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A Novel Approach to Seamless Image Stitching using S-FREAK and RANSAC Algorithm

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Abstract— Image stitching is increasingly becoming popular in the fields of image processing, computer vision, virtual reality, computer graphics, human computer interaction and multimedia. Image stitching or mosaicing is a technique in which several images of overlapping domain of view are combined together for a panoramic image of high resolution. Image stitching surveys depict that it is still now a puzzling problem for the construction of panoramic images. The input to a stitching algorithm is multiple, overlapping images captured from different camera views and the output is a panorama of wider field of view made by merging and stitching the individual images. Feature extraction, feature matching, homography estimation and stitching are the steps performed to make panoramic images. Traditional image stitching methods based on different feature extraction techniques require long registration time for high resolution images. In this work, a novel image stitching method based on S-FREAK is proposed by combining SIFT (Scale Invariant Feature Transform) and FREAK (Fast Retina Keypoints). The feature descriptors from one image are matched with the other to find the best closeness and only the features with best closeness are kept while the rest ones are discarded. A transformation model is estimated from these features and the image is warped correspondingly. Image stitching is a technology for solving the field of view (FOV) limitation in images.

Keywords— Image stitching, homography, feature matching, feature extraction, image mosaicing

I. Introduction

Multiple view image stitching, also known as image mosaicing or panorama stitching is a long-felt need in the area of digital image processing with applications in robotics, architecture, industrial inspection, computer graphics, surveillance and film making. The goal of image stitching is to create a panorama from different overlapping images of the same scene, possibly captured at displaced locations. Calibration, registration and blending are the three main stages needed to generate panoramic images [1].

A. Calibration

Image calibration aims to reduce the differences between an ideal lens model and a combination of camera-lenses used. These dissimilarities are due to optical defects such as distortions and exposure differences between images. In order to reconstruct the three-dimensional structure of a pixel coordinates scene, both intrinsic and extrinsic camera parameters are enhanced. Intrinsic camera parameters associate a mapping between the camera coordinates with the pixel coordinates in the image frame. Extrinsic camera parameters characterize the location and orientation of the camera reference frame with respect to a known reference frame.

B. Registration

Image registration is the process of aligning more than two images which are captured from different perspective points. The goal of image registration is to establish a geometric mapping between images so that they can be correlated and applied to subsequent stages in image stitching. Image blending is performed to get a smoother traversal from one image to other, so as to obtain a seamless image. There are different methodologies for image registration depending on feature type, dimensionality etc. Feature based image registration techniques essentially consists of four steps.

- Feature detection- identification of unique and relevant features.
- Feature matching- finding corresponding features between images.
- Transform model estimation-parameters that align the images are determined by the use of the correspondences.
- Image transformation- alignment of images.

C. Blending

Image blending is performed across the stitch to obtain a seamless stitching. In order to find the degree of similarity between pixels, the images are shifted or warped with each other. Such methodologies which use pixel-to-pixel matching are generally called direct methods. To compare the images, a suitable error metric is preferred. Techniques like incremental algorithms and Fourier based methods are also used for direct matching. But all these methods need a computation for each pixel. The whole process becomes computationally intensive when the complexity of algorithm is high and the image dimension is large. Therefore, these methods are usually not preferred in commercial image stitching softwares.

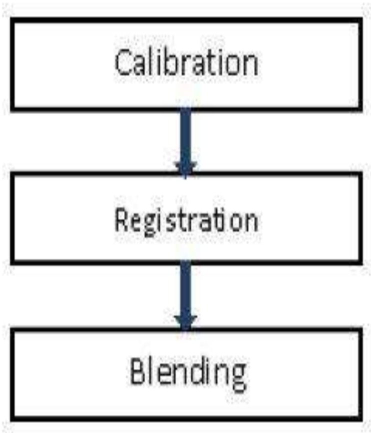

Fig 1.1 : Overview of stitching[1]

II. related work

In [2] Tan Su et al. proposed a unified optimization framework which stabilizes the stitching. The method is a hand-taken stitching method that can produce the most optimal stabilization and stitching results.

A continuity aware Kalman filtering scheme for the stabilization and jitter removal was proposed by Wei Xu[3]. For achieving long high-resolution panoramic views, an efficient stitching scheme with constrained and multi-grid SIFT (Scale Invariant Feature Transform) matching schemes, concatenated image projection, min-space feathering and warping is proposed. All together, this approach can considerably reduce the computational load and memory requirement in panoramic stitching, making a feasible high-resolution stitching (e.g., 1920x1080 pixels) and long panoramic sequences possible by utilizing standard workstations.

In [4] the two general approaches of image stitching techniques such as direct and feature based methods are explained. Feature based methods are employed to find a relationship between the images making use of the different feature descriptors obtained from the processed images. The five steps performed for obtaining a panoramic image are feature extraction, feature matching, outlier elimination, stitching and blending. Feature extractors like SIFT (Scale Invariant Feature Transform), SURF(Speeded Up Robust Feature), ASIFT (Affine SIFT) and ASURF (Affine SURF)are utilized for creating panorama. Other than this, correlation is also used for creating panoramic images. The methods are evaluated based on the quality of the output mosaic and the time needed to generate the panorama.

Shishir Maheshwari[5] used the Harris corner detection algorithm for corner detection. The features and the feature descriptors are detected. The feature descriptors formed around the corner matches from one image with that of the other image for the best closeness. The features with best closeness are kept while the rest are discarded. From these features, a transformation model is estimated and corresponding image warping is done. After warping the image on a common mosaic plane, the final step is to remove the intensity seam. For the purpose of image blending, graph cut method with minimum cut/ maximum flow algorithm is used.

A method for constructing panorama from standard definition streams using a fast stitching method was proposed by Tomoyuki Shimizu et al.[6] based on global motion tracking for motion-compensated frames. In this method there are two stages; in the first stage a projection matrix is calculated between stitched frames by compensating for global motion of each input stream. Some matching errors which may occur in the first stage are compensated with fine adjustment in the second stage.

An algorithm with real time stitching of images acquired from multiple moving cameras, estimating homography in both spatial and temporal domains is proposed by Shang-Hong Lai and Shuo-Han [7]. RANSAC (Random Sample Consensus) is employed in spatial domain while linear interpolation is used in the temporal domain. Linear blending in the overlapping region is performed to obtain a panorama with cylindrical warping.

III. image stitching approaches

Image stitching techniques are broadly classified into two approaches: Direct and feature based techniques. Direct techniques compare every pixel's intensity of an image with that of the other whereas feature based techniques extract distinct features from the processed images and correlate them. The latter approach is more advantageous in the sense that it is more robust against scene rotation, faster and has the proficiency to automatically determine the overlapping relationships among an unordered set of images.

A . Direct Techniques

In direct techniques, all the pixel intensities of the images are compared with each other. This technique uses cost functions to minimize the sum of absolute differences between overlapping pixels. It is computationally complex as there is a need to compare each pixel window to others [8]. They are variant to image scaling and rotation. There are many techniques for solving stitching problems using direct methods such as Fourier analysis technique. It has the advantage that this makes use of the information available in image alignment and the disadvantage is that there is a limited range of convergence[15][16].

B . Feature Based Methods

These methods establish the correspondences between points, lines, edges, corners or other geometric entities. Characteristics of robust detectors are that they are invariant to image noise, scaling, translation and rotation transformations. The two ways to identify the matching region from the input images are block matching and feature-point matching. Block matching algorithms initially calculate the correlation between the regularized blocks generated in sequential consecutive images in the set. It can be done either by normalized cross-correlation or by phase correlation using a Fast Fourier Transform. Such methods involve a series of complex calculations and are also very sensitive to the slight difference between the images. Feature based methods extract different features from each image and matches these features to establish a global correspondence between all the images [9]. Feature descriptors are used to extract the features points from the given images for matching it with other images. There are many feature detection techniques such as SIFT , SURF , FAST(Features from Accelerated Segment Test Technique)etc. Feature based methods are robust and are potentially fast[18-19].

IV. feature extraction methods

In feature extraction, all important feature points in an image are compared with that of the other image by employing local descriptors. The steps followed in feature-based image stitching techniques are feature extraction, image registration and image blending. A suitable feature extraction algorithm makes the image stitching process more effective and efficient. Feature-based techniques resolve an association between the images based on extracted features such as points, lines, edges, corners or other shapes. The main advantage of robust detectors is that they are invariant to noise, scaling, translation and rotation transformations.

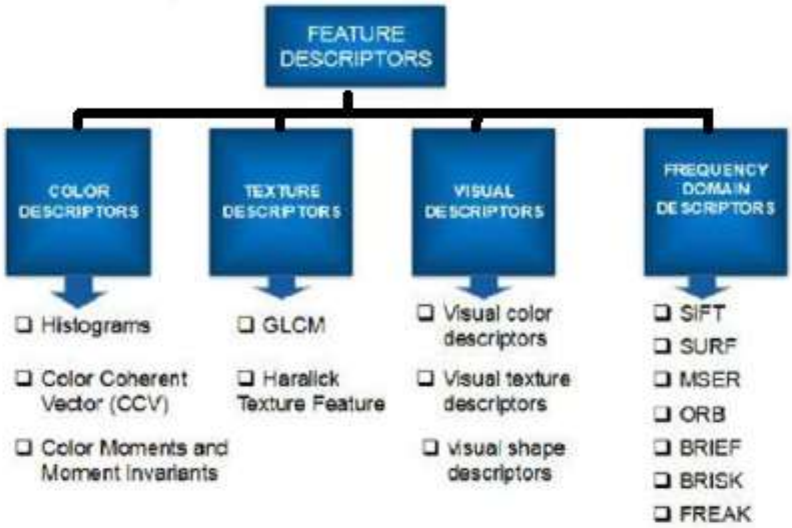

Fig 4.1 : Various feature descriptors

A .Colour Descriptors

Histogram of colour image represents the distribution of colours in an image . The histogram of a colour image consists of three separate one dimensional histograms, one for each R, G and B channels. For the HSV colour model, the hue gets unstable near the gray axis. The certainty of the hue and saturation are inversely proportional. Hence, histogram of hue component is build more robust by weighing each sample of the hue by its saturation. For the normalized RGB colour space, the chroma components r and g represent the colour information in the image. The components r and g, after normalization are scale invariant and hence invariant to light intensity changes, shadows and shading. The histogram in RGB colour space is not invariant to light changes. With pixel value normalization, scale invariance and shift invariance can be achieved with respect to light intensity changes. Since each channel is normalized independently, the descriptor also gets normalized against light colour and arbitrary offset changes. Colour coherent vector histogram bin is classified as either coherent or incoherent. Coherent type consists of pixel values that belong to a large similarly-coloured region of the image. Colour histogram lacks the spatial information of pixels hence it can give similar colour distribution for entirely different images. Colour moments provide a measurement of colour similarity between images. From the generalized colour moment, colour moment invariance can be generated. A total of 24 colour moment invariances are generated.

Colour SIFT Descriptors are used to represent the local shape of a region by using edge orientation histograms. The image gradient is possibly shift-invariant. The direction of the gradient and relative gradient magnitude will be the same under changes in light intensity (intensity channel scaling). The gradient magnitude changes have no effect as the SIFT descriptor is normalized on the final descriptor. Since the colour channels R, G and B are combined to form the intensity channel, the SIFT descriptor is not invariant to changes in colour of light.

B . Texture Descriptors

Texture is proved to be a very useful feature for browsing, searching and retrieval of images. Texture descriptor gives a measure of the properties such as coarseness, smoothness, and regularity. In order to measure the texture properties of an image, statistical, structural and spectral methods are used. One of the most known texture descriptors is GLCM (Gray Level Co-occurrence Matrix) [10]. Angular second moment, also called uniformity or energy, is the sum of squares of entries in the GLCM angular second moment measure in the image homogeneity. When pixels in an image are very similar or when the image has very good homogeneity, angular second moment will be high. Inverse difference moment (IDM) is the local homogeneity, which is high when inverse GLCM is high and the local gray level is uniform. Entropy indicates a measure of information content in the image that is required for a fruitful compression. The linear dependencies of grey levels of neighbouring pixels are indicated by correlation. When performing feature extraction using GLCM, at the time of RGB to grey conversion the time taken for image compression can be considerably reduced. GLCM is used to extract second order statistical texture features from the images and also for the motion estimation of images.

In GLCM texture extraction, features such as entropy, angular second moment, correlation and inverse difference moment are computed. Haralick texture feature captures the information about the patterns that makes a texture of the image[11].These features are calculated by employing a co-occurrence matrix which is computationally intensive in real time applications.

C . Visual Descriptors

Colour features are not robust to the changes in the background colours and are not dependent on orientation and size of the image. In order to extract colour features of an image, visual colour descriptors are used. Visual colour descriptors can be used to distinguish still images and video content. For extracting textures, visual texture descriptors are used. These descriptors consist of the visual patterns of a set of images which has the property of texture homogeneity that result from the presence of multiple colours or intensities in the image. They carry important structural information pertaining to the surfaces of objects in the image and their relationship with the surrounding environment. Shape of image objects provide a useful information for similarity matching between different objects which are extracted by using visual shape descriptors. The shape descriptor needs to be invariant to scaling, rotation and translation transformations for image retrieval.

D . Frequency Descriptors

SIFT is one of the most widely used frequency domain descriptor. There are four computational steps in SIFT technique for extracting key points . This lessens the number of keypoints that help to increase the efficiency and robustness. If the keypoints are located on the edge or have a low contrast, they are rejected. For local similarity invariant representation and comparison of the feature points, SURF is a fast and robust algorithm. By the approximation of the Hessian matrix of a given image, keypoints are found hence it is commonly called a fast-Hessian detector. The main merit of the SURF method is its rapid computation and hence it is more suitable for real-time applications like object tracking and recognition.

FAST is a feature extractor or an interest point detector for the use in real time frame rate applications. Pixels within a circle of fixed radius around a point are compared by the FAST detector . ORB (Oriented Fast and rotated BRIEF) method is a fast binary descriptor which is based on binary robust independent elementary features key point descriptor. Binary based features exhibit several merits over vector based features as they are faster to compute, more efficient to compare and need very low memory space.

For the blob detection, MSER (Maximally stable extremal regions)[12] is used. MSER algorithm is used to extract co-variant regions from the image. Hence it gives a stable connected component of some gray level sets of the image. Simple binary tests between pixels in the smoothed image patch of the original image are used by the BRIEF descriptor. BRIEF descriptor is similar in performance to SIFT detector in several ways including robustness to lighting, blur and perspective distortion. Its demerit is that it is very sensitive to in-plane rotation. Over a retinal sampling pattern of the image, the FREAK (Fast Retina Key point) algorithm finds a cascade of binary strings by efficiently comparing pixel intensities.

Method	Advantages	Disadvantages
SIFT	• Good Accuracy • Included in OpenCV • Efficient	• Slow • Poor performance in lighting changes and blur • Not suitable for real time applications
SURF	• Computation time is much lower • Good at handling image rotation	• Change in view point poorly handled • Poor performance
ORB	• Rotation invariant • Faster than SIFT	• Not robust

BRIEF	● Faster than SIFT and SURF	● Less scale invariant than SIFT and SURF

Table 4.1. A comparison of different feature extraction methods

V. The Proposed Method

The input images are obtained from the dataset of Panoramic stitching master [13]. The images need to be converted into equal size in the preprocessing stage. Feature points are extracted using different feature extractors like SIFT,SURF,FAST,ORB,BRIEF, S-FREAK,S-BRIEF(SIFT+BRIEF),S-STAR(SIFT+STAR),S-ORB(SIFT+ORB),OR- BRIEF(ORB+BRIEF) and OR-FREAK(ORB+FREAK). Based on the extracted features, a feature matching is done and a homography estimation is performed to remove outliers using RANSAC (Random sample consensus). After removing the outliers, stitching is performed by comparing the pixels to get a panoramic image. A block schematic of the proposed system is as shown in Fig5.1.

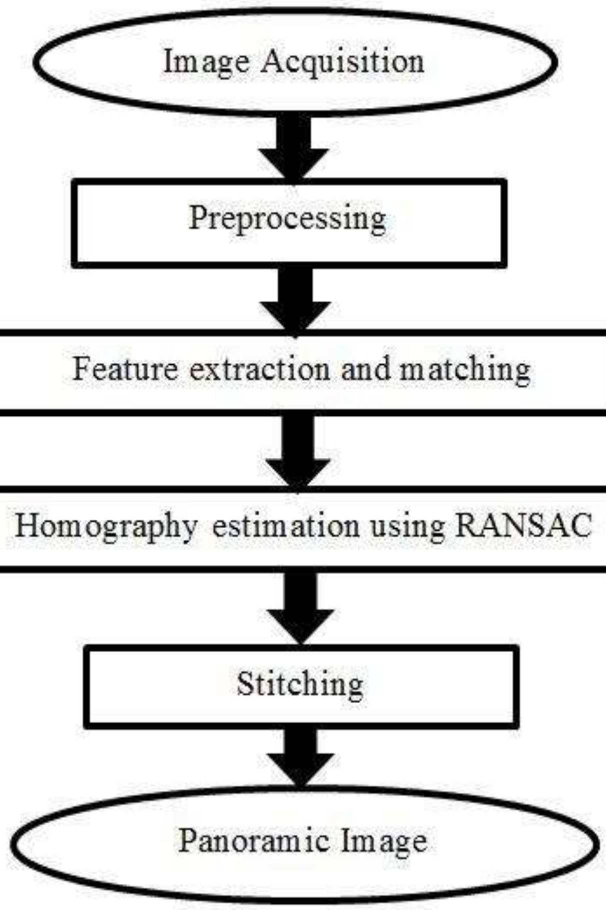

Fig 5.1 Overall block schematic of the proposed system

The different stages that are identified and their functionalities in the proposed system are as given :

- Preprocessing
- Feature extraction

- Feature matching
- Homography estimation using RANSAC
- Image stitching

A .Preprocessing

The images taken from the dataset or captured by handheld devices like mobile phone with high resolution camera are to be converted into images of equal dimension by using a preprocessing algorithm. Illumination correction and image resizing are done in this step. Images of equal resolution will be the output of this stage.

B . Feature Extraction and Matching (S-FREAK)

After pre-processing, the feature extraction and matching are performed using various feature extraction methods .By comparing these feature extraction methods, S-FREAK is found to be the best one in terms of real time , system time and user time. The components of S-FREAK are shown below which is a combination of SIFT and FREAK. In this method the following steps are performed.

a) Find the features using SIFT and store the descriptors.

b) Prepare the SIFT output which is given as the input of the FREAK stage.

c) Perform FREAK to find the feature descriptors.

d) S- FREAK feature points are extracted.

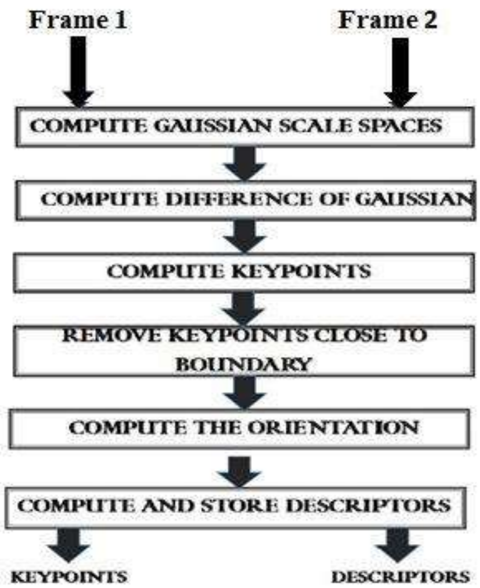

Fig 5.2 : SIFT [4]

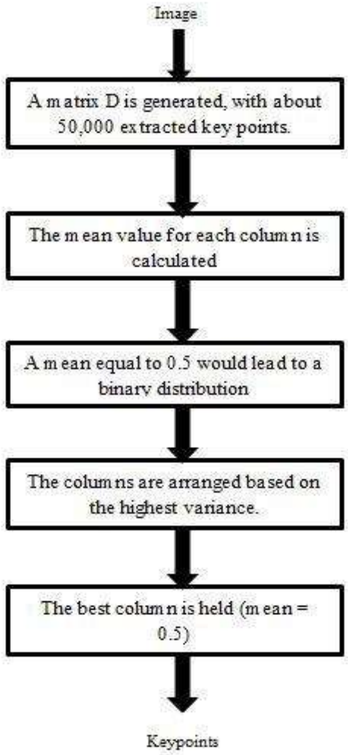

Fig 5.3 FREAK

C . Homography Estimation using RANSAC

After extracting features and matching them, outlier elimination is performed. RANSAC is a widely used robust estimation method for homographies[14] and is a method for removing outliers. This means that two features in the images do not correspond to same real world features. It is a non-deterministic algorithm in the sense that it provides a reasonable output only with a certain probability. Fischler and Bolles at SRI International first published the algorithm in 1981. A comparison of different homography estimation methods is given in table 5.1. A block schematic of RANSAC method used in the proposed system is shown in Fig.5.4.

Method	Advantages	Disadvantages
DLT(Direct Linear Transform)	● Simple ● Solve by using homography matrix	● Unstable ● Does not converges to the correct result in the presence of noise
Cost function (algebraic distance, geometric distance)	● Computationally cheap ● Better than DLT	● Slower ● Needed to pick initial estimates and stopping criteria
RANSAC(Random Sample Consensus)	● Dealing with outliers ● Outilers means that 2 features in the images doesn’t correspond to some real world features	● Needed to estimate threshold
LMS (Least Median Square)	● No need for	● Not able to

	setting threshold	cope with more than half the data being outliers.

Table 5.1. A comparison of different homography estimation methods

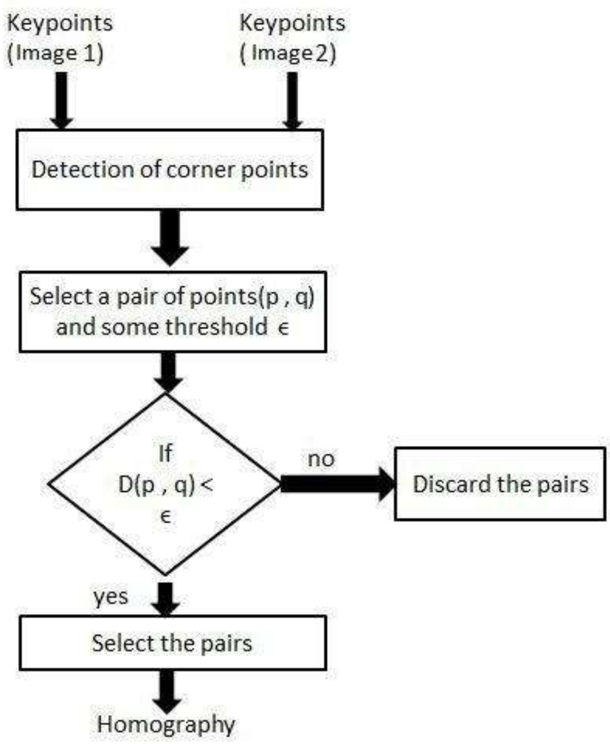

Fig 5.4 : RANSAC Method

D . Image Stitching

Stitching is used to combine the two images in the data set and produce the resultant panorama. Comparing the individual pixels are employed to combine the images. There exists a seam when two images are overlapped and this will create ghosts. Ghosts can also occur when there are moving objects in the scene. The purpose of image stitching algorithm is to create a seamless panorama. The seam in between the images is made invisible.

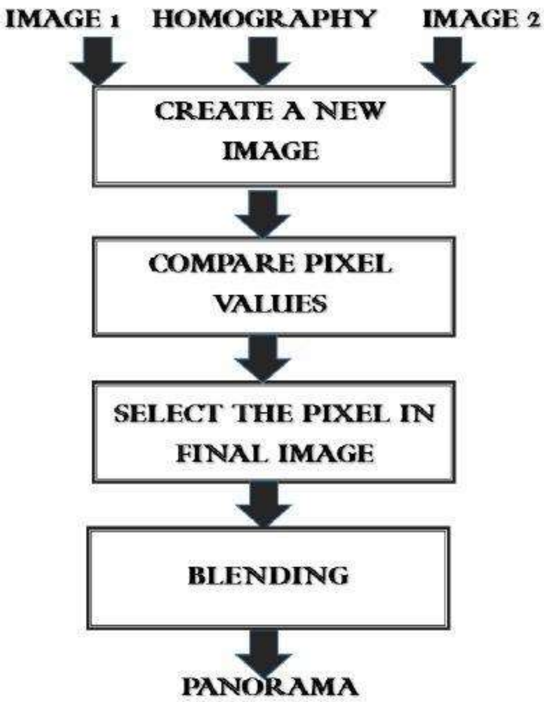

Fig 5.5 : Stitching[4]

An overview of the important algorithms used in the proposed work are given below

Algorithm: Feature Extraction(SIFT)

Input : Images

Output : SIFT keypoints

1. Calculate Gaussian scale spaces on the input images

$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y)$ (1.1)

Compute Difference of Gaussian as

$$D(x,y,\sigma) = L(x,y,k\sigma) - L(x,y,\sigma) \quad (1.2)$$

2. Obtain candidate keypoints to bring a list of discrete extrema.
3. Refine candidate keypoints location with sub-pixel precision to get a list of interpolated extrema
4. Filter unstable keypoints laying on edges and keypoints due to noise.
5. Assign a reference orientation to each keypoint to get a list of oriented keypoints
6. Construct the keypoint descriptor to evolve a list of described keypoints.

Algorithm: Feature Extraction(FREAK)

Input : Images

Output : FREAK keypoints

1. Generate a matrix D with approximately 50,000 extracted keypoints.
2. Compute the mean value of each column. If mean = 0.5 lead to a binary resolution.
3. Arrange columns based on the highest variance.
4. Extract the keypoints with best column held with mean=0.5.

Algorithm: FeatureMatching

Inputs : $L^a = \{ f^{a1} .. \}$ keypoints and descriptors relative to image a.

$L^b = \{ f^{b1} .... \}$ keypoints and descriptors relative to image b.

Output : M = Matched keypoints.

1. Set t as relative threshold (default value 0.6).
2. For each descriptor f^{a1} in L^a do

   Compute f^{a2} and f^{a3}, nearest and second nearest neighbours of f^{a1}
3. For each descriptor f in L^b calculate the distance d(f^{a1},f)
4. Select pairs that satisfy relative threshold.
5. If d(f^{a1},f^{a2}) < t * d(f^{a1},f^{a3}) then add pair (f^{a1},f^{a2}) to M.

Algorithm: Homography estimation(RANSAC)

Input: Keypoints

Outputs: Homography

1. Detect the corner points in both frames using Harris corner.
2. Process the corner points with variance normalized correlation.
3. Collect the pairs with sufficiently high correlation score.
4. Select pairs that agree with homography model.

   For some threshold s, a pair (p, q) is considered to agree with a homography H,

   $D(p, q) < s$ (1.3)

5. Repeat steps 4 till sufficient number of pairs are generated which satisfies Eq.
6. Find the best homography model, for all the pair correspondences, homography is recalculated .

Algorithm: Image stitching and blending

Input : Homography

Output : Seamless panoramic image

1. Compare pixels using mean square error and stitch
2. Use alpha blending to blend the images
3. Set alpha between 0 and 1

The equation for alpha blending :

$$I = I_1 * alpha + I_2 * (1 - alpha) \quad (1.4)$$

4.Obtain a seamless panorama.

VI. Results and DISCUSSION

A .Preprocessing

Here in preprocessing, two images are given, namely image1 and image 2. Initially an illumination correction is performed to eliminate the problems due to differences in illumination. The images are of different dimensions and suitable resizing is done to make them of equal dimensions. In the figure 6.1, image 1 is smaller than image 2 therefore, image 2's dimension is reduced to that of image 1.

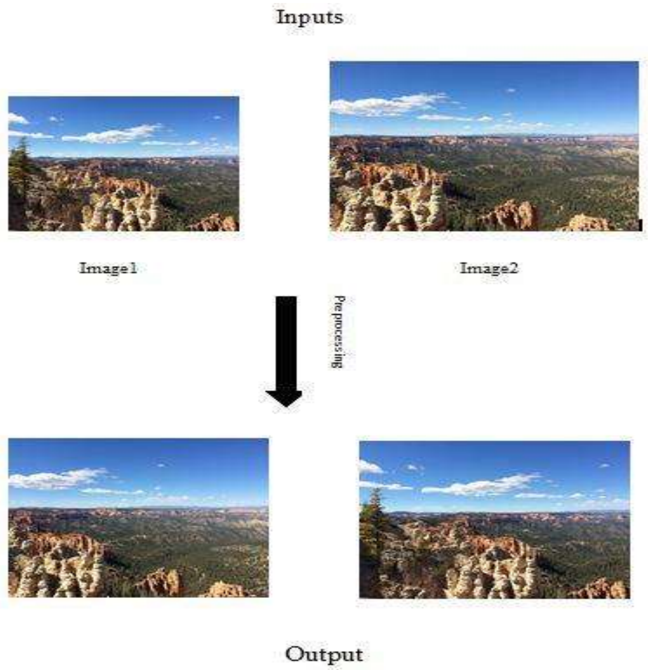

Fig 6.1 :Preprocessing

B . Feature Extraction

After preprocessing both the images are converted in to equal dimensions. Now different feature extraction methods can be employed. A list of different feature extraction methodologies and their results are shown below. The input to this stage is the output of the preprocessing stage.

Fig 6.2 : Input to feature extraction stage

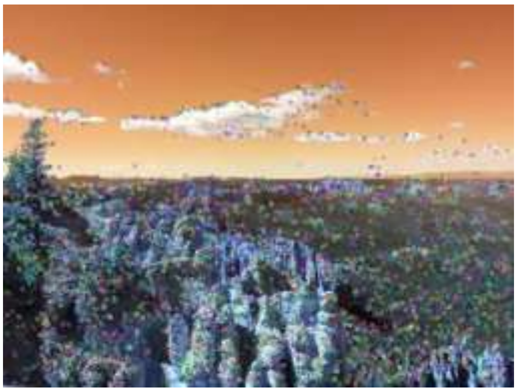

Fig 6.2 a) Output of SIFT

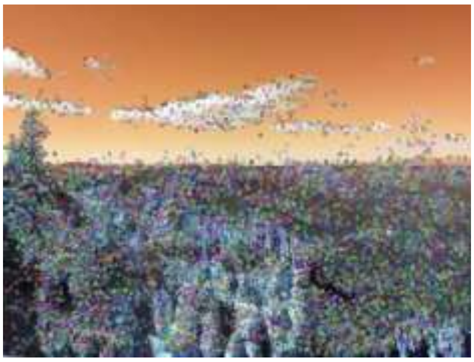

Fig 6.2 b) Output of SURF

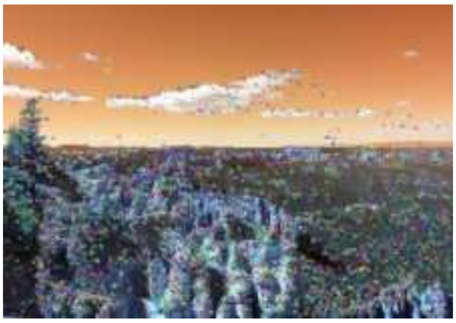

Fig 6.2 c) Output of ORB

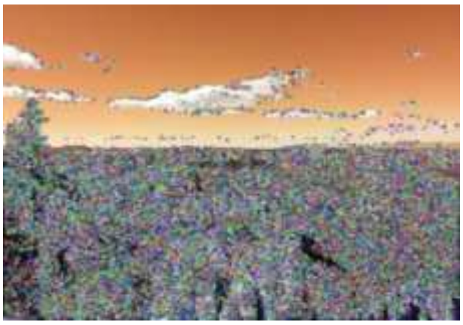

Fig 6.2 d) Output of FAST

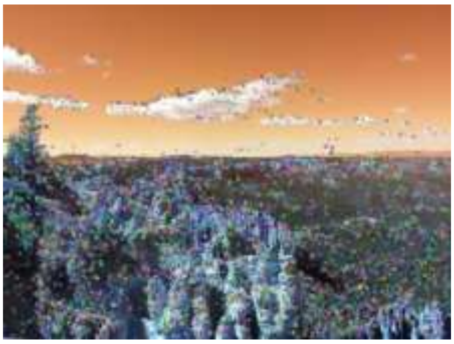

Fig 6.2 e) Output of STAR

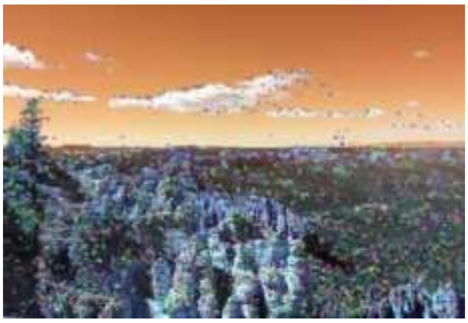

Fig 6.2 f) Output of DAISY

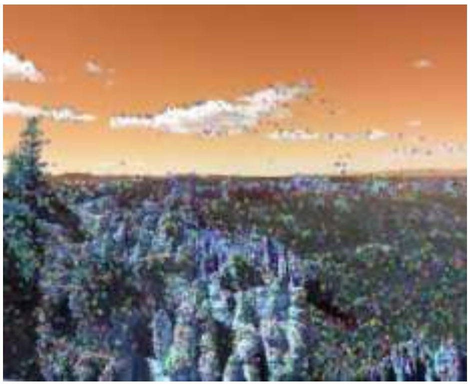

Fig 6.2 g) Output of VGG

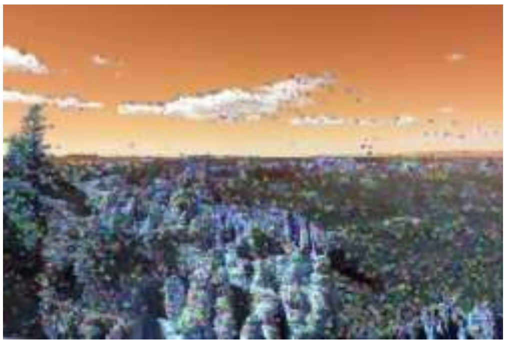

Fig 6.2 h) Output of BRIEF

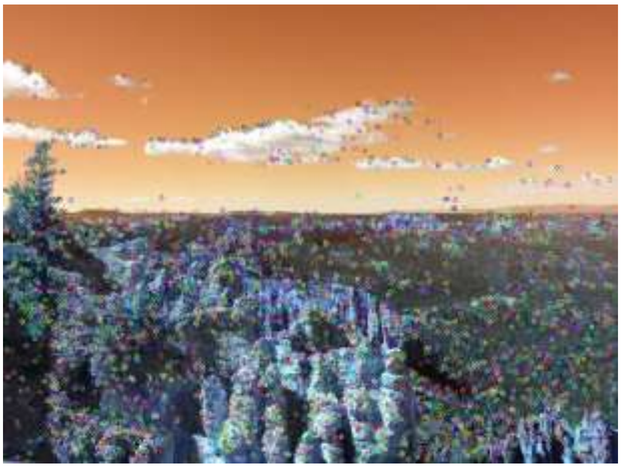

Fig 6.2 i) Output of FREAK

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Fig 6.2 j) Output of OR-BRIEF

Fig 6.2 k) Output of OR-FREAK

Fig 6.2 l) Output of S-ORB

Fig 6.2 m) Output of S-STAR

Fig 6.2 n) Output of S-BRIEF

Fig 6.2 o) Output of S-FREAK

By comparing different feature extraction methods based on real time, user time, system time and output image; it is found that S-FREAK outperforms all the other methods. The below table shows feature extraction methods and their real, user and system time. S-FREAK shows best result because it requires only less registration time compared to other methods and provides better images as shown above.

Method	Real Time	User Time	System Time
SIFT	0.558	0.896	0.8627
SURF	0.806	2.183	0.6507
BRIEF	0.302	0.406	0.9716
FAST	0.349	0.434	0.4396
FREAK	0.294	0.377	0.8627
STAR	0.323	0.391	0.9517
DAISY	0.455	0.555	0.9716
ORB	0.328	0.399	0.8344
VGG	0.299	0.360	0.9716
S-FREAK	0.896	1.195	0.441
S-BRIEF	1.366	1.831	0.524
S-STAR	0.953	1.218	0.393
S-ORB	1.032	1.224	0.459
OR-BRIEF	0.207	0.698	0.371
OR-FREAK	0.752	0.705	0.395

Table 6.1 : Comparison of different feature extraction methods based on time

As seen in the table, OR-BRIEF and OR-FREAK has lesser time than S-FREAK but their outputs are of poor quality. The graph below clearly gives a visual representation of the feature descriptors along with their time.

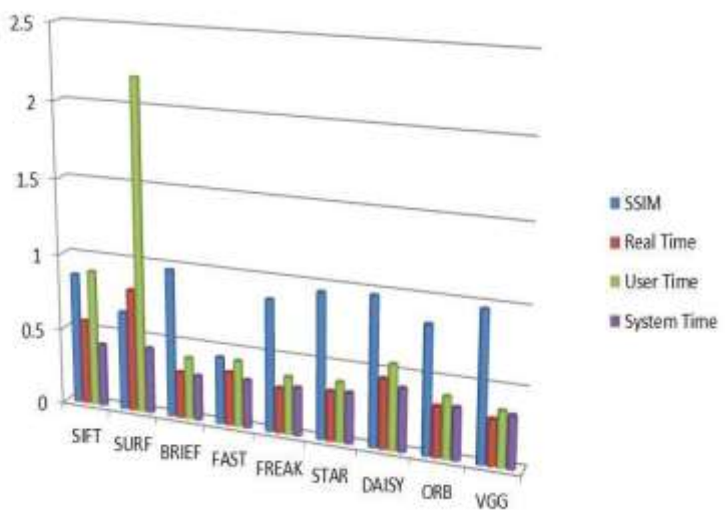

Fig 6.3 : A visual representation of comparison of feature extraction methods

C.Feature Matching

Matching between the two images needs to be done as the next step in image mosaicing. The input to this stage is the output from feature extraction step and S-FREAK is found to be the best feature extraction method in this context. The output is as shown below in Fig. 6.4

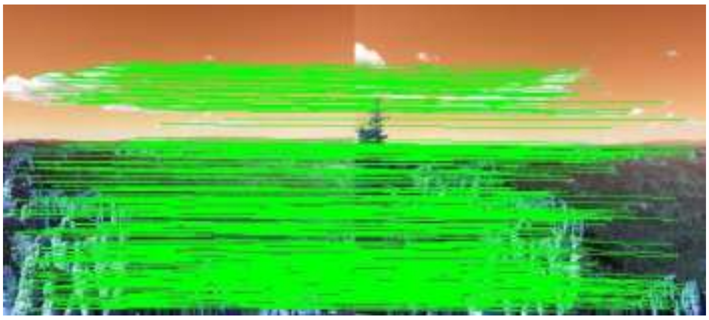

Fig. 6.4 Output of feature matching

C. Panoramic Image

The final panoramic output is as shown below. The image1 and image 2 are stitched to get the panoramic image as shown Fig 6.5.

Fig 6.5 panoramic Image

Advantages of the proposed method include

- Panorama stitching using S-FREAK provides better image alignment than other methods.
- Computation of feature extraction is much faster here with good quality images.
- Distortion and ghost image are eliminated in the stitching process.
- Jointly stabilizes and stitches the images.
- This method is capable of handling scenes with parallax issues.
- The results are visually appealing and the method is effective under a variety of scenarios.
- Robust for camera zoom, orientation and changes in illuminations.

VII. CONCLUSION

Image mosaicing/stitching is a method to create panoramic image, where images are assembled with some common FOV(Field of view). It provides us a lot of useful data which are required to extract valuable information not only from a single image but from the stitching stage output image as well, which consist of the shape, structure and colour information . But these also carry information about the possible camera motion, movements of objects in the scene and calibration as well. Parallax problem exists when objects are close to the camera. In addition to that projective transformation generally produces shape distortion in non-overlapping regions which causes wrong depth perception to the viewer. Therefore, image stitching is a challenging task. The exposures for images captured by different cameras may be inconsistent due to different light directions thus making the video stitching a difficult task. The proposed combination of methods outperforms the existing methods as the image registration time for high resolution images is drastically reduced and this makes it faster in stitching applications.

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