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# IMAGE MOSAICING USING SIFT AND CORNER DETECTION ALGORITHM

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## Abstract

Image Mosaicing is the process of combining two or more images of the same scene into one image and generate panorama of high resolution image. Mosaicing is blending together of several arbitrarily shaped images to form one large radiometrically balanced image so that the boundaries between the original images are not seen. In this paper, we have described the basic methods used to generate panorama image. Here objective is to provide different methods and algorithms used to generate panoramic image and also to present a new image mosaicing algorithm based on SIFT and corner detection algorithms. When there are scale variations and rotations SIFT can give better performance and when there are less rotations corner detection algorithms can perform better. Hence in this paper we are trying to use both algorithms for an image, so that the mosaicing quality can be increased.

***Keywords:*** **Mosaicing, panorama, image blending**

## I. Introduction

Image mosaicing also called as image stitching where we stitch two or more images and generate one single image. Nowadays almost all digital cameras come with the feature of image panorama, but still it is not giving good result and lots of improvement has to be done. So this field of image processing required lots of efforts and many new algorithms can be developed. Image mosaicing is used in many applications like video conferencing; from multiple nodes create 3D view, astronomy, telemedicine, cartoons, virtual museums, architectural Walkthroughs.

There are 2 types of image mosaicing [1]

- Direct method
- Feature based

The direct method estimate the transformation parameters based on the intensity difference in area of overlap. Feature based methods mosaic the images by first automatically detecting and matching the features in the source images, and then warping these images together. Below table gives comparison between direct method and feature based method

Direct method can provide accurate registration. It has range of coverage is limited. It is sensitive to noise. It can handle only translation and small rotation. Feature based method reduces computational complexity. It has high range of coverage. Sensitivity to noise id reduced. It is suitable for fully automatic mosaicing.

Direct methods use all of the available data and can provide very accurate registration this is the advantage of it. These approaches include Fourier analysis techniques and also coarse to fine optimization of cost or objective functions. From researching these methods of the past it appears a strong foundation has been laid for direct approaches involving pixel intensity operations and comparisons. In real-time implementation it seems to be highly limited and in many cases convergence towards the optimal solution appears to be a problem.

Feature based methods have become increasingly popular and widespread in mosaicing. This is partially because of the strength of new algorithms and types of invariant features which have been demonstrated in recent years such as the SIFT algorithm. Mosaicing applications using feature based methods include Real-time aerial surveillance, mosaicing of camera captured document images and panorama stitching among others. Recently, both the direct and feature based approaches have been analyzed by researchers and it was observed that feature detection and matching schemes are remarkably robust. So recent work in image mosaic focuses on the uses features and has a good success rate at automatically stitching than direct method.

Different steps required for doing image mosaicing are feature extraction, registration, stitching (merging images) and blending. Image registration is the process of aligning two or more images taken from one point or same thing is captured from different point [2].

Main purpose of doing image registration is to create geometric correspondence between images so that we can compare images and apply other steps appropriately. Registration process can be broadly divided into four categories. one in which consider pixel value of image directly[3], second is frequency domain based registration method[4] , third is the algorithms which use edges and corners and finally algorithms which consider objects and relation between features[5].

After registration next is stitching, in stitching or image merging, all images are transformed according to registration parameter on single big canvas and final step is to do image blending which make the transition from one image to another image smoother so that joint between two images can be removed.

In Harris corner detection algorithm the differential of the corner score with respect to direction [6]. Scale Invariant Feature Transform termed as SIFT is used to identify locations and scales that can be repeatable assigned under different views of the same object. Finding locations that are invariant to scale changes of the image can be accomplished by searching for stable feature across all possible scales, using continuous function of scale known as scale space[7].

Here these both algorithms are combined to form a new image mosaicing algorithm. Filter is also used so that the mosaicing can be made even better and image would be noise free.

The Harris/ Plessey operator suffers from poor localization and is expensive with respect to computation. However, it has the best detection rate of the three operators and has been shown to have a good repeatability rate. For many applications, localization is not critical. For these reasons the Harris/Plessey operator is widely used in practice.

# II. Related Work

## A. Feature Extraction and Matching

It can be started with corner detection algorithms where we have described Harris, SUSAN, Forstner and SIFT algorithms.

### (a) Harris Corner Detector

Instead of using shifted patches, Harris and Stephens [8] improved Moravec's corner detector by considering the differential of the corner score with respect to direction. Suppose two-dimensional gray scale image is used. Give it a name I. Assume image patch over the area (u,v) and shifting it by(x,y). The weighted SDD (sum of squared differences) between above two patches, S, is given by:

$$S(x, y) = \sum_u \sum_v w(u,v)\,(I(u+x, v+y) - I(u,v))^2 \quad (1)$$

By using tailor expansion and partial derivatives, we can write above equation in matrix form as,

$$s(x,y) \approx (x \;\; y)\, A \begin{pmatrix} x \\ y \end{pmatrix} \quad (2)$$

Here, A is the structure tensor,

$$A = \sum_u \sum_v w(u,v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

$$= \begin{bmatrix} \langle I_x^2 \rangle & \langle I_x I_y \rangle \\ \langle I_x I_y \rangle & \langle I_y^2 \rangle \end{bmatrix} \quad (3)$$

This matrix is a Harris matrix. and angle brackets denote averaging. Corner is described by a large variation of S in all directions of the vector ( $x\ y$ ). By analyzing the eigenvalues of *A*, this representation can be expressed in the following way: *A* should have two large Eigen values for an interest point. Based on the magnitude of the eigenvalues, the following conclusions can be made based on this argument:

1. if $\lambda_1 \approx 0$ and $\lambda_2 \approx 0$ then this pixel ( $x$ , $y$ ) has no feature interest.

2. if $\lambda_1 \approx 0$ and $\lambda_2$ has some large positive value, then an edge is detected.

**3.** if $\lambda_1$ and $\lambda_{2\ \text{have}}$ large positive values, then corner is found.

### (b) SUSAN

SUSAN is an acronym standing for Smallest

Univalue Segment Assimilating Nucleus. SUSAN places a circular mask or called window over the pixel to be tested. The region of the mask is M. pixel in mask is represented by m. The nucleus is at m0. The brightness of pixel with in mask is compared with that of the nucleus. Every pixel is compared to the nucleus using following function:

$$c(\vec{m}) = e^{-\left(\frac{\left(I(\vec{m}) - I(\vec{m}_0)\right)}{t}\right)^6} \tag{4}$$

Here, t represent radius. Power of the exponent is determined empirically. The area of SUSAN is given by,

$$n(M) = \sum_{\vec{m} \epsilon M} c(\vec{m}) \tag{5}$$

If $c$ is rectangular function, then $n$ is the number of pixels in the mask which are within $t$ of the nucleus. The response of the SUSAN operator is given as:

$$R(M) = \begin{cases} g - n(M) & if\ n(M) < g \\ 0 & otherwise, \end{cases} \tag{6}$$

For corner detection, two further steps are used. Firstly, the centroid of the SUSAN is found. A proper corner will have the centroid far from the nucleus. The second is that all points on the line from the nucleus through the centroid out to the edge of the mask are in the SUSAN.

## (c) Forstner Corner detector

In some cases, one may wish to compute the location of a corner with subpixel accuracy. To achieve an approximate solution, the Förstner algorithm solves for the point closest to all the tangent lines of the corner in a given window and is a least-square solution. The algorithm relies on the fact that for an ideal corner, tangent lines cross at a single point. Below diagram (Figure 1) shows how algorithm detect corner using this algorithm.

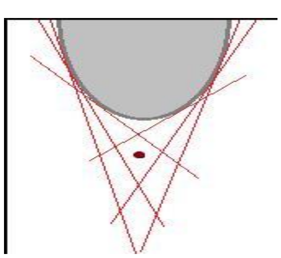


**Figure 1. Corner detection using forstner method**

## (d) SIFT Algorithm

Scale Invariant Feature Transform termed as SIFT [8] is used to identify locations and scales that can be repeatedly assigned under different views of the same object. Detecting locations that are invariant to scale changes of the image can be accomplished by searching for stable feature across all possible scales, using continuous function of scale known as scale space. The scale space of an image is defined as a function,

$L(x, y, \sigma)$ , that is produced from the convolution of a variable - scale Gaussian, $G(x, y, \sigma)$, with the input image, $I(x, y)$:

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{7}$$

To efficiently detect stable keypoint locations in scale space, David G. Low proposed using scale-space extrema in the difference of Gaussian function convolved with the image:

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y)$$

$$= L(x, y, k\sigma) - L(x, y, \sigma) \tag{8}$$

The difference-of-Gaussian function will have a strong response along edges, even is the location along the edge is poorly determined and therefore unstable to small amounts of noise.
A 2X2 Hessian matrix computed at the location and scale of the keypoint is:

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \tag{9}$$

and then rejecting the keypoints for which,

$$\frac{Tr(H)^2}{Det(H)} > 10 \tag{10}$$

## B. Homography Calculation Using RANSAC

For deleting wrongly detected points RANSAC algorithm is used in image mosaicing. We have briefly explained this algorithm below.

RANSAC is an abbreviation for "RANdom SAmple Consensus". It is an iterative method to estimate parameters of a mathematical model from a set of observed data which contains outliers. It is a non-deterministic algorithm in the sense that it produces a reasonable result only with a certain probability, with this probability increasing as more iterations are allowed. The algorithm was first published by Fischler and Bolles at SRI international in 1981

A basic assumption is that the data consists of "inliers", i.e., data whose distribution can be explained by some set of model parameters, and "outliers" which are data that do not fit the model. In addition to this, the data can be subject to noise. The outliers can come, e.g., from extreme values of the noise or from erroneous measurements or incorrect hypotheses about the interpretation of data. RANSAC also assumes that, given a (usually small) set of inliers, there exists a procedure which can estimate the parameters of a model that optimally explains or fits this data.

The input to the RANSAC algorithm is a set of observed data values, a parameterized model which can explain or be fitted to the observations, and some confidence parameters. RANSAC achieves its goal by iteratively selecting a random subset of the original data. These data are hypothetical inliers and this hypothesis is then tested as follows:

1. A model is fitted to the hypothetical inliers, i.e. all free parameters of the model are reconstructed from the inliers.

2. All other data are then tested against the fitted model and, if a point fits well to the estimated model, also considered as a hypothetical inlier.

3. The estimated model is reasonably good if sufficiently many points have been classified as hypothetical inliers.

4. The model is re-estimated from all hypothetical inliers, because it has only been estimated from the initial set of hypothetical inliers.

5. Finally, the model is evaluated by estimating the error of the inliers relative to the model.

This procedure is repeated a fixed number of times, each time producing either a model which is rejected because too few points are classified as inliers or a refined model together with a corresponding error measure. In the latter case, we keep the refined model if its error is lower than the last saved model.

Possible variants of the RANSAC algorithm include:

- Break the main loop if a sufficiently good model has been found, that is, one with sufficiently small error. May save some computation time at the expense of an additional parameter.

- Compute this error directly from model without re-estimating a model from the consensus set. May save some time at the expense of comparing errors related to models which are estimated from a small number of points and therefore more sensitive to noise.

- An advantage of RANSAC is its ability to do robust estimation of the model parameters, i.e., it can estimate the parameters with a high degree of accuracy even when a significant number of outliers are present in the data set. A disadvantage of RANSAC is that there is no upper bound on the time it takes to compute these parameters. When the number of iterations computed is limited the solution obtained may not be optimal, and it may not even be one that fits the data in a good way. In this way RANSAC offers a trade-off; by computing a greater number of iterations the probability of a reasonable model being produced is increased. Another disadvantage of RANSAC is that it requires the setting of problem-specific thresholds

- RANSAC can only estimate one model for a particular data set. As for any one-model approach when two (or more) model instances exist, RANSAC may fail to find either one. The Hough transforms an alternative robust estimation technique that may be useful when more than one model instance is present.

## C. Image Blending

Blending is applied to make seamless stitching. Two popular methods of blending the images are- one is called alpha blending, which takes weighted average of two images and another is Gaussian pyramid. In alpha blending, the weighting function is usually a ramp. At the stitching line, the weight is half and half, while away from the stitching line one image is given more weights than the other. The cases that alpha blending works extremely well is when image pixels are well aligned to each other and the only difference between two images is the overall intensity shift. Alpha blending will merge two images seamlessly. However, if the images are not aligned well, the disagreements will show in the blended image. Gaussian pyramid approach essentially merges the images at different frequency bands and filters them accordingly. The lower the frequency band, the more it blurs the boundary. Gaussian pyramid blurs the boundary while preserving the pixels away from the boundary. It does not work well, however, if the two images are at significantly different intensity levels. The transition is not as smooth as alpha blending for this case.

# III. Literature Survey

-Cai Suo Zhang in citation Xin Zhang et al., 2012, Advanced Materials Research, 433-440, 6151 [9] has cited as The Harris corner detection algorithm is widely applied in image mosaic, which is simple and stable. However, the algorithm has a disadvantage that it obtains a lot of false corners when there exists some noise in an image. An improved Harris corner detection algorithm is proposed in this paper. The new algorithm reduces the noise impact greatly. The experimental results show that the improved algorithm not only reduces false corner points greatly, but also retain the majority of true corners. As a result, it improves the detection accuracy and reduces the chance of error matching in image registration.-

- Zhan-Long Yang Inst. of Intell. Control & Image Eng., Xidian Univ., Xi'an Bao-Long Guo [10] have cited in their paper as: The traditional feature-based algorithm was found to be sensitive to rotations and scales. In this paper, an automatic image mosaic technique based on SIFT (Scale Invariant Feature Transform) was proposed by using the rotation and scale invariant property of SIFT. Keypoints are first extracted by searching over all scales and image locations, then the descriptors defined on the keypoint neighborhood are computed, through to compare the Euclidean distance of their descriptors to extract the initial feature points pair, then eliminate spurious feature points pair by applying RANSAC, finally transform the input image with the correct mapping model for image fusion and complete image stitching. Experimental results demonstrate the proposed algorithm is robust to translation, rotation, noise and scaling.

-Meiqun Jiang Adv. Digital Process. Lab., Xiamen Univ., Xiamen, China Qingwei Liao ; Jingxin Hong; Shengluan Huang [11] they have cited in their paper a proposeasal of mosaic algorithm based on SIFT(Scale Invariant Feature Transform). Keypoints and their descriptors are exacted by SIFT, which ensures the algorithm robust to translation, rotation, noise and scaling. Then proposed matching algorithm is used to match the keypoints. First, rough match pairs are obtained by Nearest Neighbor algorithm. Second, match rate information of the neighbor keypoints and the global information are calculated to update the match precision, so each keypoint matching rate spreads to its neighborhood, which eliminates a large number of mismatches to achieve the exact match. Third, RANSAC is applied to obtain the transformation matrix. Finally, two images are stitched by linear weighted fusion algorithm. The experiment results confirm the feasibility and improvement of our mode.

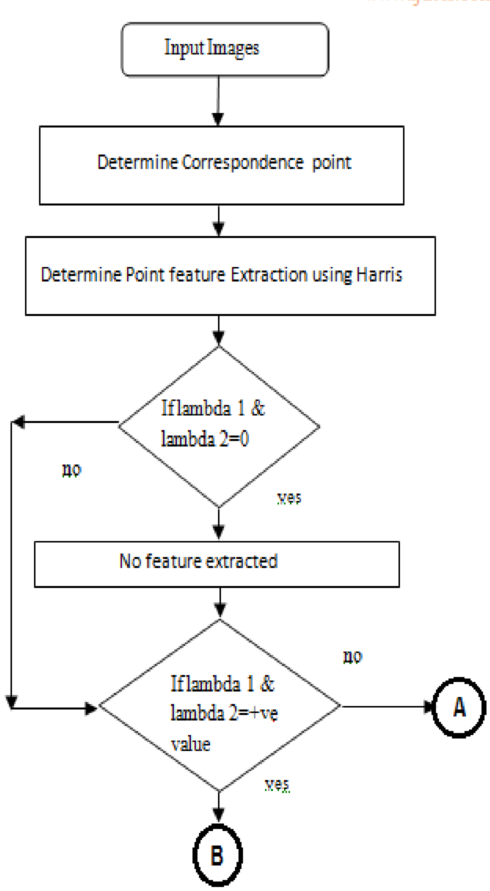
-In Yang zhan-long Guo bao-long," IMAGE MOSAIC BASED ON SIFT", International Conference on Intelligent Information Hiding and Multimedia Signal Processing, IEEE 2008. [7], one SIFT based algorithm is presented. In this paper an automatic image mosaic technique based on SIFT (Scale Invariant Feature Transform) was proposed by using the rotation and scale invariant property of SIFT. Keypoints are first extracted by searching over all scales and image locations, then the descriptors defined on the keypoint neighborhood are computed, through to compare the Euclidean distance of their descriptors to extract the initial feature points pair, then eliminate spurious feature points pair by applying RANSAC, finally transform the input image with the correct mapping model for image fusion and complete image stitching.

- In Pengrui Qiu,Ying Liang and Hui Rong "Image Mosaics Algorithm Based on SIFT Feature Point Matching and Transformation Parameters Automatically Recognizing" [8] A mosaic algorithm of different scale image registration and adaptive is proposed in this thesis, against to the large amount of calculation and poor robustness, as well as cannot well solve the problem of image mosaic of images who are in different scales in the traditional image mosaic method. The match and mosaic of different scale and rotated images is achieved through feature point matching and automatically recognizing of transform geometric parameters between images.

-In Corner Detection D. Parks, J.P. Gravel [12] has given a comparison of different operators and given as the Harris/ Plessey operator suffers from poor localization and is computationally expensive. However, it has the best detection rate of the three operators and has been shown to have a good repeatability rate. Localization is not critical for many applications. For these reasons the Harris/Plessey operator is widely used in practice.

# IV. Proposed Methodology

The traditional image mosaicing method is more complex because of large amount of calculations and has poor robustness as it cannot solve the problem of image mosaic of images which are in different scales. The chance of error matching in image registration and impact of noise is also an issue which affects the image mosaicing. In the above section any one of the image feature extraction algorithms is used for image mosaicing. Both SIFT and Corner Detection [13] algorithms have their own advantages. The combination of these two algorithms can give higher parameter identification and mosaic accuracy, and good adaptability to image translation, rotation and scale transformation hence improve the mosaicing quality still better. Below figure shows the basic steps needed in image mosaicing technique. Image is first captured and then corresponding points are determined, later point features are extracted and matching points are found using different algorithms like SIFT, Harris etc., finally image is stitched and blended to give the mosaiced image.



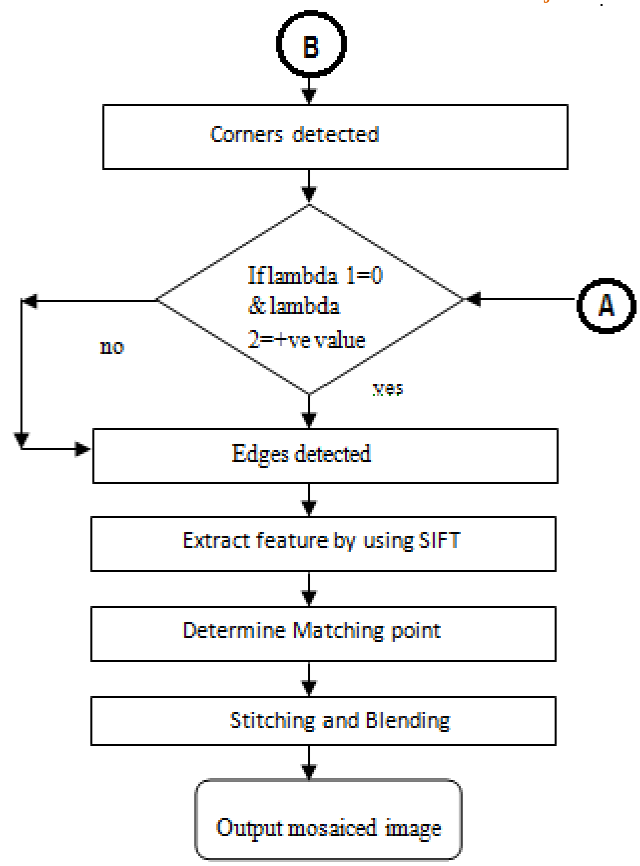




**Figure 2. Steps in Image Mosaicing**

# V. Conclusion and Future Work

Due to the wide range of applications, image mosaicing is one of the important research area in the field of image processing. Here we have presented some of the very fundamental and basic techniques used in image mosaicing. By doing the combination of different algorithms and according to the applications we can make new and better image mosaicing algorithms. SUSAN, Harris and SIFT are popular feature extraction algorithms.

In this research paper we have compared different algorithms and their results before using our own approach that combines best features of SIFT and Comer Detection algorithms to get better results. In future we would like to improve the results of image mosaicing by combining other algorithms with our approach.

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