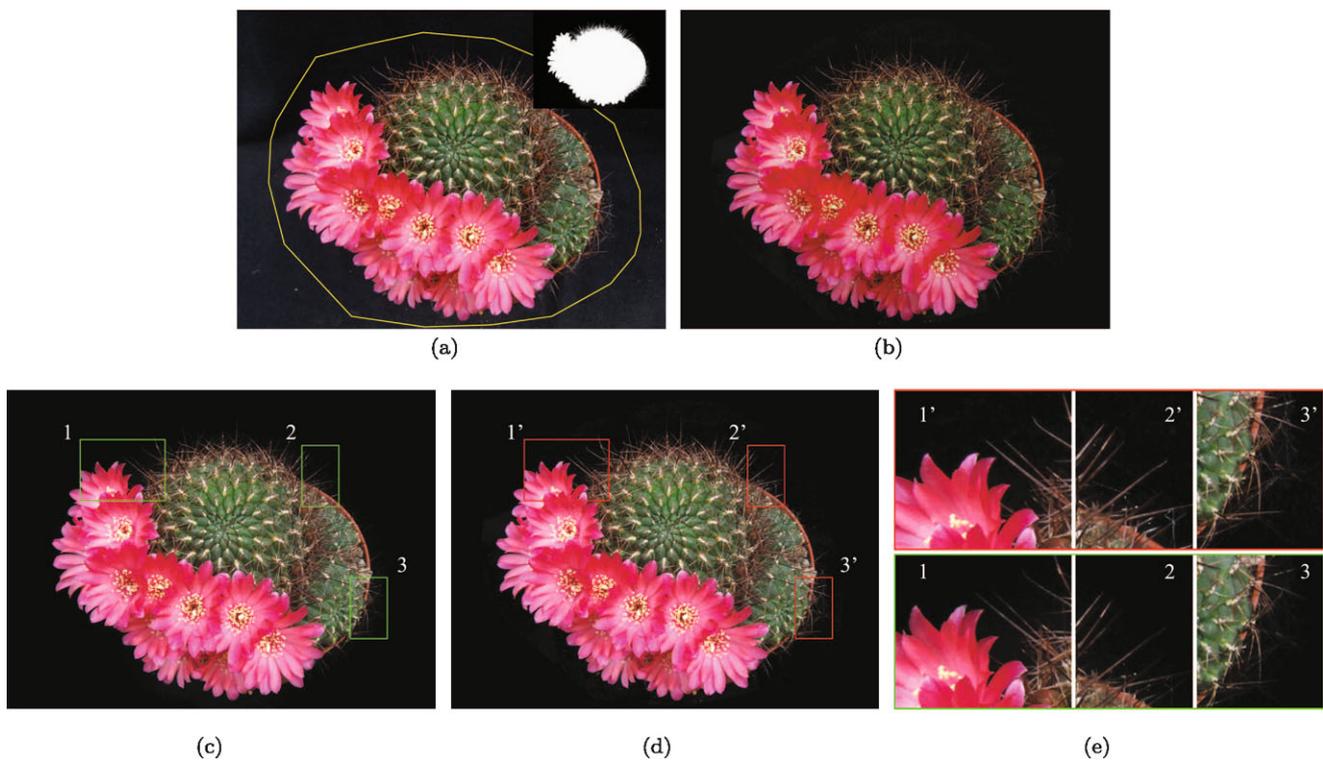
Fig. 7 Tidying up the background. (**a**): original photo, the manually selected boundary, and the alpha matte created by Levin's method; (**b**), (**c**), (**d**): results using original Poisson method, alpha blending, and our method, respectively; (**e**): zoom-in view

while both of them keep the color appearance of the plant, the latter one preserved more details of the spines near the boundary. Figure 7(b) shows the result obtained using original Poisson method, where the color appearance has a significant undesired change.

The limitation, as pointed out earlier, is that our method needs the textures in both the source and target images are sufficiently similar near the pasting boundary.

6 Conclusions

We have given a content-aware image copy-and-paste technique, in which the intensity mismatch between source and target images along the pasting boundary is diffused into the pasted image under the control of a weight map. This prevents a visible seam while ensuring that the color style of the significant parts of the selected region are preserved when pasting. Matting techniques are used to construct the weight map. Diffusion is performed using a framework of mean-value coordinates rather than solving the original Laplace equation. Experimental results show the advantages of our method over existing approaches.

Our method can be regarded as a general image editing framework where the alpha matte controls an additive correction term, rather than the image intensity as done in traditional alpha blending.

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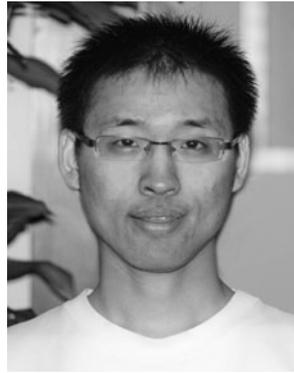
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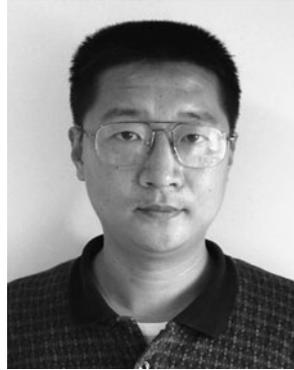
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