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Automatic Unbounded Panoramas

Nadia Guerroui #1, Mohamed Nadjib Kouahla *2, Hamid Séridi *3

 # Dept. of Computer Science, University of Mentouri II ,
Constantine, Algeria
1 n_guerroui@yahoo.fr
**1,2,3 LabSTIC Laboratory, University of 8 May 1945,*
Guelma, Algeria
2,3 {kouahla,seridi@labstic.net}

Abstract— **This paper presents the possibility of using image completion combined with a large image database to create an infinite panorama. Existing methods employ extending textures found in the input source image, into the unknown region. Such methods do not work in this case since the neighboring scene will almost never be a simple extension of the current image. Texture-synthesis will also never allow the creation of an infinite panorama since all the information is not stored in a single source image.**
Mainly we combine two versions of the implementations a feature based approach to create a panoramic view with the methods of scene matching using a portion of the original input image to find the best matching neighboring scenes and then composites these images in a seamless way.

Keywords— **Image mosaicing, Infinite panorama, Feature Matching, Sift, Gist descriptor, Image blending, Robust Point Matching (RPM).**

I. Introduction

Panorama stitching or photo stitching is the process of combining multiple photographic images with overlapping fields of view to produce a panorama. The automatic construction of large, high-resolution image mosaics is an active area of research in the fields of computer vision, image processing, and computer graphics [2].Image mosaicing is a very challenging research topic and there are still many open problems to be solved, especially in case of real-world scenes. In graphics, image mosaics play an important role in the field of image based rendering, which aims to render photorealistic views from collections of real world images[3],[4]. For applications such as virtual travel and architectural walkthroughs, it is desirable to have complete panoramas, i.e., mosaics which cover the whole viewing sphere and hence allow the user to look in any direction [10]. Image alignment algorithms can discover the correspondence relationships among images with varying degrees of overlap. Panoramic view generation algorithms take the alignment estimates produced by registration algorithms and blend the images in a seamless manner [3].

II. Constructing a Panorama

The process of building a panoramic image consists of five principal stages including: taking a series of photos, locating correspondence points in each pair of images, estimating a transformation matrix between related photographs in order to calculate a new location of images in the panorama and, finally, stitching photos together [5]. Typically for mosaicing, images can be acquired by three methods namely translating a camera parallel to the scene or rotating a camera about its vertical axis keeping optical centre fixed or by a handheld camera [10]. Each image in the series acquired for panoramic image stitching partially overlaps the previous and the following images. Images acquired by translating a camera does not give 3D feel to the panoramic image and is generally not preferred. Rotation of camera provides this 3D feel [5]. Image mosaicing techniques can be mainly divided into two categories: feature-based methods, and featureless methods.

Feature-based methods assume that feature correspondences between image pairs are available, and utilize these correspondences to find transforms, which register the image pairs. A major difficulty of these methods is the acquisition and tracking of image features. Good features are often hand-selected, and reliability of feature tracking is often a problem due to image noise and occlusion. On the other hand, featureless methods discover transforms for image registration by minimizing a sum of squared difference (SSD) function that involves some parameters. Since featureless methods do not rely on explicit feature correspondences, they bear no problems associated with feature acquisition and tracking. However, methods in this category typically require that the change (translation, rotation, etc) from one image to another be small, and that good guesses for the parameters of the transform be given as initial values to the program. Moreover, since there is no guarantee that the parameter estimate process will definitely lead to the optimal solution even when the above requirements are met, special efforts must be made to prevent the parameter estimate process from falling into local minima.

III. The Scene Matching And Image Composing Methods

With using the traditional methods of creating a panorama, much time and effort are needed to capture the necessary images on location, and then to composite the images into a panorama in a photo-editing program. However, another key requirement for compositing a panorama in this way is that the idea of a panorama must have been pre-meditated. If the desire to view a panorama occurs post-image-capture, the only option is to travel back to the original location and capture the necessary images. The problem with this option is that not only is it time and monetarily consuming. A possible solution to this whole problem is image completion using a large image database [7].

Existing featureless image mosaicing techniques include cylindrical/spherical panoramas, affine transform based panoramas, and projective transform-based panoramas. Cylindrical/spherical panoramas [1],[7] are commonly used by various commercial software products because of their ease of construction. However, this class of methods requires the camera to be mounted on a leveled tripod, and allow only camera pan and tilt around the tripod. Because of these restrictions, the application domain of cylindrical/ spherical panoramas is quite limited.

First, we describe a feature based approach to create a panoramic view. Salient features are robustly detected from the input images by a robust algorithm called Scale Invariant Feature Transform (SIFT) [1],[9]. SIFT features are very well-suited for image stitching problem because they are invariant to scale, orientation and affine distortion.

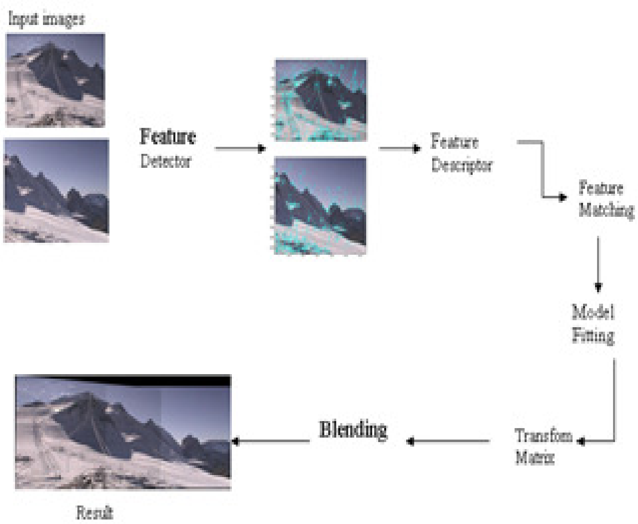

Fig. 1 Steps in building a panoramic image [5]

Second, we present the possibility of using image completion combined with a large image database to create an infinite panorama.

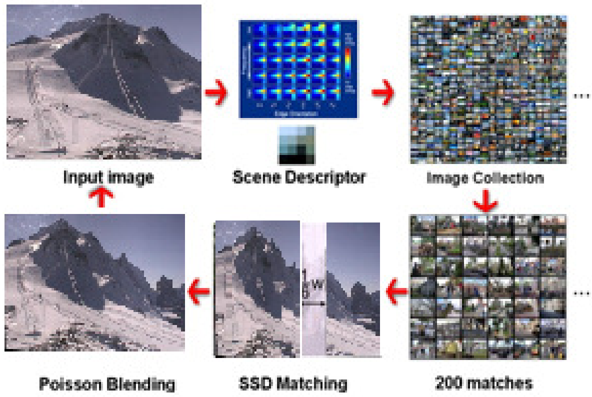

Fig. 2 Methods used to composite parts of the infinite panorama

The algorithm performs scene matching using a portion of the original input image to find the best matching neighboring scenes and then composites these images in a seamless way[8] [6]. It can be divided into four parts:

A. Finding Similar Images

Due to the huge size of an Image DB it is quite obvious that we have to speed up our search. To do this we used descriptors - smaller dataarrays computed from our original Images - and just searched over the Descriptor Database [7] [8].

- Our first attempt to do this, we used the Tiny LAB Descriptor which scaled all Images down to 16x16 and stored the Color-information.
- It is easy to imagine that this Descriptor is kind of suboptimal when we want to find Images with similar Content. Therefore we used the Matlab implementation of the Gist Descriptor, which works on orientations in different parts of the Images and therefore finds scenes with similar Content.
- The gist descriptor uses absolutely no color-information, and works just on orientations. But similar scenes often have similar colors and so the last attempt to find "near" images was a weighted merge of gist and LAB descriptor, which gives in average the best results. GIST shouldn't be the only descriptor to find best looking pictures to continue the infinite panorama.

B. Computing The Best Translation For Every Image

Now that we have our query Image, the query mask and similar images we have to process the images, so that the border becomes invisible to the unknowing beholder. The first step to do this is to find the translation with the highest correspondence of the two images in some "border-zone" [7].

C. Computing The Best Cut For Every Image

Having found the best translation we start adjusting the seam using a graphcut algorithm. To compute the costs for each pixel we at first convert the images to the gradient domain and then compute the difference between the two images in gradient domain. Afterwards we add some costs depending on the pixels distance to the original border [8].

D. Blending

After computing the optimal cut we use a Poisson blending to merge the two images. The algorithm used is able to search for a relatively close matching neighboring scene and composite the images in a seamless manor. The remaining problem with this study is extending the panorama to an infinite length without having the resulting searched images fall into an infinite range of low frequency images.

IV. Proposed Method

There are mainly two categories of variables in point set matching: point correspondence and spatial mapping. As the methods proposed in this paper, we only need to model point correspondence.

A sequential image stitching procedure requires only keeping the current source image in memory during image stitching, which is more suitable the generation of automatic panorama.

Only point correspondence is concerned, point set matching can be formulated as a graph matching problem. Fig 3 summarizes the operation of our proposed method.

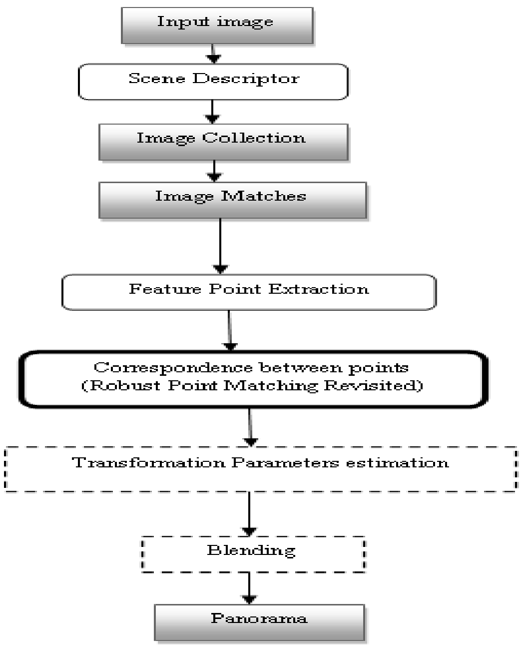

Fig. 3 Proposed mosaicing system

The shape context (SC) feature descriptor can be used because of its strong discriminative nature, while edges in the graphs constructed by point sets are used to determine the orientations of SCs. Like lengths or directions, oriented SCs constructed in this way can be regarded as attributes of edges. By matching edges between two point sets, rotation invariance is achieved [11]. SC is very discriminative and quite robust to various types of disturbances, which makes it a useful tool for nonrigid point set matching. But one deficit of the implementation is about wide panoramas. If there are lots of images which are connected to each other, it cannot stitch those together because of the linear behavior of the homography matrix calculation.

We will try to combine the two methods described before, and using robust point matching Revisited (RPM) method [12], which can guarantee the global optimality of the solution and does not need to regularize deformation for simple transformations such as similarity transform.

Finally, we set the resulting image as the input image and we repeat the process. The next iteration will append a scene to the whole panorama image, but the “input image” will refer to the last selected image

V. Conclusions

This introduces the main image mosaicing steps. It includes images pre-processing, image matching, and image fusion .Two methods for fully automatic panorama stitching were presented. The remaining problem with this study is extending the panorama to an infinite length without having the resulting searched images fall into an infinite range of low frequency images. Even though the panoramas created thus far may not look plausible or realistic. For comparison, we use human scored images to evaluate the panorama quality and we implemented the image mosaicing method presented in [4],[5],[8].

Figure 4 shows the four panoramic images which were created using a series of aerial images : R1 and R3 show the enhanced mosaic using gradient based method and graph cuts based method respectively. R3 shows a panorama obtened by autostitch [13]. R4 shows a panorama by using proposed method. In the performed tests the proposed method gives the best results on the mosaic.

Figure 5 shows another example of panoramic image using satellite images generated by proposed method with no apparent errors.

Finally, The steps of construction the mosaicing image are interdependent, in the sense that the success or failure of in a step induced respectively an improvement or deterioration in the next step, which need minimizing errors of each step to perform a correct panorama.

The above experimental results have demostrated the effectiveness of the proposed method, which is applicable to any mosaicing algorithm that generates mosaicing output from a sequence of images.

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EXPERIMENTAL RESULTS

R1

R2

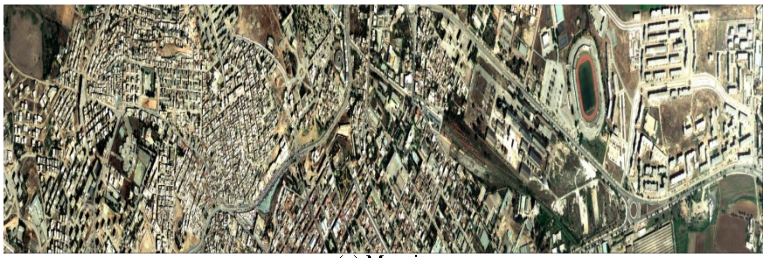
R3

R4

Fig.4 The four panoramic images created by using 8 images : (R1) is a panorama creation tool using [1] [9] with 04 images, deficiency of the implementation , is about wide panoramas ,because of the linear behavior of the homography matrix calculation ; (R2)with autostitch ;(R3) With "Blending using graph cuts.";(R4) Proposed method

(a) (b) (c) (d)

Input images



(e) Mosaic

Fig.5. An example of the proposed method