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Efficient Image Stitching in the Presence of Dynamic Objects and Structure Misalignment

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ABSTRACT

This paper presents a new method for simultaneously eliminating visual artifacts caused by moving objects and structure misalignment in image stitching. Given that the input images are roughly aligned, our approach is implemented in two stages. In the first stage, we discover motions between input images, and then extract their corresponding regions through a multi-seed based region growing algorithm. In the second stage, with prior information provided by the extracted regions, we perform a graph cut optimization in gradient-domain to determine which pixels to use from each image to achieve seamless stitching. Our method is simple to implement and effective. The experimental results illustrate that the proposed approach can produce comparable or superior results in comparison with state-of-the-art methods.

Keywords: *Image Stitching, Motion Estimate, Region Growing, Graph Cut*

1. Introduction

Image stitching refers to creating a high-resolution panorama that seamlessly combines two or more images with overlapping fields of view [1]. There are many good existing methods for creating pleasing panoramas. However, they usually have a number of requirements to produce satisfactory results: limited camera translation, limited motion of objects in the scene and similar exposure settings between images.

Generally, there are three problems which often occur in the field of image stitching, namely exposure difference, structure misalignment and ghosting artifacts. In this paper, we are concentrating with two of them, one is ghosting effect caused by moving objects within a scene, and the other is structure misalignment in the overlapped region, which is usually due to inaccuracy of registration methods, motion parallax and etc.

For the problem of de-ghosting, Uyttendaele etc propose to use regions of difference [2]. This technique identifies dynamic objects by checking the source images to see where pixels differ by more than a threshold, and then decide which objects to keep and which ones to erase using a weighted vertex cover algorithm. This algorithm works well, but it may fail when images are not prior well-registered and exposure correction. In addition, it does not establish the correspondence for regions relating to the same object. Thus, ambiguous situation may occur when multiple moving objects exist in the scene. Another technique with excellent results is proposed by Agarwala [3]. Its main idea is to place a seam along the edges of objects in the picture, and then pick pixels from one photo or another based on which side of the seam they fall. Similar works have also been done in [4,5]. However, these techniques require the user manually labels all regions of moving objects, therefore is not suitable for our goal of a fully automated solution.

Several methods have been proposed to alleviate the structure misalignment problem in image stitching. The most famous method in this field could be using optimal seam [6]. These methods first compute the color dif- ference in the overlapped area between the two input images. Alternative way includes computing the difference in gradient or texture feature domain [7,8]. Then the task of finding the optimal boundary is formulated as the minimization of an energy function, which is usually solved by graph cut [9]. More sophisticated approach can be found in [10], which is based on structure deformation and propagation. Moreover, this method can simultaneously achieve structure consistency as well as color correction within the same framework.

After extensively reviewing the previous work on misalignment correction and de-ghosting, we can find that existing approaches have its own advantages as well as disadvantages. Moreover, we did not find any work in the literature, which can simultaneously deals with both of them. In this paper, we propose a novel technique to address them together. After detecting feature correspondence between two images, the first step is to discover motions by interactively applying Random Sample Consensus (RANSAC) [11] in a divide and conquer manner. Once motions are found, we take feature pixels belonging to them as seed points, and use a region growing method to roughly extract moving objects. However, to completely remove ghosting artifacts, we have to accurately determine which regions in the input images are not static. To this end, we formulate it as a labeling problem, and remove ghosting artifacts and structure misalignment together via graph cut. The paper is organized as follows. Section 2 gives the detail of the proposed algorithm. The experimentation results are provided in Section 3, followed by conclusions in Section 4.

2. Our Image Stitching Algorithm

For clarity, in this paper, we consider the basic case of stitching two roughly aligned images. Our algorithm is implemented in two stages. In the first stage, we discover the motions between two input images, and then extract their corresponding regions. With prior information provided by the extracted regions, the second stage is to find an optimal seam, which can simultaneously eliminate visual artifacts caused by the moving objects and structure misalignment. We formulate the task as a labeling problem, and solve it by graph cut. The following sections describe the details of the algorithm.

2.1. Motion Discovery

Let us denote the two images to be stitched as I_S and I_T, and assume that feature correspondence between them has been already established through Scale-invariant feature transform (SIFT) matching [12]. To extract motions between them, we cluster the correspondence by interactively applying RANSAC in a divide and conquer manner. More specifically, we first select the homography with largest no. of coincident key points. Then we remove these points and apply RANSAC again in the remaining points until the no. of points to be matched is below some threshold.

The above process is similar to the work of [13] and [14]. Different from them, before implementing RANSAC, we remove mismatches by our previous proposed method [15]. The reason is, from our experiment, we found that the stability of result is very poor if there exists lots of mismatches in the correspondences, especially when we try to find multiple motion models in them. The output of this stage is a set of motions, in which the one with largest no. of coincident image points corresponds to the background (the global background motion), and the others correspond to the moving objects (the local motion). **Figure 1** shows an example scene, where two motions are detected by fitting two homography transformations to the feature matches. One for the background (**Figure 1**(**a**)), the other for the chair (**Figure 1**(**b**)).

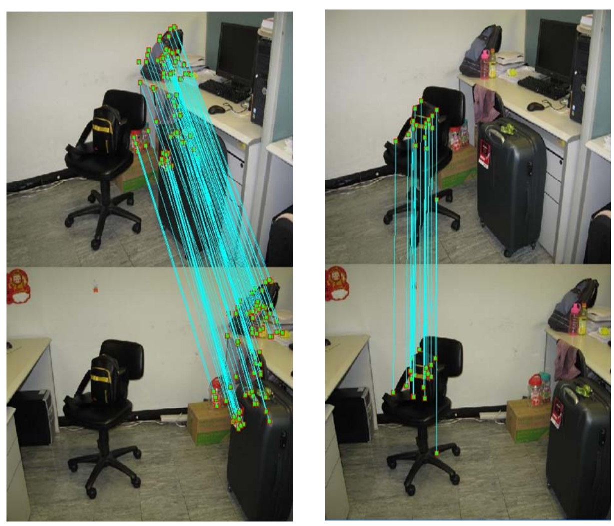
2.2. Locating Moving Region

After finding a set of motions, the next step is to find their corresponding regions, so as to using pixel values from only one of the contributing images for them to eliminate ghosting artifacts. This task can be solved by multiple-seeds based region growing algorithm [16].

Formally, assuming there are N local motions found in the last step and each local motion m_i *is defined by a* homography transformation H_i with associated feature correspondence $\left(x_k^i, y_k^i\right)$, where $1 \le i \le N$. Similarly, the global background motion m_g is denoted by a homography transformation H_g with associated feature correspondence $\left(x_k^g, y_k^g\right)$. Next, for each m_i, we take $\left(x_k^i, y_k^i\right)$ as seed points, and gradually grow them by including neighboring pixel p, which obey one of the following criteria:

Criteria 1: Motion cues

We assume that the background is dominant in the scene. Based on this assumption, motion cues are defined as the discrepancy between the local motion and the



(a) (b)

Figure 1. Fitting motion models using SIFT matches. In this scene, the camera is translating and the chair moves. We detect both motions by fitting two homography transformations to the feature matches. One for the background (Figure 1(a)), the other for the chair (Figure 1(b)).

global background motion, which is written as:

$$\left|I_S\left(p\right)-I_T\left(f_i\left(p\right)\right)\right|<\left|I_S\left(p\right)-I_T\left(f_g\left(p\right)\right)\right| \quad (1)$$

where $f_i\left(p\right)$ and $f_g\left(p\right)$ are mapping functions generated by location motion m_i and global motion m_g, which map the pixel p in I_S, to the $f_i\left(p\right)$ and $f_g\left(p\right)$ in I_T respectively. Their definitions are as follows:

$$f_i\left(p\right)=\mathbf{H}_\mathbf{i}p \quad (2)$$

$$f_g\left(p\right)=\mathbf{H}_g p \quad (3)$$

Criteria 2: Color similarity

$$\left|I_S(p)-I_S(seed)\right|<\varepsilon_1 \quad (4)$$

Here, ε_1 stands for the intensity threshold.

The advantage of using both cues is two fold: on one hand, motion cues can effectively determine the neighboring pixels which have the consistent motion with the seed. On the other hand, the color similarity ensures the extracted region smooth and complete, in case using object motion information alone can only detect a part of the moving object. We run the region growing algorithm twice. The first time is to generate a set of region $\left\{R_1^s,R_2^s,\cdots,R_N^s\right\}$ in I_S. Similarly, the second time is to generate a set of $\left\{R_1^T,R_2^T,\cdots,R_N^T\right\}$ in I_T with the inverse motion filed relating I_T and I_S. Accordingly, the applied region growing criteria are changed to (5) and (6) as follows:

$$\left|I_T\left(p\right)-I_S\left(f_i^{-1}\left(p\right)\right)\right|<\left|I_T\left(p\right)-I_S\left(f_g^{-1}\left(p\right)\right)\right| \quad (5)$$

$$\left|I_T\left(p\right)-I_T\left(seed\right)\right|<\varepsilon_1 \quad (6)$$

where $f_i\left(p\right)=\mathbf{H}_i^{-1}p$ and $f_g\left(p\right)=\mathbf{H}_g^{-1}p$. To conclude, the result of this stage is a set of region pair $\left\{R_1^s,R_2^s,\cdots,R_N^s\right\}$, where R_i^s and R_i^t are related to the regions which are consistent with motion m_i in two images.

2.3. Optimal Seam Selection

With the information provided by the extracted regions, we can now create a seam which is able to eliminate structure inconsistence between images as well as being avoided passing through moving objects. To do so, we formulate it as a labeling problem, and solve it by graph cut. In the following, I_f represent the final composite image with the overlapped region Ω. f_p denotes the label for every pixel $p\in I_f$, which is assigned either 0 or 1. If f_p = 0, the value pixel p comes form image I_s, otherwise, it comes from I_t

In order to make the final composite image I_f like as if the image were captured without the moving objects in the scene, we use information from only one image for each extracted region pair $\left(R_i^s,R_i^t\right)$, and ignore corresponding information in the other images. In other words, we preassign the same label f_p for pixels in the R_i^s and R_i^t as follows:

$$f_p=\begin{cases}1 & if\ \left(R_i^s\cap\Omega\right)>\left(R_i^t\cap\Omega\right)\\ 0 & otherwise\end{cases} \quad (7)$$

Next we consider the label assignment for the remaining pixels in Ω, and define a objective function, $E\left(f\right)$ as the sum of two terms: a data term p,q over all pixel C_i and an interaction term V_s over all pairs of neighboring pixels p,q:

$$E\left(f\right)=\sum_p V_d\left(p,f_p\right))+\sum_{p,q}V_s\left(p,q,f_p,f_q\right) \quad (8)$$

where the data term encourages transitions between the extracted regions and their nearby pixels to be natural and seamless. We use the following cost function to express this desired property:

$$V_d\left(p,f_p\right)=\exp\left(-\frac{d_{f_p}\left(p\right)}{2\sigma^2}\right) \quad (9)$$

where σ is the Gaussian scale and is set to 1 in the experiment. $d_{f_p}\left(p\right)$ is the distance between the pixel p and its nearest region that is pre-assigned with label f_p. This can be calculated by distance transformation [17].

The interaction term takes gradient smoothness into account and penalizes pixel dissimilarity in the gradient domain, which makes the seam favor smooth area in Ω and in turn reduces the structure complexity along the seam. Specifically, we define it as follows [10]:

$$\begin{aligned}&V_s\left(p,q,f_p,f_q\right)\\&=\begin{cases}\left(1-\beta\right)S_m\left(p,q\right)+\beta S_d\left(p,q\right) & if\ f_p\neq f_q\\ 0 & if\ f_p=f_q\end{cases}\end{aligned} \quad (10)$$

$$\begin{aligned}S_m\left(p,q\right)=&\left\|\nabla I_S\left(p\right)-\nabla I_T\left(p\right)\right\|\\&+\left\|\nabla I_S\left(p\right)-\nabla I_T\left(p\right)\right\|\end{aligned} \quad (11)$$

$$\begin{aligned}S_d\left(p,q\right)=&\left\|\nabla I_s\left(p\right)\right\|+\left\|\nabla I_s\left(p\right)\right\|\\&+\left\|\nabla I_T\left(p\right)\right\|+\left\|\nabla I_T\left(p\right)\right\|\end{aligned} \quad (12)$$

where S_m and S_d are two costs measuring the gradient smoothness and similarity between the neighboring pixels p and q. $\left\|\nabla\right\|$ denotes the norm of the gradient for each pixel. β is a weight used to balance the relative influence of the two costs, which is set to 0.3 in our experiments. We use the graph cut algorithm to find a labeling to minimize the objective function.

3. Experiment Results

Having already illustrated the proposed image stitching algorithm by an example, we proceed by further demonstrating the performance of our method in two examples captured in different conditions. Comparison with other methods using our implementation is also given.

3.1. Result Analysis

We first show a simple case, where only one moving object exists in the scene. The two sources images, as shown in **Figures 2(a)** and **(b)** are provided as input. **Figure 2(c)** is the initial alignment, where the visual artifact (indicated in the red box) is obvious because of moving objects and inaccuracy registration. **Figures 2(d)** and **(e)** show the result of Auto Stitching [18] and Panorama Maker [19], respectively. As can be seen, although the structure misalignment is alleviated, it does not help in solve the problem of ghost effect. **Figure 2(f)** is obtained by our method, in which only one instance of the moving object is kept in the final composite image and structures are properly aligned. This demonstrates that our method can handle moving object and structure misalignment within the same framework.

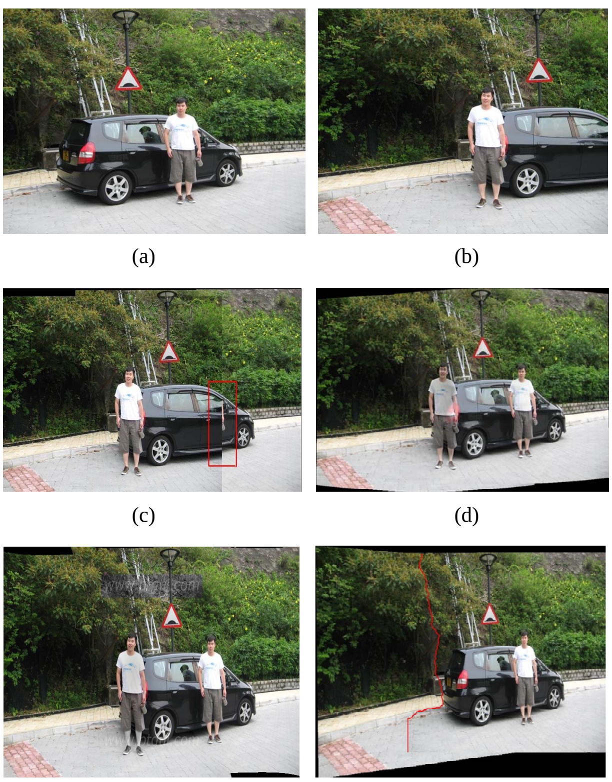


Figure 2. (a) and (b) are the two registered images. (c) The initial alignment. (d) Auto stitching (e) Panorama factory (f) our method.

Next, we apply our algorithm to a more complicated example. This scene is challenging because it contains multiple moving objects, and also exists occlusion between them. **Figure 3** shows the process. **Figure 3(a)** and **(b)** are the original images. Our algorithm first detects motions between images, and then roughly extracts their corresponding region (one for the red box (**Figure 3(c)**), and the other for the bag (**Figure 3(d)**). After that, by taking gradient similarity and transition smoothness into account, we obtain the final panoramic image by selecting an optimal seam in an intelligent manner (indicated by a red curve in **Figure 4(c)**). As can been seen, our seam favors smooth area in the overlapped region and being avoided passing through moving object. Thus, the final composite image is pleasing and structure consistent, while the artifacts caused by moving objects and misregistration still exist in AutoStitching (**Figure 4(a)**) and Panorama Factory (**Figure 4(c)**).

3.2. Computation Times

We finally discuss the computation time needed for our

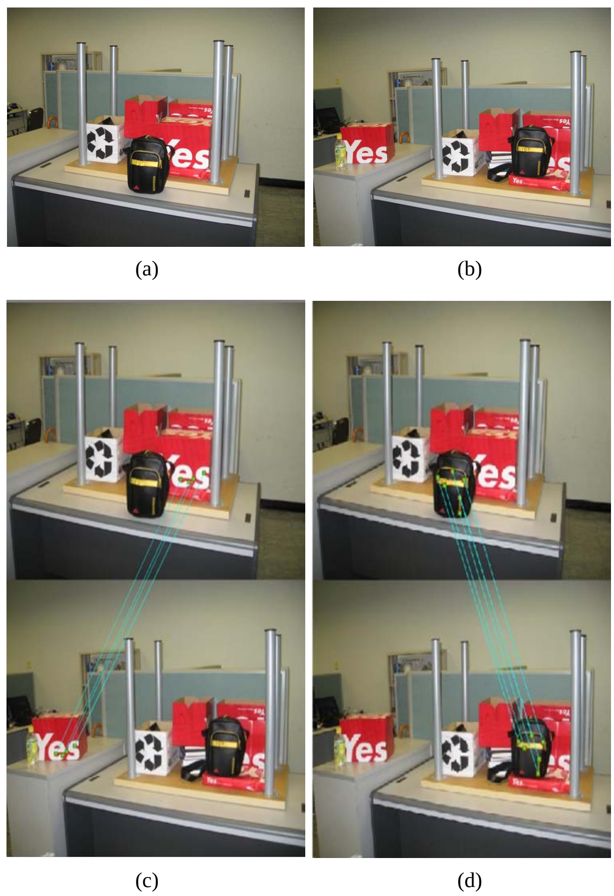
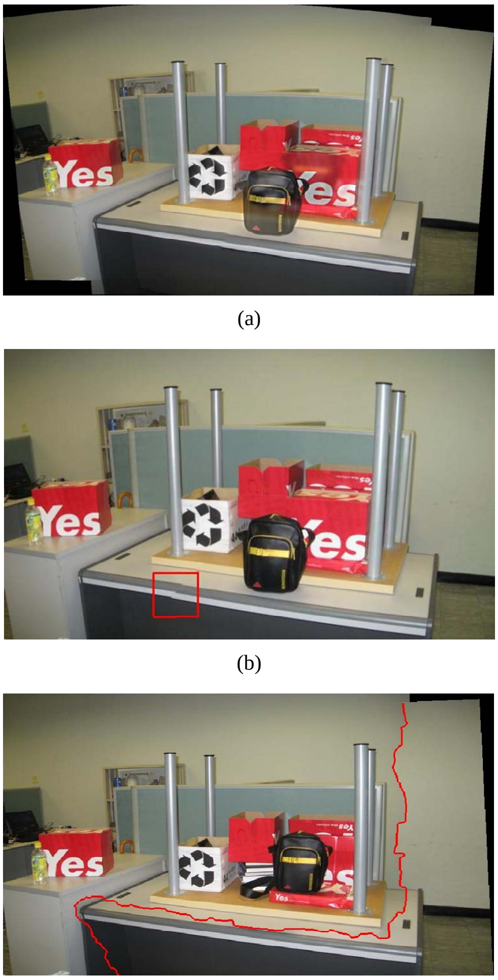


Figure 3. (a) and (b) are the two registered images. (c) (d) Detected two motions, one for the red box, the other for the bag.



(a)

(b)

(c)

Figure 4. (a) AutoStitching (b) Panorama Factory (c) Out Method.

method. To give an idea for the possible reader, we consider the **Figures 2(a)** and **(b)** (640 × 480 pixels) as a benchmark. In reporting this result, we use a PC with an Intel Core(TM)2 Duo processor with a 2.4 GHz clock speed 1 GB RAM, and use matlab as our coding platform to perform the algorithm.

We tabulate the computation times for each step in **Table 1**. As can be seen, the total time needed for image stitching is 18.65 s. In the same setting, the time needed for AutoStitching and Panorama Factory was 12.16 s and 19.1 s, respectively. Therefore, the computation time of our method is acceptable.

4. Conclusions

A novel technique has been presented to achieve seamless image stitching without producing visual artifacts caused by moving objects and structure misalignment. The proposed method includes two major components: 1) Motion discovery 2) a graph cut based optimization framework for seamless stitching. We create data cost to ensure that transition between moving objects and their nearby pixels to be natural and seamless, and smooth cost to encourage the seam favor smooth area. Thus, moving object removal and structure correction are simultaneously achieved within the same framework.

There are also some minor limitations for our method. First, our framework relies heavily on feature matches to extract every independent motion in the scene. Thus, it may fail when correspondence between motions are not detected. Second, our framework can not handle the exposure difference, which is another challenge problem in the filed of image stitching. Therefore, future work aims at making our framework robust to these phenomena, and also extending it to videos and multiple images.

Table 1. Computation time for each step of the proposed approach.

Step	Computation time (second)
Motion discovery	12.52
Locating the moving region	1.78
Optical seam selection	4.35
Total time	18.65

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