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Performance Comparison of Image Stitching Methods under Different Illumination Conditions

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ABSTRACT:

The Image stitching is the method of obtaining a broader or wider field-of-view called as developing panorama of a images or scene from a sequence of partial views. This has been an attractive applied research area because of its multiple applications; including resolution enhancement, motion detection, medical imaging and monitoring global land usage. There are number of image stitching algorithms have been developed. This paper provides overview of the existing image stitching algorithms by classifying them into several categories. For each category, the fundamental concepts are first explained and then the required modifications made to the basic fundamental concepts by different researchers are explained. The resultant effectiveness of image stitching basically depends on matching of the intensity of images, the overlap removal, the techniques used for blending the image. In this paper, the various basic techniques for the process of image stitching under various light conditions is highlighted and their important applications in the relative places has been reviewed.

Keywords: - Image stitching, panorama, Registration, Blending, Homography

I. INTRODUCTION

Nowadays, image stitching is gaining a lot of importance in the research areas applicable for its scientific significance and the potential derivatives in real universal applications.

1.1 *What is image stitching*?

Image stitching or mosaicing is the technique of alignment of multiple overlapping photographic images into a large composition which basically represents a part of a 3D scene. The method of combining multiple photographic images to produce a single image of that scene is called panorama. Multiple images of sky is taken to produce single panorama then it is Astrophotography panorama. There are various steps of image stitching like image segmentation, feature extraction and matching .further it needs image rotation matrix before making final image panorama [1,2]. In Image segmentation, partitioning the image in to two parts that is more meaningful and easier to analyze is called image segmentation. There are various techniques for image segmentation techniques like OTSU'S method, K-means clustering, Watershed segmentation and Histogram based method [3].there are some techniques for feature point extraction i.e Harris corner detector ,Hessian detector ,SIFT (Scale Invariant Feature Transform) ,SURF (Speed Up Robust Feature), ORB (Oriented FAST rotated BRIEF technique).

1.2 *Basic Image stitching process*

Image stitching is the basic process of combining various photographic images with overlapping fields of view to produce a segmented panorama for obtaining high-resolution image. The process of image stitching can be divided basically into three main steps or components 1. Calibration 2.image registration and 3. Blending [5]. Further it also needs image rotation matrix estimation.

a. **Calibration**: Image calibration is useful to minimize differences between an ideal lens model and the camera-lens combination that was used. These differences results due to optical defects like exposure differences between distortions and images. Extrinsic and Intrinsic camera parameters must be recovered for

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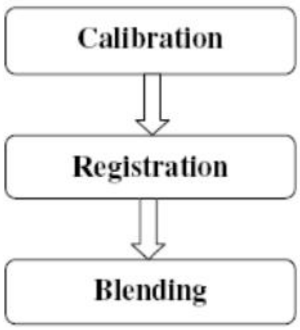
the purpose of reconstructing the 3D structure of a photographic image from the pixel coordinates of its image points.

b. **Registration**: Image registration is the important part of a stitching procedure. Its purpose is basically to create geometric correspondence between images. Therefore, we can compare these images taken and apply other steps appropriately.



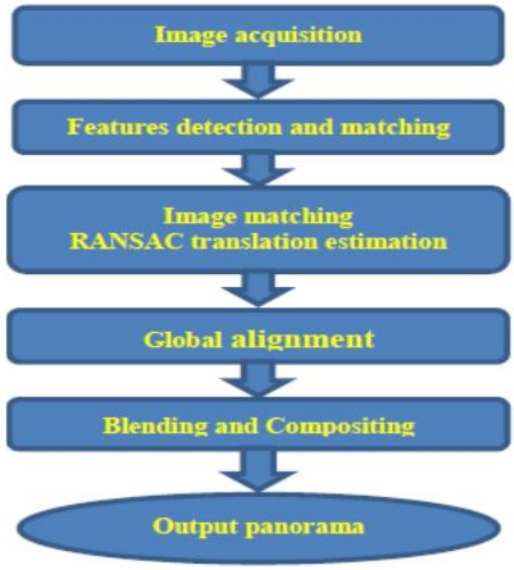


Fig.1 Process of image stitching [5] ; Fig. 2: The block schematic of basic panoramic image

Image registration is basically defined as the method of alignment of two or more images which are captured from different point of wider view or perspectives. This method can achieve good results of image matching when dealing with images taken with good texture and small changes of camera view angle. However, for photographic images with poor texture or large changes of camera view angle, the power of this technology on image matching certainly decreases. Random Sample Consensus (RANSAC) is a robust calculation method which is broadly used for the purpose of feature matching. The integration of RANSAC and affine invariant feature extraction technology is valuable for the purpose of optimization of image matching.

c. **Blending**: Blending process is applied across the stitch so that the stitching would be seamless.

d. **Rotation matrix estimation**: Using the tracking results of features, we estimate the camera motion in the input frame. The camera motions can be modeled as 3-D rotation between images. Usually, the users need to move little while capturing pictures for panoramic photo images, thus without loss of accuracy and the camera motion is modeled by 3-D rotation. 1.3

The model of Image stitching based on features techniques : In this section, a image stitching model which is based on feature based techniques will be highlighted. As shown in Fig.1, the model of image stitching basically consists of five successive stages i.e 1. images acquisition 2. Features detection 3. Matching 4. RANSAC estimation 5. Global alignment and 6. image blending (Fig 2).

II. LITERATURE SURVEY

Image stitching or Mosaicing is basically considered as most active applied research area in computer graphics and computer vision. As per Author [5] Image stitching techniques can be categorized into two general techniques i.e feature and direct based methods. Direct techniques is the process of comparing all the pixel intensities of the images with each other and feature based method aim to find a relationship between the images through distinct features extracted from the processed images. The last approach has the benefit of being more robust against scene movement, faster, and has the capability of automatically discovering the overlapping relationships among an unordered set of images. Authors [6] concluded that Reconstruction of hand torn paper documents is a challenging task in forensic and investigation sciences. Image stitching is technique of combining two or more photographic images of the same particular scene into one high resolution image which is called as panoramic image [7]. Author [8] suggested an improved algorithm for Harris corner detection is proposed and developed in this paper since the feature points of images with high pixel, large size, and low contrast ratio cannot be extracted accurately, especially for seas security monitoring.

Parallax-tolerant Image Stitching Algorithm [9], requires the alignment of images in a way that they can be stitched along a common local origin. Here Images with large parallax can be efficiently stitched. But This method fails with the images having very large parallax and when the images are full of salient features. In that case, the method does not work as no non-salient features exist. Automated Image Sitching algorithm for microscopic images [10], is based on the feature extraction. First SURF [11] is used for feature extraction, which is then followed further by Histogram Equalization method for image preprocessing.

It can stitch both common images as well as microscopic images. But Images with parallax cannot be handled by this algorithm. For that, the need of reference to the specialized algorithms for parallax handling is there. Using adaptive normalization for image stitching [12], it normalizes the image locally, adjusting the contrast, associate local statistics to the image, done using Wallis Filtering. This algorithm is simpler as compared to other algorithms as well computationally efficient and stable. This algorithm works well as a whole, but to achieve the best result, it requires different stitching methods for different constituents of the images, which can increase the complexity of the algorithm. Dominant plane homography for Parallax handling of image stitching[13], Larger parallax problem found in image stitching algorithm is handled as- Matching points are selected as pairs and the cost of clusters are measured, Standard seam cutting method is modified to obtain a valid seam, Global distortion of the image is accepted as compared to the local distortion. But this algorithm cannot handle when the image does not contain larger parallax and is full of salient features.

For this method to work, images should contain at least non-salient features. Projection interpolation image stitching [14], Calculates the homography matrix and then it's inverse. The inverse matrix is decomposed and then interpolated into sub-matrixes, which is then composed into new one. As per author [15] Warped image is converted into a new matrix, Local alignment is improved and geometric structure is preserved and Ghost effect is removed. Parallax error is minimized .but in this case Images with larger parallax, more affine transformations cannot be handled by this algorithm.

III. PROBLEM DEFINITION, SOLUTION WITH PROPOSED SYSTEM WORK FLOW

The method of combining astrophotography with panoramic landscapes presents many challenges dealing with subject motion and image noise.

In order to capture image of sufficient signal, Low light levels require the use of long shutter speeds and/or high ISOs in camera. However, high ISO's result in a low signal to noise ratio and further it is to be noted that long exposures are sensitive to thermal noise and hot pixels. Also motion of earth create blur of star scap. Compounding the noise issue, stars are also susceptible to motion blur due to the earth’s rotation hence it limits the maximum feasible exposure time. The noise and blur generated by motion of the star can be removed by combining short exposure instead of capturing one large image. Blur can reduce by light streak technique. Noise can remove by using spatially variant registration step and warp the image on to the spherical surface. First the multiple continuous images are taken which include both the sky and land. Then segmentation is done to separate land and sky. Now here images are taken at night thus there is much more noise and blur which is removed by using light streak technique. Next the feature points are extracted which are use for feature matching process. Feature point are extracted by using SIFT algorithm which is more robust among all other algorithm then for feature matching is done by using RANSAC. Finally camera motion is estimated using rotation matrix, and we can project the input frame on to the panorama surface which is

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spherical surface using the rotation matrix

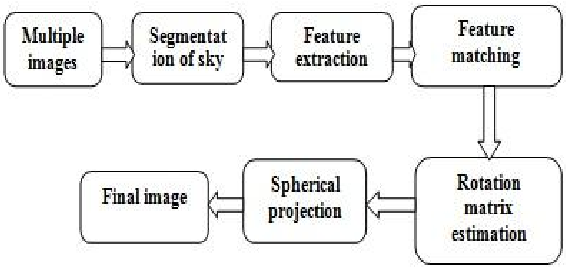

Fig.3 System work flow

4.1 **General Concepts of Different Blocks of Image Stitching Systems**

Image segmentation partitioning the image in to two parts that is more meaningful and easier to analyze is called image segmentation. There are many techniques for image segmentation which are as below. 1. OTSU'S method 2. K-means clustering 3. Watershed segmentation 4. Histogram based method

4.1.1 **OTSU'S Method**: Images are generally in the form of color image or gray image. If the image is color image then it is converted in to gray image.

Color image Gray image Binarized the mask using OTSU'S method Hole filling in astronomical portion Final image after hole filling in terrestrial portion The algorithm assumes that the image obtained contains two classes of pixels which are foreground pixels and background pixels.

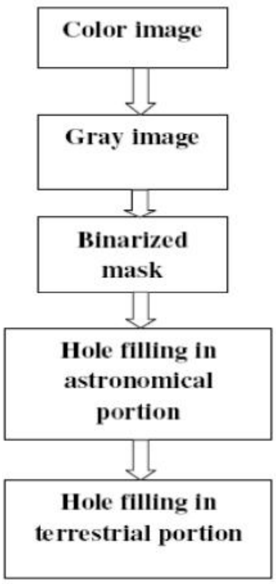

FIG 4: Flow of OTSU'S method

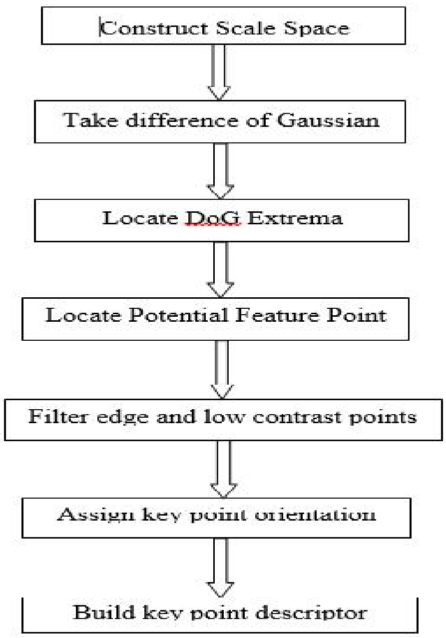

Fig 5: SIFT feature detection algorithm

4.1.2 **K-means algorithm:** The K-means algorithm is an iterative technique which is used to partition an image into clusters. In this case the basic algorithm is Cluster centres are picked first, either randomly or based on some heuristic. Each pixel in the image are assigned to the cluster which have minimum distance between the cluster centre and the pixel .The cluster centres are recomputed by the method of averaging all of the pixels in the cluster Steps 2 and 3 are repeated until no pixels change clusters.

In this case, distance is measured by squared or absolute difference between a pixel and a cluster centre. The

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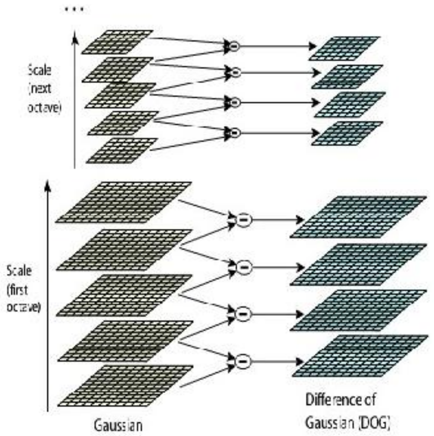
cluster difference is typically based on pixel intensity, texture, color and location, or a weighted combination of these factors.

4.1.3 **Histogram-based methods** Due to this method require only one pass through the pixels, histogram-based methods are very powerful when compared to other image segmentation methods. Here first histogram of all image pixel is computed, and the peaks and valleys decide the clusters in the image. For the measurement Color or intensity can be used.

4.1.4 **Watershed transformation** The gradient magnitude of an photographic image as a topographic surface is calculated first in this technique. Watershed lines are defined by pixels having the highest gradient magnitude intensities (GMIs), which represent the region boundaries.

4.2 Feature extraction and matching

4.2.1 SIFT: Scale Invariant Feature Transform is an algorithm developed by D.G.Lowe. The algorithm helps in the process of detection and description of local features of the image. The features detected by the algorithm are accurate, stable; moreover it is invariant towards scale and rotation. Its applications include robotic mapping, object recognition and navigation, 3D modeling, image stitching, gesture recognition, individual identification of wildlife video tracking, and match moving. The Flowchart of SIFT algorithm is depicted in Fig.5



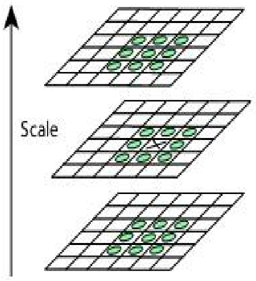


Fig 6: DoG at varying octave **Fig7: Neighbouring pixels with which key point is compared**

Scale-Space Extrema Detection : Under this heading the scale space theory is used to determine the key points that are nothing but interest points. For detecting the key points first of all consider an image say I(x, y) and convolve that image with the Gaussian filter, G(x, y, σ) at varying scales. The convolved images having different scales are grouped by octave and a variable k is selected in order to get a fixed number of blurred images per octave. The formed images are subtracted at different scales in order to get the difference of Gaussian (DoG) as shown in Fig.6.DoG helps in removing the problems arising due to key point localisation.

DoG acts as effective tunable band pass filter and extract a range of components which can be used as key points. The DoG can be used as an approximation for the Laplacian operator. The convolution of Gaussian filter to the image is represented in Equation 3.1 and DoG is represented using Equation 2.

$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$ (1)

$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$ (2)

Key point Localization: The key point is known as key point when the key point is local maxima or minima. Each pixel from the DoG images are compared with 8 neighbouring pixels having same scale on the same plane, whereas rest eighteen pixels are at the plane lying above and below it with different scales. The twenty-six neighbouring pixels for the candidate key point are shown in Fig For determining the accurate position of key point, interpolate the key point with the help of nearby data that was the initial approach. But according to

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new approach determine the location and scale of the candidate key point using Taylor series expansion. Using Taylor expansion, the extreme points and location are carefully determined. The Taylor expansion of DoG at origin in given by the following equation: This new approach of interpolation helps in improvising the stability as well as matching. During the process, the candidate key points with low contrast are removed using the second order Taylor expansion method at particular offset, if the value is more than 0.03 then it is considered otherwise it is discarded.

Also the DoG functions have high responses along edges, even though the candidate key points are prone to small intensity of noise. So, for increasing the stability, remove the key points that are not having properly determined locations and are having strong edge responses. Orientation Assignment Here, every key point is having one or more orientations depending on the local image gradient directions. This step helps to achieve invariance to rotation because the key point descriptor can be presented relative to this orientation and thus invariance to image rotation achieved. First of all Gaussian-smoothed images L(x, y, s) having scale s is considered so that all the computations are scale-invariant. For an image L(x, y) with scale s, the gradient magnitude, m(x, y), and orientation, ?(x, y), are calculated using pixel differences: The computation of magnitude and direction for the gradient are done at every pixel in the neighbouring region around the candidate key point in the Gaussian-blurred image L.

An orientation histogram of 36 bins is created, with each bin having 10 degrees. Each sample of the neighbouring window is added to the histogram bin which is weighted by its gradient magnitude also by a Gaussian-weighted circular window with 1.5 time s to the scale of the candidate key point. The peaks of the histogram basically correspond to dominant orientations. Once the histogram is completely filled, the orientations which correspond to the highest peak and local peaks which are within eighty % of the highest peaks assigned are considered as the key point. For multiple orientations, an additional key point is created which have the same location and scale as that of the original key point for each additional orientation.

Key point Descriptor Generation : This step insures invariance to scale and rotation and image location, Now estimate a descriptor vector for every key point such that the descriptor is partially invariant and highly distinctive to the variations such as accuracy, illumination, 3D viewpoint, stability etc. normally This step is basically performed on the image scale which is closest in scale to the scale of the key point. Firstly a set of orientation histograms are generated on 4x4 pixel neighbourhoods with 8 bins each. The obtained magnitude and orientation values are computed from histograms of samples in a 16 x 16 region around the key point such that 4 x 4 sub regions of the original neighbourhood region are formed. The diagram showing generation of feature vector is shown in Fig 8.

The magnitudes are then weighted by a Gaussian function method with 1.5s of the obtained descriptor window. The descriptor now becomes a vector from all the values of the histograms. It should be noted that as there are 4 x 4 = 16 histograms each having 8 bins, so the vector has total 128 elements. And further this vector is normalized to unit length to enhance invariance due to affine changes in illumination. For reducing the effects of non-linear illumination, set a threshold of 0.2 and once again the vector is normalized. Even though the dimension of the descriptor (128) is high, descriptors having lower dimension than this are not performing well across the matching range and thus the computational cost remains low because of the approximate Best Bin First (BBF) method used to find the nearest- neighbour. It is also seen that feature matching accuracy is above fifty % for variation in viewpoint up to 50 degrees. Thus SIFT descriptors prove invariant to small affine changes.

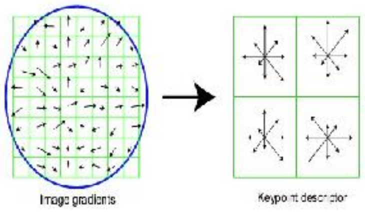

Fig 8 : Generation of feature vector

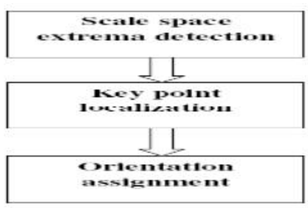

Fig 9: Flow of Feature extraction using SIFT

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4.2.2**Harris corner detector** Moravec corner detector gives equation for Change of intensity for the shift which is given as below

$$E(u,v) = \sum_{x,y} w(x,y)\,[I(x+u,y+v) - I(x,y)]^2$$

w(x,y)= Window function ,I(x+u,y+v)= shifted intensity, I(x,y)= Intensity

Moravec detector have problem that is noisy response due to a binary window function and only a set of shifts at every 45 degree is considered. It responds too strong for edges because only minimum of E is taken into account. Harris corner detector solves these problems. To overcome noisy response due to a binary window function

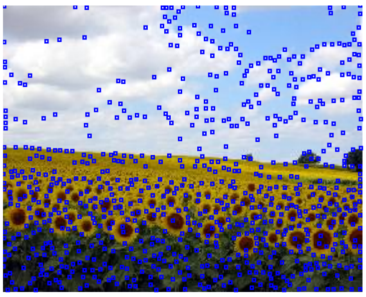
Harris use Gaussian function.

$$w(x,y) = \exp\left(-\frac{(x^2-y^2)}{2\sigma^2}\right)$$ M is 2×2 matrix obtain from image derivative.

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

k is impirical constant which have the range (0.04-0.06) ;λ1 and λ2 are eigen value of M

Here H indicates the corner of the image.



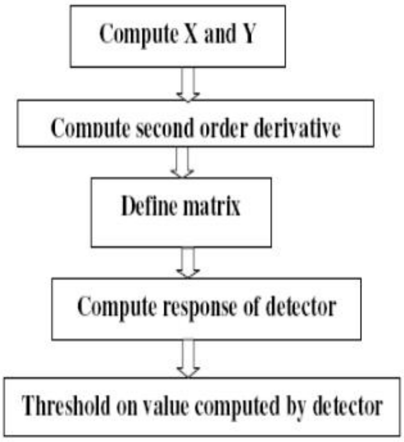


Fig.10: Feature extraction using Harris corner detector [2]; Fig 12: Flow of Feature extraction using Harris detector

4.2.3 **Hessian detector** Robust feature matching is required to estimate the camera motions automatically without user restriction. For that feature points are first extracted. Due to noise and quantization error the features are not well detected in the lowest resolution, fast Hessian detector is applied. Even though the number of extracted features is small the recent study about feature detector for visual tracking shows that fast Hessian detector has the best repeatability. The Laplacian operation is used to calculate the binary calculation for fast process. Determinant of Hessian function as saliency operator which determine if there is corner detected or not. The matrix of second order partial derivatives defines the Hessian of an image with respect to coordinates. If determinant of this matrix gives large positive values, it indicates eigenvalues are large and have the same sign. If such occur strong edges are present at multiple orientations, such as corners. In the presence of opposing edges its response is strongest and it is therefore a good blob detector.

International Journal of Engineering Technology Science and Research
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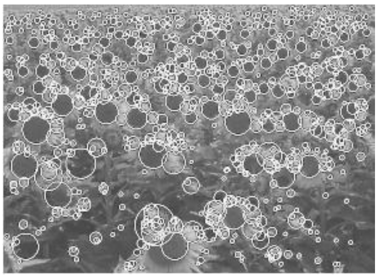
Volume 4, Issue 9
September 2017



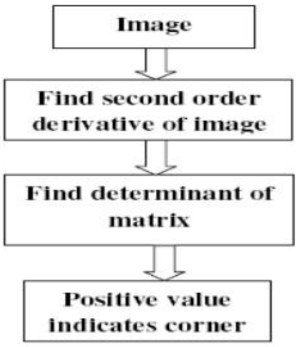


Fig.12: Feature extraction using Hessian detector; Fig 13: Flow of Feature extraction using Hessian detector

Star Feature Extraction: Our method can be summarized in two main steps. First, in the blurred image, the user selects an image region that contains a light streak.

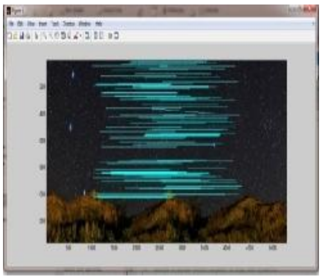
A small-scale L1-norm optimization is performed in this case to produce the blur kernel. And in the second step, the process of a non-blind motion deblurring is performed using the blur kernel derived in the first step to produce the final sharp image. Light Streaks and Blur Kernels Given a static, bright object in the scene, point-sized, the motion path of the camera shake can be easily found in the blurred image in the form of a light streak techniques. These bright objects must have intensities much higher than other regions in their local neighborhoods so that they can remain observable as bright light streaks even after being smeared by motion blur. To get a light streak which approximates the blur kernel well, it is necessary that the bright object is very tiny or stays far away from the camera. For example, distant street lights can be considered as point lights and their light streaks in the blurred image are very similar to the blur kernel. Secular highlights can also be utilized for the same purpose, as they are usually very bright and small. This experiment has shown that replacing the Laplacian filter with other derivative filters does not affect the result much. Here we note that although shift-invariant motion blur model is being considered, kernel estimation against the blurred image as in the previous technique has been avoided. In this case the correctness of the blur kernel now depends on the accuracy of the user selected region. Of course, one can use the extracted blur kernel to initialize the alternating optimization loop in traditional single-image motion deblurring to accelerate its convergence. Feature matching Therefore, we can easily compare images and apply other steps appropriately.

From the feature matching step, we can identify images that have a large number of matches between them. We can consider a constant number of images, which have the greatest number of feature matches to the given current image, for that we can use RANSAC for the purpose to select a set of inliers that are basically compatible with a homography between the images.

V. SIMULATION AND IMPLEMENTATION

5.1 *Feature extraction using different techniques*

5.1.1 Simulation result of Feature extraction using Harris detector (fig 14)



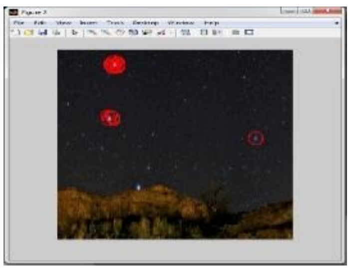


Fig.14:Feature extraction using -Harris detector; Fig 15: using Hessian detector Fig. 16: using SIFT

5.1.2 Simulation result of Feature extraction using Hessian detector (fig 15)

5.1.3 Simulation result of Feature extraction using SIFT (fig 16)

Table 1: comparison of three methods of feature detectors used in image stitching

Detector Type	**Detected Features**	**Time (Sec.)**	**ImageType**
Harris Corner Detector	340	0.6	Daylight Image
Hessian Detector	566	0.45	
SIFT	455	1.3	
Harris Corner Detector	30	0.45	Night Image
Hessian Detector	23	0.38	
SIFT	12	1.34	

5.2 ***Results Obtained Due To These Various Methods***

5.2.1 Comparison of the Techniques In terms Of Detected Features and Time Required Input Images

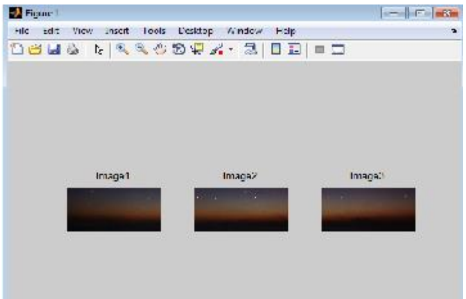


Fig. 17: Input images

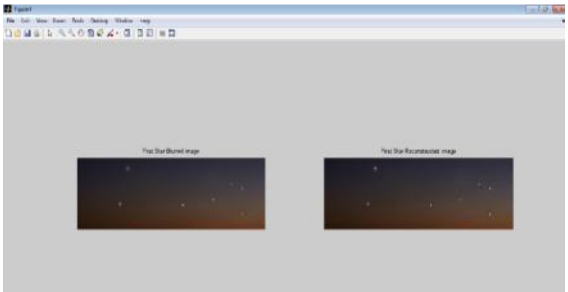


Fig. 18: Start point of Sky

As shown in figure we have taken three images for the panorama construction. Here we can take n number of images for the panorama making. Star Points: As shown in the figure the star sky point is blur using the star blur algorithm as we have to reconstruct the star point first is to highlight the white blob of start.

Segmentation:

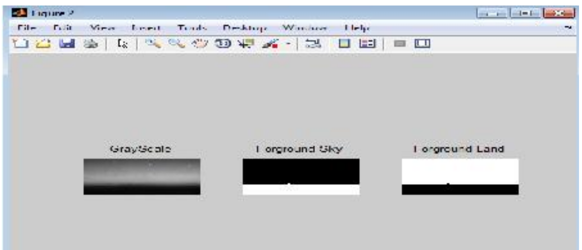


Fig. 19: Segmentation

FIG 20: Highlighting Star

As shown in the figure 20 segmentation process is done using the OTSU segmentation method so here we have Extract the Sky region and Land region using the segmentation method so we can work on only sky region. Highlighting Star: As show in the figure 21 the start point is highlighting for the matching of star so here we have to apply light stick algorithm.

Star Blur image:

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Volume 4, Issue 9
September 2017

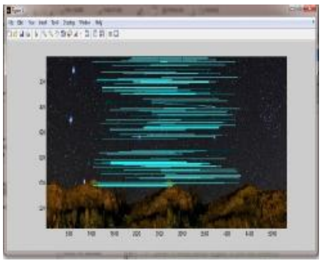

Fig. 21: 2nd star Blur image

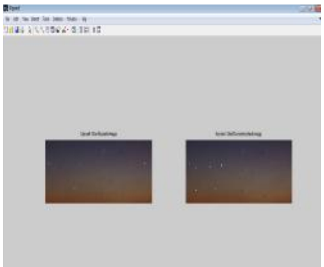

Fig. 22: Matching Start Point

Fig. 23: Final panorama

As shown in fig- 21, the 2nd image of star is blurring and reconstructed using the light stick algorithm as the above method. Matching Feature: As shown in the figure 22 the star point is matching of next image by using the RANSAC algorithm. Figure 23 shows the final panorama of the 3 input images by using the proposed image wrapping algorithm. As shown in table 1 , results obtained shows that for daylight condition , SIFT algorithm works better as it requires less time for more features extracted where as for night light condition it is shown that Harris/Hessian detector performs better than SIFT detectors.

VI. CONCLUSION

The panorama stitching program implemented in this Research successfully overcomes two major obstacles to generating night sky panoramas i.e. low SNR and motion blur. In this paper, the various techniques for the process of image stitching under various light conditions is highlighted and their applications in the relative places has been reviewed.

Results obtained shows that for daylight condition, SIFT algorithm works better as it requires less time for more features extracted where as for night light condition it is shown that Harris/Hessian detector performs better than SIFT detectors .By including spatially variant registration steps into the panorama workflow, the algorithm was able to combine several shorter exposures into a lower noise final image without motion artifacts. Image can be deblurred using light streak algorithm. In future work the present algorithms can improved to get better results in terms of more feature detections and requiring lesser time for detections under variable

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