Sequential Image Stitching for Mobile Panoramas

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***Abstract*—This paper presents a sequential image stitching approach for creating high-quality panoramic images on mobile devices. In this approach, each source image in the image sequence is stitched onto the panoramic image sequentially using two operations: optimal seam finding and transition smoothing. In the seam finding process, graph cut optimization finds an optimal seam and creates labeling in the overlapping area between the current panoramic image and the current source image. The current panoramic image can be updated by merging the current source image using the labeling information. If there are visible stitching artifacts in the seam, a transition smoothing operation is performed to hide the seam and remove the stitching artifacts. In the transition smoothing process, a gradient vector field is created from the gradients of corresponding pixels in the current labeled source image to construct a Poisson equation. A composite image can be recovered from the gradient vector field by solving the Poisson equation with boundary conditions. The current panoramic image is updated by merging the composite image.**

The approach presents several advantages. The use of graph cut optimization guarantees finding optimal seams and avoids blurring and ghosting problems caused by objects moving between capture of input images or by spatial alignment errors. The gradient domain transition smoothing process reduces color differences and further improves image quality. The sequential panorama stitching procedure enables us to produce high resolution panoramic images with limited memory resources. The approach is implemented and it produces high quality panoramic images on mobile devices. It shows good performance for both indoor and outdoor scenes.

***Index Terms*—Image stitching, image blending, optimal seam finding, transition smoothing, graph cut optimization, panorama stitching, mobile panorama, multigrid solver, mobile image processing, mobile computational photography**

I. INTRODUCTION

Many applications in computer vision and computational photography that could only work on PCs before, can now be implemented and run on mobile devices, including mobile augmented reality [1], [2] and mobile image matching and recognition [3]. In this paper, we are interested in creating high-quality panoramic images on mobile devices. User can take an image sequence for a wide range of scenes with a camera phone, see a panoramic image of the scenes on the camera phone immediately, and send it to friends.

Image stitching is an important step in creating high quality panoramic images. A simple copying and pasting of overlapping areas of source images may produce visible artificial edges in the seam between source images, due to differences in camera responses and scene illuminations, or spatial alignment errors. Image stitching can find optimal seams in the overlapping areas of the source images, cut the images along the seams, and blend them together seamlessly.

Current approaches for image stitching in the literature can be divided into two main steps [4], optimal seam finding and transition smoothing. Optimal seam finding algorithms such as [5], [6], [7], [8], [9] search for optimal seams in overlapping areas where differences between source images are minimal. Labeling between all pixels of the composite image and source images can be created according to the optimal seams. The composite image is produced by copying corresponding pixels from the source images using labeling information. Different optimal seams can be obtained by defining different cost functions. This kind of approaches can avoid ghosting and blurring problems caused by spatial alignment errors or by objects that move between captured images. It works well when the source images are similar enough. However, when they are too different for the algorithms to find ideal seams, stitching artifacts may remain. Transition smoothing algorithms reduce color differences between source images for hiding seams and removing stitching artifacts. Alpha blending [10], [11] is a simple and fast transition smoothing approach that uses weighted combination to create the composite image. The main disadvantage of alpha blending is that moving objects will cause ghosting and small registration errors can cause blurring of high frequency details. Recently, gradient domain image blending approaches [7], [4], [12], [13], [14], [15], [16] have been applied to image stitching and editing. A new gradient vector field is created with gradients of source images to construct a Poisson equation and a new composite image can be recovered from the new gradient vector field by solving the Poisson equation with boundary conditions. Such algorithms can adjust the color differences due to illumination changes and variations in camera gains for the composite image globally. It can produce high quality composite images. However, memory and computational costs are also high.

We present a sequential image stitching approach for producing high quality panoramic images on mobile devices. We stitch each source image onto the panoramic image sequentially with optimal seam finding and transition smoothing processes. Ghosting artifacts caused by moving objects and blurring caused by spatial alignment errors can be avoided by optimal seam finding with graph cut optimization. Stitching artifacts and color differences can be removed by the transition smoothing operation with gradient domain image blending. The sequential panorama stitching procedure enables us to process large source images and create high resolution panoramic

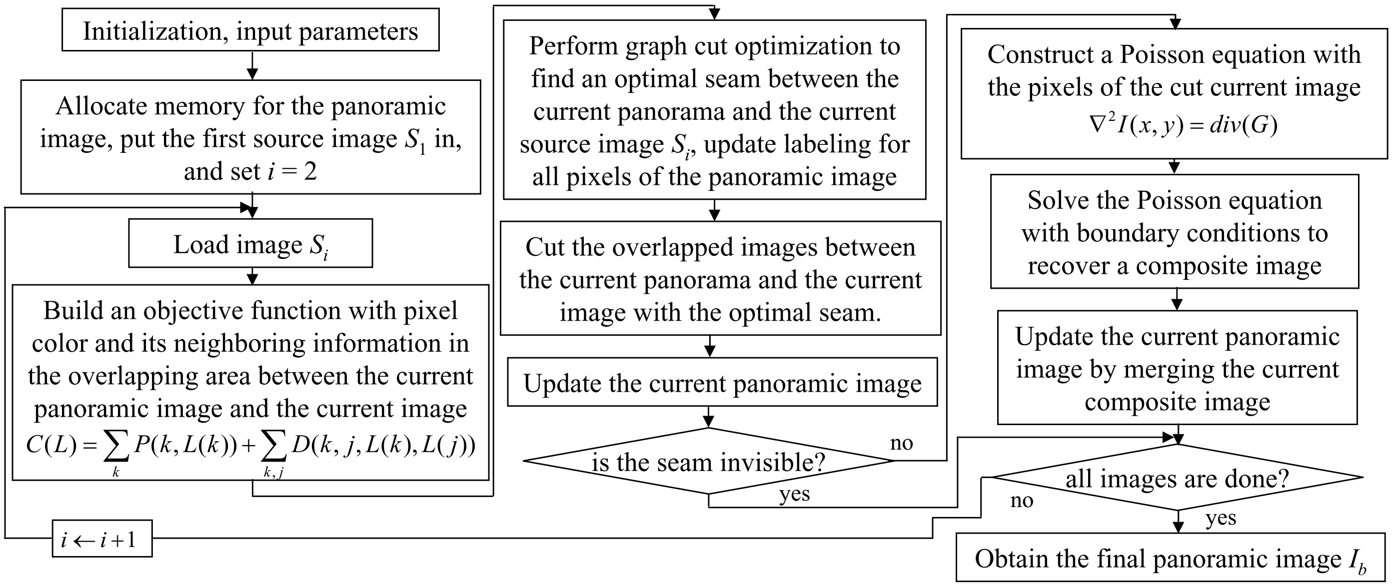

Fig. 1. Work flow of the sequential image stitching approach for creating mobile panoramic images.

images on limited-resource devices such as mobile phones. The approach is implemented in our mobile panorama system and tested in several different types of scenes. This results in good performance and high-quality panoramic images.

We introduce the work flow of our approach in Section II. The details of the sequential image stitching approach with optimal seam finding and transition smoothing processes are described in Section III. Applications and result analysis are discussed in Section IV. Section V concludes with a summary.

II. Overview of Our Approach

Figure 1 shows the work flow of the sequential image stitching approach. The size of the final panoramic image can be computed with the offsets and sizes of source images in the image sequence. We initialize the panoramic image with the first source image and update it by stitching other source images sequentially.

During panorama stitching, each source image is processed by two processes, optimal seam finding and transition smoothing. In optimal seam finding, an objective function is constructed with the property of pixels and color differences between corresponding pixels in the overlapping area of the current panoramic image and the current source image. The optimal seam is found by graph cut optimization. Meanwhile, labeling for updating the current panoramic image is created and the overlapping area can be cut with the seam information. The current panoramic image is updated with the current source image with the labeling. If the seam in the overlapping area remains visible, transition smoothing is needed to further reduce the differences between the current panoramic image and the current source image. We do that by creating a new gradient vector field with the gradients of the current labeled source image to construct a Poisson equation. A new composite image is recovered from the new gradient vector field by solving the Poisson equation with boundary conditions. We update the current panoramic image by merging the new composite image.

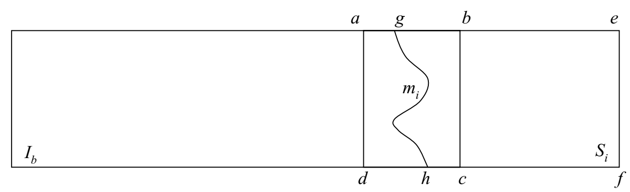

Fig. 2. Sequential image stitching.

The stitching process is repeated until all source images are processed. Finally, we can obtain the final panoramic image in which there is no stitching artifacts and ghosting problems caused by moving objects or spatial alignment errors.

III. The Sequential Image Stitching Approach

We assume that the source images in an image sequence $S_1, S_2, \ldots, S_i, \ldots, S_n$ have already been aligned. We stitch them onto the panoramic image sequentially.

As shown in Figure 2, suppose that I_b is the current panoramic image and S_i is the current source image. The overlapping area between these two images is $abcd$. We need to find an optimal seam m_i in the overlapping area to cut the overlapping images and create labeling for the pixels of the panoramic image in the overlapping area, so that we can merge I_b with S_i.

Considering implementation on mobile devices, we create a simple and efficient objective function $C(L)$ with two items, pixel property P and color differences D between corresponding pixels,

$$C(L) = \sum_k P(k, L(k)) + \sum_{k,j} D(k, j, L(k), L(j)), \qquad (1)$$

where $C(L)$ is the objective function; L is pixel labeling; $P(k, L(k))$ depends on the property of pixel k; $D(k, j, L(k), L(j))$ is the color difference over all pairs of neighboring pixels k, j.

In the case of sequential image stitching, there are two images in the overlapping area. We set the label of pixels in the current panoramic image I_b as 0 and in the current source image S_i as 1;

For the item of $P(k, L(k))$, we set it as a large number for pixels in invalid areas, otherwise as 0. The invalid areas are created by the image mapping process. This means that the seam is not allowed to go into the invalid areas;

Of course, we can add other items into the objective function to consider other properties when cutting the source images. For example, we can add an item to consider edge information, however this will need more computational and memory costs.

The optimal seam finding or labeling problem can be cast as a binary graph cut problem. We apply a max-flow approach [17] to solve it. The approach uses "alpha expansion" to minimize the cost function and obtain an optimal solution.

We update the current panoramic image I_b by merging the current source image S_i along with the optimal seam. If the seam is invisible, the stitching process for S_i has completed and we can continue with the next source image. If the seam and stitching artifacts are still visible, further processing is needed to hide the seam and remove these artifacts. In this approach, we create a gradient domain transition smoothing process to reduce the differences between the current panoramic image I_b and the current source image S_i.

We create a gradient vector field (G_x, G_y) by copying the gradients of corresponding pixels in the area of $gefh$ in the current source image using the same labels created by the optimal seam finding process. With the gradient vector field, a divergence vector $div(G)$ can be computed. Suppose $I(x, y)$ is the composite image. We use the divergence vector as a guidance vector and construct a Poisson equation

$$\nabla^2 I(x, y) = div(G), \tag{2}$$

where ∇^2 is the Laplacian operator

$$\nabla^2 I(x, y) = \frac{\partial^2 I(x, y)}{\partial x^2} + \frac{\partial^2 I(x, y)}{\partial y^2} \tag{3}$$

and $div(G)$ is the divergence vector field

$$div(G) = \frac{\partial G_x}{\partial x} + \frac{\partial G_y}{\partial y}. \tag{4}$$

The partial differential equation (2) can be solved after specifying boundary conditions; we use Neumann boundary conditions and set the gradients at the boundary to zero.

Since the Poisson equation 2 is linear, we use standard finite differences to approximate each item. The discrete form can be described as

$$\begin{aligned} &I(x+1, y) + I(x-1, y) + I(x, y+1) \\ &+I(x, y-1) - 4I(x, y) \\ &= G_x(x, y) - G_x(x-1, y) + G_y(x, y) - G_y(x, y-1). \end{aligned} \tag{5}$$

The approximation of finite differences shown in equation (5) gives a large system of linear equations. One equation corresponds to a pixel in the final composite image. The large system of linear equations is over-constrained. We solve for least-squares optimal vector I using a full multigrid algorithm described in [18].

Finally, a new composite image I_i can be recovered from the gradient vector field (G_x, G_y) by solving the Poisson equation with boundary conditions. We update the current panoramic image I_b by merging the new composite image I_i.

After stitching the current source S_i onto the current panoramic image I_b, we load the next source image S_{i+1} as the current one and continue the stitching process until all source images are processed. Finally, we can obtain the final panoramic image produced with the whole image sequence.

In the sequential image stitching process, we only need to store the panoramic image and the current source image other than all source images in memory, which is good for mobile implementation.

IV. Applications and Result Analysis

The approach is implemented in our mobile panorama system for creating high quality panoramic images on Nokia N95 8G mobile phones with an ARM 11 332 MHz processor and 128 MB RAM. It can also be run on other mobile devices. In these applications, the size of source images in image sequences is 1024×768. Since the seam finding process with graph cut optimization is slow, we downsample the source images with a scale factor 0.25 to solve the optimization problem to obtain labeling and scale the labeling back for the final composite image.

A. Applications in Image Stitching of Outdoor Scenes

We applied the approach to panorama stitching for image sequences captured in outdoor scenes. Figure 3 shows an example with 12 source images. From the image sequence we can see that there are some differences in color and luminance between adjacent images. Figure 3 (top) shows the result produced by the stitching process only using the optimal seam finding process. From the result we can see that seams and stitching artifacts between adjacent images are still visible and further processing is needed to remove them and create the final panoramic image. The optimal seam finding process takes 48.12 seconds when the downsampled source images are used.

Figure 3 (middle) shows the panoramic image produced by the sequential stitching process with optimal seam finding and transition smoothing processes. From the result we can see that all seams are invisible and all stitching artifacts are removed comparing with the top figure. The stitching process takes 147.82 seconds.

B. Applications in Image Stitching of Indoor Scenes

We applied the approach to image stitching for indoor image sequences. Figure 4 shows the 9 source images and results. From the image sequence, we can see that the color and illuminations of source images are different. From the result

Fig. 3. An outdoor panoramic image created with 12 source images.

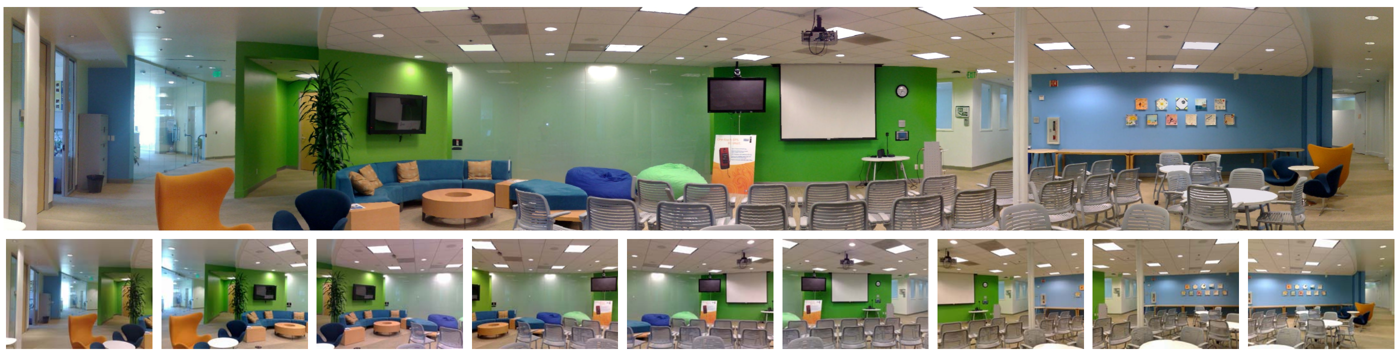

Fig. 4. An indoor panoramic image created with 9 source images.

Fig. 5. A panoramic image for a scene with moving objects.

using both optimal seam finding and transition smoothing we can see that the approach works well for the indoor scene.

C. Applications to Scenes with Moving Objects

We applied the approach to image stitching for the scene with moving objects. Figure 5 shows the application. In this case, there are many moving objects in the source images of the image sequence. The result is produced by the sequential panorama stitching with both optimal seam finding and transition smoothing processes. From the result we can see that the optimal seam finding process can find correct seams to avoid ghosting and blurring problems. The stitching result is very satisfying.

The approach has been tested with many image sequences in different conditions. Figure 6 shows more panoramic images created with the approach. The results are satisfying.

TABLE I
COMPARISON OF MEMORY CONSUMPTION BETWEEN GLOBAL AND SEQUENTIAL IMAGE BLENDING

A	2	3	4	5	6	7	8	9	10
B	11.4	13.3	15.1	16.9	19	20.5	21.4	23.4	24.2
C	10.1	10.8	11.4	12.2	13	13.6	13.7	14.7	15.0

D. Comparison of Memory Consumption

Table I shows a comparison between global image blending and sequential image blending. In the table, row A means the number of source images used, B shows the memory consumption using global blending, and C shows the memory

Fig. 6. More examples of panoramic images created by the sequential image stitching approach.

consumption of sequential blending. The unit of memory consumption is MB. From the results we can see that the more source images in blending, the more memory the sequential blending saves. It is suitable for implementation on mobile devices.

V. Conclusions and Discussion

We have presented a sequential image stitching approach and implemented it in a mobile panorama system on mobile devices for producing high quality panoramic images.

The approach creates a sequential procedure for panorama stitching. Each source image is stitched onto the panoramic image with two processes including optimal seam finding and transition smoothing. Graph cut optimization is applied in the optimal seam finding process and gradient domain image blending is used in the transition smoothing process. The combination of these two processes enables us to produce high quality panoramic images and avoid ghosting or blurring problems caused by moving objects or spatial alignment errors. During panorama stitching, the approach only needs to keep the panoramic image and the current source image other than all source images in memory, which is good for implementation on mobile devices.

The approach is implemented in our mobile panorama system for creating high quality panoramic images. It has been tested in different applications. Examples and results applied to indoor and outdoor scenes are presented in this paper. From the results we can see that the approach works fine on mobile devices and the results are satisfying.

The main disadvantage of the approach is that the computational cost is high.

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