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A FAST PANORAMA STITCHING METHOD OF IMAGE SEQUENCE

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***Abstract*—The traditional image stitching result based on the SIFT feature points extraction, to a certain extent, has distortion errors. The panorama, especially, would get more seriously distorted when compositing a panoramic result using a long image sequence. To achieve the goal of creating a high-quality panorama, the improved algorithm is proposed, including altering the way of selecting the reference image and putting forward a method that can compute the transformation matrix for any image of the sequence to align with the reference image in the same coordinate space. Additionally, the improved stitching method dynamically selects the next input image based on the number of SIFT matching points. Compared with the traditional stitching process, the improved method increases the number of matching feature points and reduces SIFT feature detection area of the reference image. The experimental results show that the improved method can not only accelerate the efficiency of image stitching processing, but also reduce the panoramic distortion errors, and finally a pleasing panoramic result has been obtained.**

Index Terms—Image stitching, Scale Invariant Feature Transform, multi-view panorama, Structure from motion, image alignment, Random sample consensus.

I. INTRODUCTION

Image stitching is the process of combining multiple photographic images with overlapping fields of view to produce a segmented panorama or high-resolution image. It is also known as image mosaics [1]. Most common approaches of image stitching require exact overlaps between images and identical exposures to produce seamless results. In addition of using image stitching in computer vision and computer graphics applications, there are some digital cameras can stitch their photos internally. On the other hand, the human visual system has a field of view of around 135 × 200 degrees, but a typical camera has a field of view of only 35 × 50 degrees. Therefore, panoramic image mosaics works by taking lots of pictures from an ordinary camera and stitching them together to form a composite image with a much larger field of view.

The image stitching can be divided into three main components: calibration, image registration, and blending. The goal of camera calibration is to produce an estimate of the extrinsic and intrinsic camera parameters. During the image registration, multi-images are compared to find the translations that can be used for the alignment of images. After registration, these images are merged (blended) together to form a single image.Image calibration aims to minimize differences between an ideal lens model and the camera-lens combination that was used. These differences are resulted from optical defects such as distortions and exposure differences between images. Intrinsic and extrinsic camera parameters are recovered in order to reconstruct the 3D structure of a scene from the pixel coordinates of its image points. Extrinsic camera parameters define the location and orientation of the camera reference frame with respect to a known world reference frame. Intrinsic camera parameters link the pixel coordinates of an image point with the corresponding coordinates in the camera reference frame. Image registration is the core of a mosaics procedure. Its purpose is to create geometric correspondence between images that can compare images and apply other steps appropriately. Image registration is defined as the process of aligning two or more images which are captured from different point of perspectives. Image blending is processedto make the transition from one image to another image smoother. So, the joint between two images can be removed. Blending is applied across the stitch so that the stitching would be seamless. There are two popular ways of blending the images. One is called alpha "feathering" blending, which takes weighted average of two images. Another popular approach is Gaussian pyramid. This method essentially merges the images at different frequency bands and filters them accordingly.

The use of image stitching in real time applications is considered as a challenging field for image processing experts. It has wide applications in the field of video conferencing, video matting, video stabilization, 3D image reconstruction, video summarization, video compression, satellite imaging, and several medical applications. The applications of image stitching were extended to additional applications, such as video compression and video indexing. Another important application of panoramic image stitching is the localization systems. It is a highly accurate real-time outdoor localization system

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that can work on current mobile devices. The most important characteristics of their approach are its high degree of accuracy and its low computational demands that make it suitable to run on off-the-shelf mobile phones. Image stitching applications also include video summarization. A large number of cameras record video around the clock, producing huge volumes.

The overview of the paper is as follows. Section 1 presents a brief introduction about Image Stitching. Section 2 concise the review of Image stitching techniques. Section 3 discusses the stages of image stitching model. Section 4 depicts an overview of the system. Section 5 illustrates the extensive analysis which is conducted on global image database, which were discussed with results. Section 6 draws the conclusion with the findings and recommendations for the future work.

II. RELATED WORK

In the last few years, there are many researchers implemented and proposed various panorama image stitching systems. For example, Steve Mann and R. W. Picard [5] introduced several formal cost functions for the evaluation of the quality of image stitching. This approach is established in various applications, including generation of panoramic images, object blending, and removal of compression artifacts. The aim of a panorama image stitching algorithm is to produce a visually plausible mosaic with two desirable properties [2]. First one is the image stitching should be as similar as possible to the input source images, both geometrically and photo metrically. Then second one is the seam between the stitched images should be undetectable. While these requirements are widely acceptable for visual examination of a stitching result, their definition as quality criteria was either limited in previous approaches. Researchers presented several cost functions for these requirements, and define the panorama image stitching as their optimum. The image stitching quality in the seam region is measured in the gradient domain. The mosaic image should contain a minimal amount of visible seam artifacts.

David Lowe proposed a distinctive descriptor called Scale Invariant Feature Transform (SIFT) for object recognition and extended the proposed work in 2004 [20] making the descriptor more robust and invariant to rotation, translation, scale and partially invariant to changes in 3D viewpoint and illumination. It is able to extract invariant features from the images at different scales. SIFT has been applied in many fields since it was put forward. These features focusing on speed by using some algorithm like image registration, object recognition, camera calibration and image retrieval. SIFT features are invariant to image scale, rotation, addition of noise, change in viewpoint and illumination. Limitation of SIFT is that it extract 128- dimensional feature vector for each interest point which causes huge computation of feature matching.

SURF algorithm is achieved by relying on integral images for image convolutions can be computed and compared much faster. SURF algorithm not only guarantees the similar robustness with SIFT algorithm [23] but also it increases the computational efficiency a lot. After finding features and matching feature, they used RANSAC to select a set of inliers that are compatible with a homograph between the images. Then, they applied a probabilistic model to verify the match; then they used bundle adjustment to solve for all of the camera parameters jointly and finally they have applied the multi-band blending strategy [15]. The idea behind using multi-band blending is to blend low frequencies over a large spatial range and high frequencies over a short range. This task can be performed over multiple frequency bands using a laplacian pyramid. There are two main approaches to stitch multiple images for panorama: optimal seam finding and transition smoothing.

Optimal seam finding algorithms search for a seam in the overlapping area so that the differences between two adjacent images on the visible seam are minimized. The optimal seam can be found by graph-cut, dynamic programming or other algorithms uses for finding optimal seam. Then each input image is copied to the corresponding side of the seam. The advantage of optimal seam finding algorithm is its low computational and memory cost. But the main problem of optimal seam finding is that sometimes the seams are also visible and artifacts may arise in the final panorama. Transition smoothing algorithm can reduce the seam artifacts by smoothing the transition between images.

A main approach is to transform the color of all the images in the image sequence to match the basis image. Transform matrix across images can be represented as a linear model or a diagonal model [6], in which the mapping parameters are computedfrom the averages of each channel over the overlapping areas or from the mapping of histograms. These approaches are not sensitive to the quality of geometric alignment, but the correctness of color correction needs to be improved. Feature based methods begin by establishing correspondences between points, lines, edges, corners or other geometric entities. For example, an approach proposed by Pablo d' Angelo (2007) used Harris corner to detect the features and use a normalized cross-correlation of intensity values to match them [3].

One of the simplest algorithms is using alpha blending [8] to combine adjacent images through weighted combination. Pyramid blending on the other hand blends the frequency bands of the images and different frequency bands are combined with different blending masks. Gradient domain techniques [7] are also widely used in which they operate directly on the gradient field of an image and the blending is typically carried out by solving a Poisson equation with boundary conditions. While these approaches can reduce artifacts effectively, they require large computational costs and memory consumption. In addition, these approaches focus on smoothing the transition in the surrounding area of the overlapping area. If the illumination and color differences among images are very big, while seams can be smoothed to almost invisible, the color tones change from one image area to another image area shown on the final panorama which makes the image look unnatural. Thus color correction is often used before the stitching process to balance colors and luminance in the whole image sequence.

The methods for automatic image matching fall broadly into two categories as direct and feature based matching. Direct methods minimize the sum of absolute differences between overlapping pixels or use any other cost functions available. These methods are

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computationally complex as they compare each pixel window to other and are not invariant to image scale and rotation. Harris corner is not invariant to scale changes and cross correlation is not invariant to rotation. Hence these methods are not suitable for robust feature matching.

III. IMAGE STITCHING MODEL

The imagestitching model consists of five stages: images acquisition, features detection and matching, RANSAC estimation, global alignment, and image blending, as shown in Figure 1. The first stage of any vision system is the image acquisition stage. Image acquisition can be broadly defined as the action of retrieving an image from some sources. The second step in image stitching process is the features detection which is considered as the main image stitching stage. Features can be defined as the elements in the two or more input images to be matched. It relies on the idea that instead of looking at the image as a whole, it could be advantageous to select some special points in the image and perform a local analysis on these ones. The features of corners are more stable features over changes of viewpoint.

The other most important feature of corner is that if there is a corner in an image than its neighborhood will show an abrupt change in intensity. There are many requirements of a local feature detector, such as it should invariant to translation, rotation, scale, affine transformation, presence of noise, and blur. It must be robust to occlusion, clutter, and illumination changes. It should also be repetitive. Finally, there should be enough points to represent the image with time efficient. There are many features descriptors such as SIFT, SURF, HOG, GLOH, PCA-SIFT, Pyramidal HOG (PHOG) and Pyramidal Histogram Of visual Words (PHOW). In image matching step, to find out which picture is a neighbor of another picture, homography Using RANSAC is used. RANSAC (RANdom SAmple Consensus) [21] is a non-deterministic algorithm, because it doesn't ensure to return acceptable results. It is used to estimate parameters for homography of a mathematical model from a set of observed data which contains outliners iteratively.

Global alignment step is used to find a globally consistent set of alignment parameters that minimize the mis-registration between all pairs of images. Initial estimates of the 3D location of features in the scene must first be computed, as well as estimates of the camera locations. Then, bundle adjustment applies an iterative algorithm to compute optimal values for the 3D reconstruction of the scene and camera positions, by minimizing the log-likelihood of the overall feature projection errors using a least-squares algorithm. In order to does this process necessary to extend the pair wise matching criteria to a global energy function that involves image parameters. Once it is computed the global alignment, to perform local adjustments such as parallax removal to reduce double images and blurring due to local mis-registration. Finally, if it is given an unordered set of images to register, need to discover which images go together to form one or more panoramas.

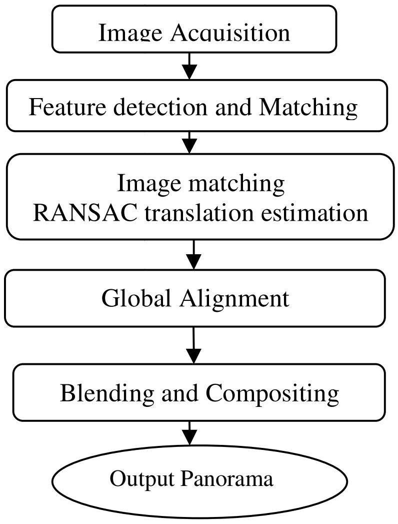

Fig. 1 Block Diagram of Image Stitching Model

Local all of the input images are registered with respect to each other and decide how to produce the final stitched (mosaic) image. This involves selecting a final compositing surface, e.g., flat, cylindrical. Finally, it must decide how to blend them in order to create an attractive looking panorama.

IV. OVERVIEW OF THE SYSTEM

The proposed method has a thorough study on panoramic image, an important application of virtual reality technology, and proposes a feature based method of generating a panorama description of solutions and algorithms for each step were given in details, including Harris corner detection algorithm, Swipe Mosaics algorithm and Levenberg-Marquardt algorithm and so no. Many previous image stitching methods require simple camera rotation or planar scene. Violation of these assumptions may lead to severe problems. Traditional seam-cutting, Outliers Rejection with Local Homographic and Cholesky decomposition to analytically solve the linear system are some of the existing description. They have the limitations of consuming a lot of system resources and registration time and many matching errors in image registration process. To overcome these problems, panoramic image is obtained by a best possible alignment; one can go one step further and leverage structure-from-motion algorithms to estimate the full 3D camera poses. The main contribution of this proposed system is combining both mesh-based framework and optimized image alignment. Since it can produce visually plausible panoramic images with input taken from different viewpoints, this method is considered as novel image stitching approach.

4.1 System Description

4.1.1 Leverage Structure-From-Motion

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The Structure-From-Motion (SFM) is a photogrammetric range imaging technique for estimating three-dimensional structures from two-dimensional image sequences that may be coupled with local motion signals. Humans perceive a lot of information about the three-dimensional structure in their environment by moving through it. One of the most widely used feature detectors is the SIFT and it uses the maxima from a Difference-Of-Gaussians (DOG) pyramid as features. The first step in SIFT is finding a dominant gradient direction. To make it rotation-invariant, the descriptor is rotated to fit this orientation. Another common feature detector is the SURF (Speeded Up Robust Features). In SURF, the DOG is replaced with a Hessian matrix-based blob detector.

The features detected from all the images will then be matched. One of the matching algorithms that track features from one image to another is the Lukas–Kanade tracker. Structure from Motion photogrammetric with Multi View Stereo [12] provides hyper scale land form models using images acquired from a range of digital cameras and optionally a network of ground control points. SFM for cultural heritage structure analysis is used in order to properly estimate situations as well as planning and maintenance efforts and costs, control and restoration. The first operational phase is an accurate preparation of the photogrammetric surveying where is established the relation between best distance from the object, focal length, the Ground Sampling Distance (GSD) and the sensor's resolution.

4.1.2 Swipe Mosaics

The automatic construction of large, high-resolution image mosaics is an active area of research in the fields of photogrammetric, computer vision, image processing, and computer graphics. Image mosaics can be used for many different applications One way is to record an image onto a long film strip using a panoramic camera to directly capture a cylindrical panoramic image. Another way is to use a lens with a very large field of view such as a fisheye lens. Mirrored pyramids and parabolic mirrors can also be used to directly capture panoramic images. A less hardware-intensive method for constructing full view panoramas is to take many regular photographic or video images in order to cover the whole viewing space. These images must then be aligned and composited into complete panoramic images using an image mosaic or "stitching" algorithm.

A post processing stage can be used to project such mosaics onto a convenient viewing surface, i.e., to create an environment map represented as a texture-mapped polyhedron surrounding the origin. Second, the accumulated mis-registration errors, which always present in any large image mosaic has done. For example, if a sequence of images were registered using pair wise alignments, there is usually a gap between the last image and the first one even if these two images are the same. To overcome this problem, a local motion estimates (block-based optical flow) was completed between pairs of overlapping images, and used these estimates to wrap each input image so as to reduce the mis-registration. The overall flow of processing in the mosaics system is illustrated in Figure 2.

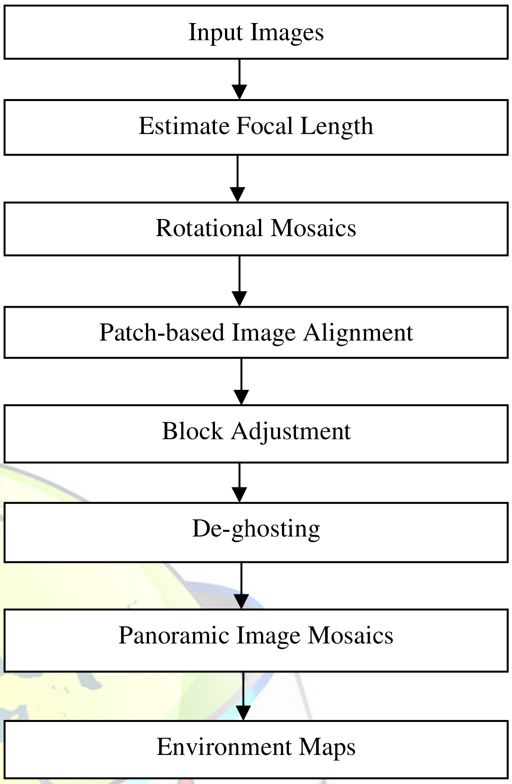

Fig. 2 Process of mosaics system

First, if the camera intrinsic parameters are unknown, the user creates a small mosaic using a planar projective motion model, from which a rough estimate of the focal length is computed. Next, a complete initial panoramic mosaic is assembled sequentially using rotational motion model and patch based alignment technique. Then, global alignment (block adjustment) is invoked to modify each image's transformation (and focal length) such that the global errors across all three possible overlapping image pairs are minimized. Lastly, the local alignment (de-ghosting) algorithm is invoked to reduce any local mis-registration errors. The final mosaic can be stored as a collection of images with associated transformations, or optionally converted into a texture-mapped polyhedron or environment map. The creation of a cylindrical panorama, a sequence of images is taken by a camera mounted on a leveled tripod. If the camera focal length or field of view is known, each perspective image can be warped into cylindrical coordinates.

Fig. 3 Overlapping of Cylindrical Images

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Figure 3 shows two overlapping cylindrical images by mapping coordinates $p = (X, Y, Z)$ to 2D cylindrical screen coordinates (θ, v) using

$$\theta = tan^{-1}(\frac{x}{z}) \quad (1)$$

$$V = \frac{Y}{\sqrt{X_2+Z_2}} \quad (2)$$

$$v = y/(\sqrt{x_2+z_2} \quad (3)$$

Where θ is the panning angle and v is the scan line.

Once each input image is wrapped, constructing the panoramic mosaics becomes a pure translation problem. In practice, small vertical translations are needed to compensate for vertical jitter and optical twist. Therefore, both a horizontal translation and a vertical translation to are estimated for each input image.

Fig. 4 Portion of a Cylindrical Panoramic Mosaic

Figure 4 shows a portion of a cylindrical panoramic mosaic built using this simple translational alignment technique. To handle larger initial displacements, a hierarchical coarse-to-fine optimization scheme is used. To reduce discontinuities in intensity and color between the images being composited, a simple feathering algorithm is applied, More precisely, for each warped image being blended, first the distance map, *d(x)* is computed, which measures either the city block distance or the Euclidean distance to the nearest transparent pixel $(\alpha = 0)$ or border pixel. Construction of a cylindrical panorama: (a) two warped images; (b) part of cylindrical panorama composited from a sequence of images. Where w is a monotonic function. Once registration is finished, the ends can be clipped (and optionally the top and bottom), and a single panoramic image are written out. The cylindrical/spherical image can then be displayed with a special purpose viewer like Surround Video. Alternatively, it can be wrapped onto a cylinder or sphere using texture-mapping.

4.1.3 Alignment Framework

In this work, image mosaics are represented as collections of images with associated geometrical transformations. The first stage of our mosaic construction algorithm computes an initial estimate for the transformation associated with each input image. The hierarchical motion estimation framework shown in Figure 5 which consists of four parts: pyramid construction, motion estimation, image warping and coarse -to-fine refinement. It is greatly simplifies the computation of the gradients and Hessians required in our gradient descent algorithm. Thus, to register two images $I_0(x)$ and $I_1(x)$. In both instances, the correspondence between images and the reconstruction of 3D object needs to be found. i.e., $x = f(x; m)$, where, x is computed using some parametric motion model m. The trick is then to find a deformation of $I_1(x)$ which brings it into closer registration with $I_0(x)$ and which can also be used to update the parameter m.

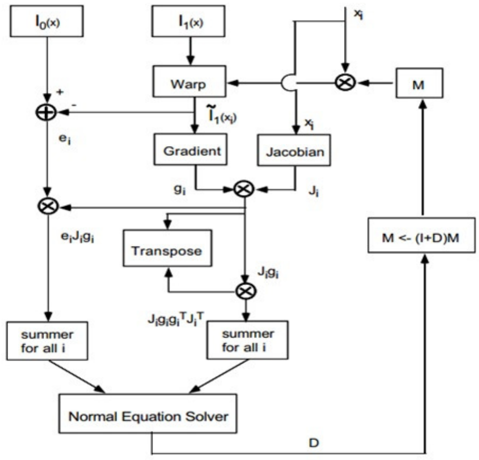

Fig. 5 Image Alignment Frame Work

The warp/register/update loop can then be repeated. To describe how this can be done for two different transformation models, namely 8-parameter planar projective transformations, and 3D rotations, and how this can be generalized to other motion models and parameters. For simplicity of notation, pixels are numbered so that the origin is at the image center, i.e., $c_x = c_y = 0$, allowing us to dispense with *T*. The same methodology as presented above can be used to update any motion parameter p on which the image-to-image homography *M(p)* depends, e.g., the location of the optical center, the aspect ratio, radial distortion, etc. The Jacobian matrix, can be used to directly improve the current motion estimate by first computing local intensity errors and gradients, and then accumulating the entries in the parameter gradient vector and Hessian matrix. This straightforward algorithm suffers from several drawbacks: it is susceptible to local minima and outliers, and is also unnecessarily inefficient. The computational effort required to take a single gradient descent step in parameter space can be divided into three major parts: The warping (re sampling) of $I_1(x\ )$ into $\tilde{I}_1(x)$, computation of the local intensity errors and accumulation of the entries.

4.1.4 Global Alignment (Block Adjustment)

A global alignment method is efficient one that reduces accumulated errors by simultaneously minimizing the mis-registration between all overlapping pairs of images. This method is similar to the simultaneous bundle block adjustment technique used in photogrammetric but has the following distinct characteristics, Corresponding points between pairs of images are automatically obtained using patch based alignment. The objective of the function

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minimizes the differencebetween ray directions going through corresponding points, and uses a rotational panoramic representation. The minimization is formulated as a constrained least-squares problem with hard linear. First global alignment algorithm is a feature-based technique, i.e., it relies on first establishing point correspondences between overlapping images, rather than doing direct intensity difference minimization (as in the sequential algorithm). To find features, each image is divided into a number of patches (e.g., 16×16 pixels), and the patch centers are used as prospective "feature" points. For each patch center, its corresponding point in another image could be determined directly by the current inter-frame transformation.

4.1.5 Visual Odometry

Visual odometry is the process of determining equivalent odometry information using sequential camera images to estimate the distance traveled. Visual odometry allows for enhanced navigational accuracy in robots or vehicles using any type of locomotion on any surface.

4.1.5.1 Algorithm of Visual Odometry

Most existing approaches to visual odometry are based on the following stages.

1. Acquire input images: using either single cameras, stereo cameras or unidirectional.
2. Image correction: apply image processing techniques for lens distortion removal, etc.
3. Feature detection: define interest operators, and match features across frames and construct optical flow field.
   i. Use correlation to establish correspondence of two images, and no long term feature tracking.
   ii. Feature extraction and correlation.
   iii. Construct optical flow field (Lucas–Kanade method).
4. Check flow field vectors for potential tracking errors and remove outliers.
5. Estimation of the camera motion from the optical flow.

Choice 1: Kalman filter for state estimate distribution maintenance.
Choice 2: find the geometric and 3D properties of the features that minimize a cost function based on the re-projection error between two adjacent images. This can be done by mathematical minimization or random sampling.

6. Periodic repopulation of track-points to maintain coverage across the image.

An alternative to feature-based methods is the "direct" or appearance-based visual odometry technique which minimizes an error directly in sensor space and subsequently avoids feature matching and extraction. Another method, coined 'visiodometry' estimates the planar rotation-translations between images using Phase correlation instead of extracting features.

4.1.6 Egomotion

The Egomotion is defined as the 3D motion of a camera within an environment. In the field of computer vision, egomotion refers to estimating a camera's motion relative to a rigid scene. The goal of estimating the egomotion of a camera is to determine the 3D motion of that camera within the environment using a sequence of images taken by the camera. The process of estimating a camera's motion within an environment involves the use of visual odometry techniques on a sequence of images captured by the moving camera. This is typically done using feature detection to construct an optical flow from two image frames in a sequencegenerated from either single cameras or stereo cameras.

Using stereo image pairs for each frame helps reduce error and provides additional depth and scale information. Features are detected in the first frame, and then matched in the second frame. This information is then used to make the optical flow field for the detected features in those two images. The optical flow field illustrates how features diverge from a single point, the focus of expansion. The focus of expansion can be detected from the optical flow field, indicating the direction of the motion of the camera, and thus providing an estimate of the camera motion.

4.2 Procedure of the Proposed System

Steps followed in this work are as follows:

Step 1: Read the input image
The images which used for the experiment were collected from the publically available website.
Step 2: Convert RGB to Gray-scale
The given input image which is in RGB format was converted into gray-scale to get the fine features from the raw image.
Step 3: Register image pair and extract the feature
The panorama image is created by registering successive

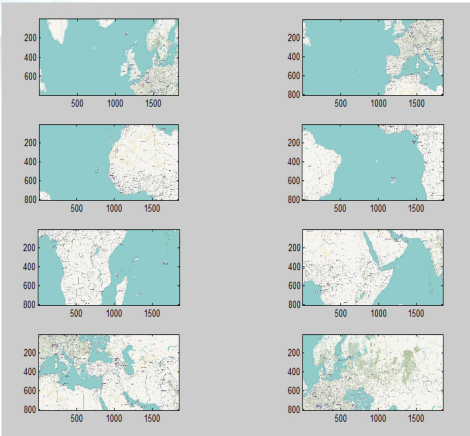

Fig. 6 Input Images

image pair using thefollowing procedure:

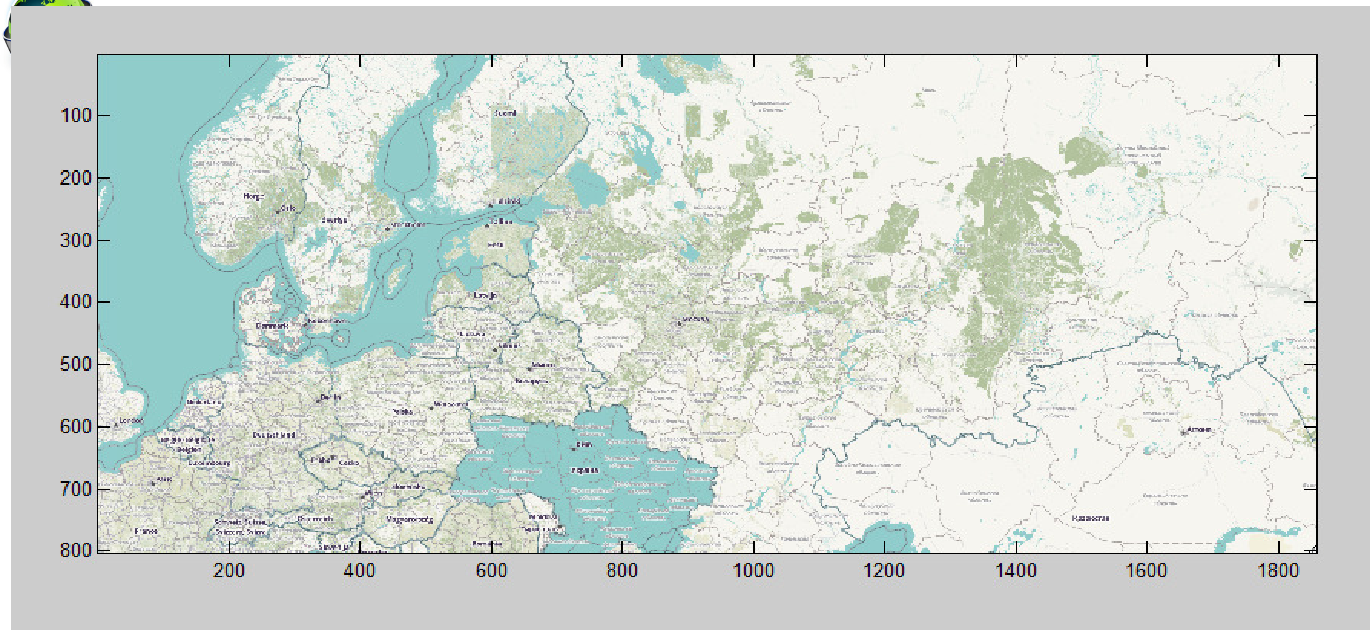

Fig. 7 Output of the Panoramic Image

i. Detect and match features between *I(n) and I(n-1).*
ii. Estimate the geometric transformation *T(n),* that maps *I(n)* to *I(n-1).*
iii. Compute the transformation that maps *I(n)* into the panorama image as *T(1)*.......*T(n-1)*T(n).*

Step 4: Calculate the transformation matrix

At this point, all the transformations in *tforms* are relative to the first image. This was a convenient way to code the image registration procedure. The first image as the start of the panorama does not produce the most aesthetically pleasing panorama. Because, it tends to distortion most of the image that form the panorama. Start by using *projective2d outputlimits* method to find the output limits for each transform. Next, Compute the average X limits for each transforms and find the image that is in the center. Only the Y limits are used here. Because scene is known to be horizontal. If another set of images are used, both X and Y limits may need to be used to find the center image.

Step 5: Initialize the panorama

Now, create an initial, empty, panorama into which all the images are mapped and use the output limit methods to compute minimum and maximum output limits over all transformations. These values are used to automatically compute the size of the panorama.

Step 6: Create panorama

Use *imwarp* to map the images in to panorama and use *vision.AlphaBlender* to overlay the image together.

V. RESULTS AND DISCUSSION

The proposed method is experimented and the results obtained are evaluated. Then the results were compared with different methods of performance measurement.

5.1 Experimental Setup and Results

Figure 6 shows the images which are given as input images. There are 8 images given into the system which was undergone the steps that were described in section 4.2. And these images are relatively unaffected by any lens distortion. So, camera calibration was not required. However, if lens distortion is present, the camera should be calibrated and images undistorted prior to creating the panorama.

Figure 7 shows the output of the panoramic image using feature based image registration techniques. The improved method accelerates the panoramic stitching time efficiency and obtains a high-resolution, high-quality panorama image.

5.2 Performance Measures

The performance of image stitching can be evaluated based on its running time. The timing statistics are shown in Table I with implementation using MATLAB 2014a on Intel or AMD x86-64 processor. Both APAP and Auto Stitch use simple blending techniques without global optimization, where the composition time is close to that of our average blending operation listed in Table 1.

Table 1 Evaluation based on Running Time of the Dataset.

Image Number	8
Feature Matching	5.6s
Image Stitching	62.0s
Average Blending	1.61s
GC Optimization	215.3s
GD Fusion	76.3s
APAP	503.4s
Auto Stitch	12s

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VI. CONCLUSION AND FUTURE WORK

This proposed method increases the number of the matching SIFT feature points by improving the traditional method, reducing the unnecessary SIFT detection area in the reference area as well. In addition, the improved method accelerates the panoramic stitching time efficiency and obtains a high-resolution, high-quality panorama image.

Compared with the traditional method, the improved method proposed in this paper starts stitching from the middle position of the image sequence. The middle image is taken as the reference image. Then, we obtain the affine matrix for any image in the sequence to the reference image according to the statistics information of all affine transformation matrixes between the adjacent images. Meanwhile, the improved method dynamically selects the next new input image to join the stitching process based on the number of statistical matching points of the adjacent images.

The experimental results verify that the improved stitching process can accelerate time efficiency and reduce the distortion of the panorama image. This improved method may be applicable for real time images. The real time image will be applied to creating the panoramic images that will produce the less distortion and also increasing the number of matching features between the images. Finally, the real time images will be suitable for constructing the panoramic images with certain pixel size in future.

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