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IMAGE MOSAICING USING FSD & FREAK DESCRIPTOR

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Abstract—Image mosaicing is a technique of combining in-formation of different images of the same scene to obtain more information in a single snap that contains every image data. In this paper a real-time image mosaicing is implemented by capturing multiple images of a continues scene with slight variation in the Field of View (FoV) of a camera sensor. Features from Accelerated Segment Test (FAST) feature detector detects invariant robust feature points of each image and Fast Retina Key point (FREAK) binary descriptor extracts feature vectors for each and every feature point. Feature matching is executed with the computation of the hamming distance between the feature points, hamming distance is high for more discriminative feature elements. Mapping of feature points is achieved with Homography computation. Distortions of an image can be cor-rected with image warping process. Robust corner points and corner point vectors are calculated for each input image followed by the number of matching points of corresponding consec-utive images validate the effectiveness of FAST and FREAK algorithms. A comparison of traditional algorithms like Scale Invariant Features Transform (SIFT), Speed Up Robust Features (SURF) shows that our experimental results with FAST and FREAK are more accurate, faster and robust.

Index Terms—Mosaicing, feature points, Panorama, FAST, FREAK, Hamming Distance, Homography, Warp.

I.INTRODUCTION

The Field of View of any scene can be increased with the image Mosaicing process. Image Mosaicing is a technique of stitching multiple images of a scene to form a single image. Most of the times single shot of camera was unable to capture the total scene of human vision because the Field of View (FoV) of the camera is 50 × 35 degrees and human vision is 180 × 135 degrees. Where 50 and 180 direct the horizontal visual range, 35 and 135 directs vertical visual range [2]. Image mosaicing [3] plays an important role to increase the Field of View (FoV) by taking the partial views of the scene and making them into a single snap that contains a total scene of each and every partial image. This process executed in five phases [4], feature detection, feature extraction, feature match-ing, transformation estimation, image warping and blending. In order to perform Mosaicing, input images ought to have some common portion that

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contains corresponding inlier points to match images. Most of the image Mosaic algorithms are based on either interest points or on the corner points matching. This paper describes corner points based real-time image Mosaicing implemented with Features from Accelerated Segment Test (FAST) feature detector that exhibits the best performance along with the binary feature descriptor Fast Retinal key points (FREAK). Evaluation of Binary descriptors have become more interesting in many computer vision applications [5] due to its high efficiency and low memory cost. FREAK encodes all intensity comparisons of an image on a particular pattern at small scale and large scale and gathers information similar to the human visual system.

Shum and Szeliski [6] and Lowe and David proposed that globally aligned panoramas with rotating camera that shaped with improved camera poses. Agarwala and Davis [7] constructed single viewpoint panorama. The conventional de-scriptors SIFT introduced by Lowe [8], forms a corner point by filtering the image with the difference of Gaussians that dominating gradients of an image. SURF descriptor [9] forms a corner point based on building a distribution with improved execution time. Still several issues have remained unsolved, how to effectively choose the perfect pairs of an image patch? How to match them? Curiously such issues are solved with a binary descriptor inspired by a human visual system and exact with retina named it as the Fast Retina Key point (FREAK) but it is only a descriptor not a detector, so FREAK needs one more detector to identify the corner points. The FAST detector simply detects invariant feature points of each input image, FREAK descriptor extracts all the feature vectors of each corner point in an image. Hamming distance measures the similarity between all binary descriptors that has identical importance on all binary descriptors since computational complexity is much simpler and used in many real-time applications. This paper addresses the real-time implementation and comparative analysis of conventional descriptors and binary descriptors for the construction of image mosaicing. This paper compares traditional descriptors SIFT and SURF with FREAK binary descriptor and a comparative assessment of conventional fea-ture detectors with the FAST detector. Our experimental results show that the combination of FAST detector and FREAK descriptor along with hamming distance computation is well suited for real-time image mosaicing applications.Section II briefs mosaic process with a flowchart. Sections III and IV describes the FAST detector and FREAK descriptor with a necessary mathematical equation and diagrams. Section V describes the similarity measurement between images. Section VI explains the role homography transformation to map the distinct images. Section VII de-scribes the warping and blending of the mosaic image to improve the vicinity level.

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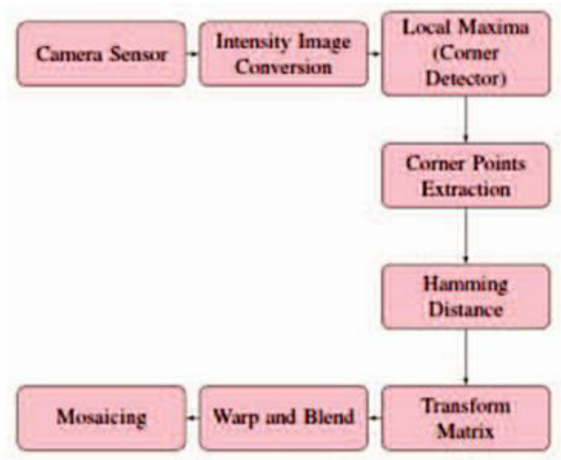

Fig. 1. Image mosaicing process.

II. IMAGE MOSAICING PROCESS

Image registration plays a vital role in image mosaicing. Image registration is a technique of aligning and mapping of pixels of distinct images [10]. The Fig. 1 demonstrate an outline of our framework, starting with camera sensor used to capture images of a scene in real-time. Four input images are captured with camera sensor each having 560 × 310 dimensions with a slight angular difference. Each colour image is converted to grayscale image followed by local maxima. FAST corner detector detects Robust Local maxima points and these points are focused on the colour image which is known as corner points. Feature matching is implemented with hamming distance calculation [11]. The geometric transformation matrix is used to map corner points of one image with the corner points of another image. Image Warping corrects the distortions of an image, each and every dimension of an image changes and Image Blending decreases the seams or artifacts of a mosaic image to produce good vicinity of an image. Finally the mosaic image is formed by the above process.

III. FEATURES FROM ACCELERATED SEGMENT TEST (FAST) FEATURE DETECTOR

FAST was introduced by E. Rosten and T. Drummond in 2006 to identify corner points of an image. Corner point detection plays a vital role in various computer vision applications like object recognition, image matching, tracking and medical application like retinal image mosaicing [12] etc. Corner points in an image have a defined position, high local information, robustly detected and they should be ideally detected in all images. Corner detection is not a new idea there are several corner detectors among them Moravec corner

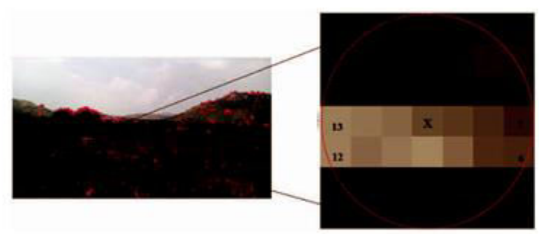

Fig. 2. Pixel X under test surrounded with 16 neighborhood pixels.

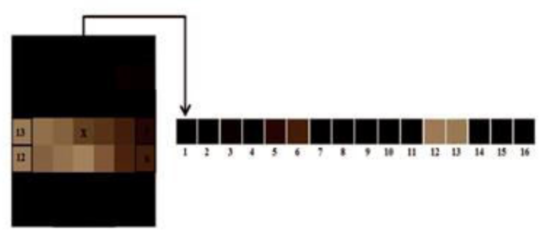

Fig. 3. Pixel X surrounded with 16 pixels stored in vector form.

detector-1977 [13], Harris corner detector-1988 [14], Wang and Brady corner detector-1992, Shi and Tomasi-1994 and SUSAN corner detector-1997 [15] are familiar algorithms. The idea behind to develop FAST corner detector was to use interest points in real-time applications like SLAM on a mobile robot. FAST algorithm [16] validate each and every pixel of an image in such a way that a pixel is corner point or not by comparing every pixel with its 16 neighbor pixels that form a circle (Bresenham circle). For every pixel X, store (form) surrounding 16 neighbor pixels as a vector as shown in Fig. 3. Each one of the 16 pixels should be any one of three states. Darker than intensity of pixel X (IX), similar to intensity of pixel X or brighter than the intensity of pixel X as shown in Fig. 2 and Fig. 3 and mathematical representation is shown in Eq. (1) as

$$S_x = \begin{cases} Darker, & for\ I_x \leq I_x - t \\ Similar, & for\ I_x - t \leq I_x \leq I_x + t \\ Lighter, & for\ I_x + t \leq I_x \end{cases} \qquad (1)$$

Here SX is the state of pixel X, IX is the intensity of pixel X and t is the threshold value.

Depending on the states the whole vector X are going to be divided into 3 subsets namely XD, XS and XL. Define a variable K that is true if pixel X is a corner point and false if pixel X is not a corner point. The process is repeated for each and every pixel of an image

Fig. 3. Representing ring as a ternary vector and segment test used to classify the vectors.

Non-maxima pixel points are suppressed in two ways, initially differentiating pixel intensity values with the center pixel intensity value if the difference between this two pixel values is greater than threshold value

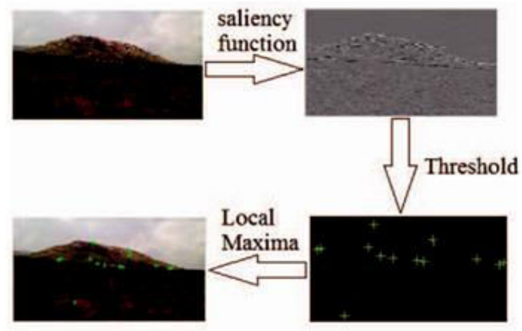

Fig. 4. Typical FAST detector processing pipeline.

't' similarly if the difference between this two pixel values is less than threshold value 't' than the difference of center pixel value and pixel intensity values are considered and entire process can be summarized with mathematical Eq. (2) as

$$Non-Max\ Suppression = \begin{cases} \Sigma(PV - X) & if\ (value - X) > t \\ \Sigma(X - PV) & if\ (value - X) < t \end{cases} \qquad (2)$$

here PV = pixel values, where X is the center pixel and t is the threshold value for detection and the pixel value is the N contiguous pixels in the 16 neighborhood pixels. The process can be accelerated by comparing the intensity of pixels I1, I5, I9 and I13 with pixel X intensity IX. At least three of four pixels should satisfy threshold criteria that is three pixels should greater or lesser than IX + t or IX − t, than only corner point exist otherwise it is not a corner point. Repeat the process for all image pixels. The FAST corner detector processing pipeline is utilized for mosaicing [17] and it is as shown in Fig. 4

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IV. FAST RETINA KEY POINT (FREAK)

In real-time image mosaicing, descriptors initially capture the substantial amount of data regarding spatial intensity patterns and robust to local image patch errors or too small deformations. Feature extraction extracts the feature point and represents a feature vector. Though traditional Descriptors are robust with a difference of gaussian and hessian matrices but lack in computation time which is not suitable for real-time applications [18]. This paper propose FREAK descriptor introduced by alahi Ortiz, and Vandergheynst in 2012. It is a unique corner point descriptor propelled by the human visual system and exactly the retina, it is a biologically inspired descriptor. A binary string is computed effectively by comparing the intensities of an image over a sampling pattern. A genuine challenge is to identify the corner points with stable, compact and robust representations invariant to noise, rotation, scale, rotation and affine transformations. FREAK is a compact and real-time descriptor. FREAK de-scriptor estimates forty three weighted Gaussian image patches.

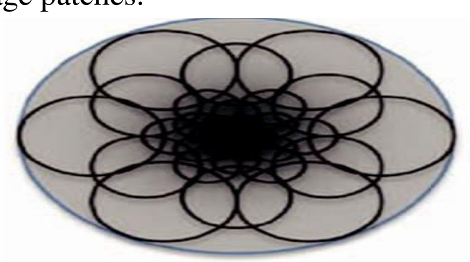

Fig. 5. FREAK sampling pattern inspired from human retina.

TABLE I
NUMBER OF FEATURE POINTS DETECTED BY SIFT, SURF AND FAST.

Input images	SIFT	SURF	FAST
Image-1	432	63	15
Image-2	420	64	17
Image-3	409	62	17
Image-4	451	70	20

around the interesting point, however Gaussian patterns are inspired by retinal pattern [19]. Near key point the density of points is high, as it moves far from the keypoint the density diminish exponentially it is as shown in Fig. 5, each circle symbolizes a receptive field and smoothen with the specific Gaussian kernel. Experimental outcomes proved that the FREAK descriptor is more rapid in computational time with lower memory load.The number of matching points between two images is defined as matching score (see Table I).Corner matching score between Image-1 and Image-2 is 9.

Corner matching score between Image-2 and Image-3 is 9.Corner matching score between Image-3 and Image-4 is 6.

V.FEATURE MATCHING

Hamming distance computation replaced the Euclidean dis-tance and dot product calculation. Hamming distance com-putes the number of bits that be different from one binary descriptor string to another [20]. Hamming distance is used to calculate the similarity metric when features of input images are binary objects. Fast and better binary descriptors like FREAK and ORB have been matched and developed rapidly feature points using Hamming distance (see Figs. 6 and 7).

Hamming distance = 4 between two binary vectors 11000110 and 10101010.

Hamming distance = 3 between "MATLAB" and "MATRIX".

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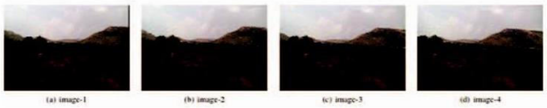

Fig. 6. Four consecutive images of a scene.

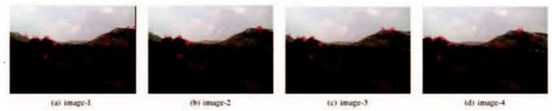

Fig. 7. FAST corner detection of multiple images of a scene.

TABLE II
COMPARISON OF SIFT, SURF, FAST AND FREAK ALGORITHMS.

Algorithm	Input images	Match score percentage	Number of corners of four images	Feature detection time (s)	Feature descriptor time (s)	Total mosaic time (s)
SIFT	Image-1 and Image-2 image-2 and Image-3 image-3 and Image-4	51.08% 55.36% 45.22%	1712	4.676	4.131	11.35
SURF	Image-1 and Image-2 Image-2 and Image-3 Image-3 and Image-4	53.33% 54.57% 48.99%	259	2.289	1.572	4.955
FAST & FREAk	Image-1 and Image-2 Image-2 and Image-3 Image-3 and Image-4	56.2% 52.9% 54.00%	69	0.225	0.3312	1.349

The hamming distance performance time is known as matching cost that compares two binary vector strings with Boolean XOR operation to deliver match metric. Hamming distance is desired for matching binary descriptors such as BRISK [21], BRIEF [22], LBP [23], FREAK and ORB [24] (see Table. II) .

VI. GEOMETRIC TRANSFORMATION

Geometric distortions can be eliminated with Geometric Transformation, the distortions may occur during the capturing of input images. There are several geometric transformations in image processing among them affine transformation is robust to many geometric distortions. Geometric transformation matrix estimates the matching point pairs and maps the inliers of one input image with the inliers of another input image. Perspective distortions can be removed with the planar homography matrix [25]. The Transformation Matrix determines the correspondence between the same feature point of different images that are used to map [26]. After transformation matrix calculation between input frames a Mosaic output image will be generated by warping present frame to the coordinates of the previous frame. The Geometric transformation matrix be-tween two homogeneous points Q(x, y, w) and Q (x , y , w) of two consecutive frames is given by

$$Q=GQ$$

where G is the Geometric matrix that relates the pixel coor-dinates in different frames, it is given by

$$G = \begin{bmatrix} G_{11} & G_{12} & G_{13} \\ G_{21} & G_{22} & G_{23} \\ G_{31} & G_{32} & G_{33} \end{bmatrix}$$

The geometric transformation $G^{k}{}_{k+1}$ is evaluated from the corresponding feature points of images I_k. And I_{k+1}. The geo-metric transformation to mosaic image I_{k+1} with the mosaiced image can be found as

$$G_k{}^m{}_{+1} = G_k{}^m G_k{}^k{}_{+1} = \pi_i{}^k{}_{=1} G_i{}^j{}_{+1} \quad (3)$$

Fig. 8. Warped image of input image-4.

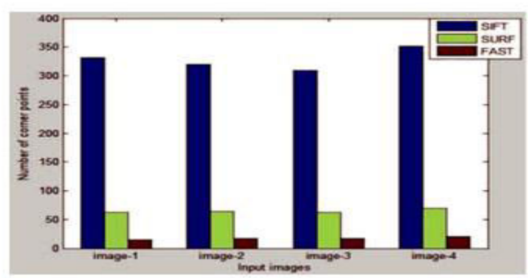

Fig. 9. Comparing number of corner points detected by SIFT, SURF and FAST algorithm.

where $G^{m}{}_{k+1}$ = final mosaic image geometric transformation
$G^{m}{}_{k}$ = Mosaic transformation with out image $I_k{}^k{}_{+1}$.
$G^{k}{}_{k+1}$ = transformation between image I_{k+1} and I_k.

VII. IMAGE WARPING AND BLENDING

Image warping transforms present image according to the geometric transformation between Source image and the target image,

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to match the objects of both images [27]. Each dimen-sion of warp image may change according to the previous image or reference image. Image warping technique corrects and adjusts the geometric distortions of an input image to exact match the Mosaicing as shown in Fig. 8. The process of removing or decreasing the artifacts or seams [28] of mosaic image is called image blending. Discrete Wavelet Transform (DWT) uses the rule of maximum selection for image blending [29]. Seams or artifacts of a mosaic image degrade the vicinity as well as the quality of mosaicing. Comparison of SIFT, SURF and FAST feature detector are shown in Fig. 9 with respect to a number of feature points (see Fig. 10).

VIII. CONCLUSION

An experimental real-time image Mosaicing using a FAST detector, FREAK descriptor and geometric transformation ob-tained robustly with more FoV of a scene. Experimental results proved that FAST detector detects robust corner points in an average time of around 0.055 s and it is 10.17 times faster than SURF and 20.78 times faster than SIFT. FREAK is 4.74 times faster than SURF and 12.47 times faster than SIFT. The fast detector and the FREAK descriptor are suitable for real-time applications than traditional SIFT, SURF feature descriptors.

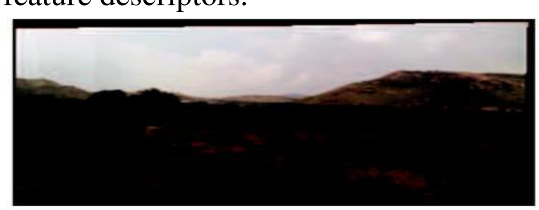

Fig. 10. Mosaic output image.

Among all binary descriptors, FREAK descriptor has quick response time. Binary string comparison is well executed with the Hamming distance computation that swapped the Euclidean distance calculation. The whole work shows that real-time image mosaic is fine with the combination of FAST, FREAK and Hamming distance algorithms. Hopefully, over next few years any general purpose embedded device that supports FAST, FREAK can perform a real-time automatic image Mosaicing and more computer vision applications.

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