Feature Based Mosaicing of Images

Deepali Bhadane, K. N. Pawar

***Abstract**: Image Mosaicing is a process of assembling the multiple overlapping images of the identical scene into a larger image. The output of the image mosaic will be the union of two input images. Image - mosaicing algorithms are used for gaining a mosaiced image. In this paper we have described the feature based mosaicing of two images. Feature based image mosaicing is the combination of corner detection, corner matching, motion parameter estimation and image stitching .For corner detection there are various algorithms - HARRIS, SUSAN,CSS. This corner detection algorithm produces an efficient and informative output mosaiced image. After corner detection RANSAC algorithm is used for Homography. After that image warping and image blending is done. Importance of Image Mosaicing can be seen in the field of medical imaging, computer vision, data from satellite, military automatic target recognition. In this paper we compare result CSS, SUSAN, HARRIS.*

***Keyword**: Image mosaicing, Feature Extraction, Image registration, corner detection using HARRIS,SUSAN,CSS algorithm, Homography using RANSAC, Image warping, Image Blending.*

I. INTRODUCTION

Image mosaicing is the process of combining multiple photographic images with overlapping fields of view to produce a segmented panorama of high-resolution image. It is commonly performed through the use of computer software; most approaches to image stitching require nearly exact overlaps between images and identical exposures to produce seamless results. Mosaicing could be regarded as a special case of scene reconstruction where the images are related to planar homography only. An Image Mosaic is a synthetic composition generated from a sequence of images and it can be obtained by understanding geometric relationships between images. The geometric relations are the coordinate system that relates the different image coordinate system.

By applying the appropriate transformations through a warping operation and merging the overlapping regions of warped images, it is possible to construct a single image is distinct from a single large image of the same object, covering the entire visible area of the scene. This merged single image is the output of mosaiced image. There are two methods of Image Mosaicing- 1) Direct Method 2)Feature based method. Direct method provides very accurate registration but they are not very robust against illumination variance whereas feature based method is robust against illumination variance, image noise, image rotation, image scaling and perspective distortions. For mosaicing of images there is various steps- Feature extraction, image registration, stitching and blending.

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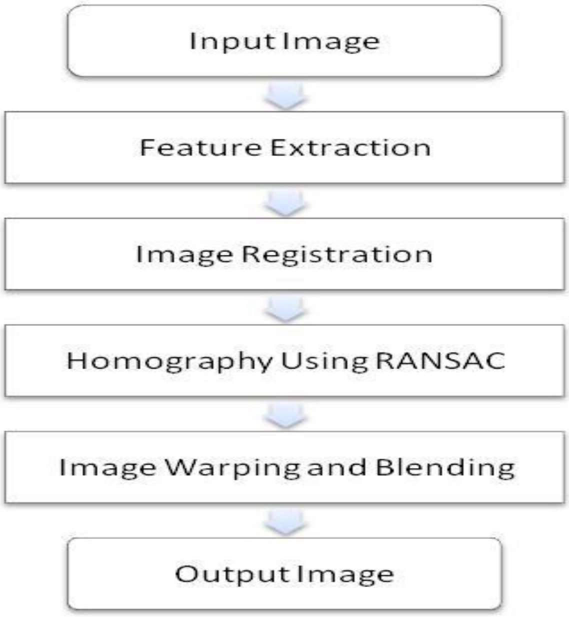

Fig: 1. Mosaicing Flow Chart

Above figure shows the Image Mosaicing Flow chart. First we take an input image; then feature should be extracted, features may be corner or edges; after the feature extraction Image registration done. Image registration is the very important step among all image analysis task in which final information is received from the combination of sources like in image mosaicing, image fusion and image restoration. Registration is the process of aligning two or more images taken from one point or same thing is captured from different point.

Main purpose of doing image registration is to create geometric correspondence between images so that we can compare images and apply other steps appropriately.

The goal of registration is to establish geometric correspondence between the images so that they may be transformed, compared, and analyzed in a common reference frame.

After registration next step is Homography, in homography undesired corners which do not belong to the overlapping area are removed. To remove the undesired corners which do not belong to the overlapped area, Random Sample Consensus (RANSAC) algorithm is used. Homography estimation is a key step in many image processing application such as image mosaicing, feature matching as it improve the stability of image registration. It provides good set of candidate matches as it provides accurate mapping between images. It removes the false matches in the image pairs. Reprojections of frames are done by defining its size, length, width. Stitching is done finally to obtain a final output mosaic image.

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II. CORNER DETECTION TECHNIQUS

Corner in image represent a lot of useful information and they play an important role in describing object features for recognition and identification. Following are the algorithms are used for corner detection.

A] HARRIS corner detection algorithm.
B] SUSAN corner detection algorithm.
C] CSS corner detection algorithm.

A. Corner detection using HAARIS:

This Algorithm was developed by Chris Harris and Mike Stephens in 1988 as a low level processing step to aid researchers trying to build interpretations of a robot's environment based on image sequences. Specifically, Harris and Stephens were interested in using motion analysis techniques to interpret the environment based on images from a single mobile camera. Harris and Stephens developed this combined corner and edge detector by addressing the limitations of the Moravec operator. The result was far more desirable detector in terms of detection and repeatability rate at the cost of requiring significantly more computation time. A local detecting window in image is designed. The average variation in intensity that results by shifting the window by a small amount in different direction is determined. At this point the center point of the window is extracted as corner point. We can easily get the point by looking at intensity values within a small window. Shifting the window in any direction gives a large change in appearance. Harris corner detector is used for corner detection. On shifting the window if it’s a flat region than it will show no change of intensity in all direction. If an edge region is found than there will be no change of intensity along the edge direction. But if any corner is found than there will be a significant change of intensity in all direction. Harris corner detector gives a mathematical approach for determining whether the region is flat, or if there is an edge or corner. Harris corner technique is very much helpful in detecting more features and that technique is rotational invariant and scale variant.

Harris corner detector is based on the auto correlation function of the signal. The basic idea of Harris detector is we find whether point shows significant change in all direction or not. If yes then point is marked as a corner point .it requires larger corner response function to detect corner.

For the change of intensity for the shift [u, v]:

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

Where w(x, y) is a window function, I(x + u, y + v) is the shifted intensity and I(x, y) is the intensity of the individual pixel. Harris corner algorithm is given below as:

1. For each pixel (x, y) in the image calculate the autocorrelation matrix M as;

$$M = \sum_{x,y} \begin{bmatrix} Ix2 & Ix\,Iy \\ Ix\,Iy & Iy2 \end{bmatrix}$$

2. For each pixel of image has Gaussian filtering, get new matrix M, and discrete two-dimensional zero-mean Gaussian function as:-

$$Gauss = \exp(-u^2+v^2)/2\delta^2$$

3. Calculating the corners measure for each pixel (x, y,), we get;

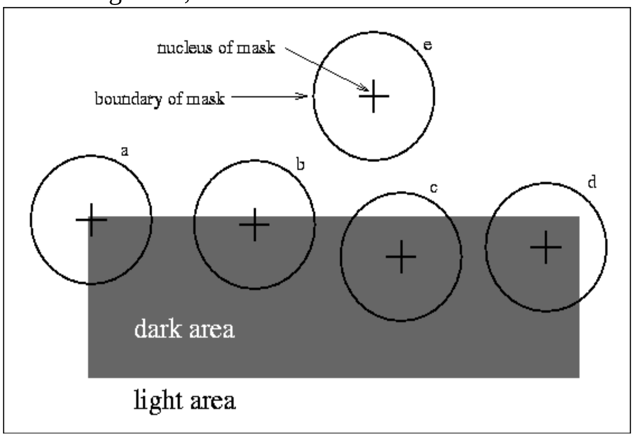
$$R = \{Ix^2 \times Iy^2 - (Ix^2Iy^2)\} - k\,\{Ix^2 + Iy^2\}^2$$

4. Choose the local maximum point. Harris method considers that the feature points are the pixel value which corresponding with the local maximum interest point.

5. Set the threshold T, detect corner points.

B. Corner detection using SUSAN:

SUSAN (Smallest Univalve Segment Assimilating Nucleus) corner detector. In SUSAN algorithm if any corner is found in that then it marked with circular shape or mask whereas in Harris algorithm corner marked with patches. If the brightness of each pixel within a mask is compared with the brightness of that mask's nucleus then an area of the mask can be defined which has the same (or similar) brightness as the nucleus .This area of the mask shall be known as the USAN” i.e. “Univalue Segment Assimilating Nucleus”. Consider following Fig. 1, showing a dark rectangle on a white background,



Five circular masks are shown at different positions on the simple image. Corners can be detected according to the area of USAN. Nucleus is on the corner when the area of USAN is up to the smallest, such as position “a”. In order to detect corners, the similar comparison function between each pixel within the mask and mask's nucleus is given by (1):

$$c(r\,,\,r_0) = \begin{cases} 1, & |I(r) - I(r0)| \le t \\ 0, & otherwise \end{cases} \qquad (1)$$

Where *r*0 is nucleus’s coordinates and *r* is the coordinates of other points within the mask; *c*(*r*, *r*0) is the comparison result; *I*(*r*) is the point’s gray value; *t* is gray difference threshold which determines the anti-noise ability and the smallest contrast that can be detected by SUSAN detector. In fact, eq^n (1) is not stable in practice, and an improved comparison function eq^n(2) is more often used because of its efficiency.

$$c(r\,,\,r_0) = exp\{-[(I(r)-I(r0))/t]^6\} \qquad (2)$$

The size of USAN region is given by (3):

$$n(r_o)=\sum_{r\in c(r0)} c(r,r0) \qquad (3)$$

And the initial response to corners is got from eq^n (4), which is in accord with the principle of SUSAN, that is, the smaller USAN region, the greater initial response to corners.

$$R(r_0)=\begin{cases} g-n(r0), n(r)<g \\ 0, \quad n(r)\geq g \end{cases} \qquad (4)$$

In eq^2(4), g is geometric threshold which determines the acute level of a corner, the smaller the acuter. It enhances the corner information of an image. At last, corners can be found by non-maximum inhibition.

SUSAN detector does not use spatial derivatives not smoothness the image. Instead, a circular mask is applied around every pixel and gray scale values of all the pixels within the mask are compared to that the center pixel (the "nucleus").calculate similar brightness to the nucleus

Drawback:

We are not getting image smoothness by using this algorithm.

C. Corner detection using CSS:

The Curvature scale space technique is suitable for recovering invariant geometric features of planer curve at multiple scales. The CSS technique is suitable for recovering invariant geometric features of a planar curve at multiple scales,[14] Mokhtarian et al. proposed two CSS corner detectors [15,16] for gray-level images. These CSS detectors perform well in corner detection and are robust to noise, but they have problems too.

The CSS is defined as:

$$K(u,\sigma)=\frac{\dot{X}(u,\sigma)\ddot{Y}(u,\sigma)\ddot{X}(u,\sigma)\dot{Y}(u,\sigma)}{(\dot{X}(u,\sigma)2-\dot{Y}(u,\sigma)2)^{1.5}}$$

Where $\dot{X}(u,\sigma) = x(u) \otimes \dot{g}(u,\sigma)$,

$\ddot{X}(u,\sigma) = x(u) \otimes \ddot{g}(u,\sigma)$,

$\dot{Y}(u,\sigma) = y(u) \otimes \dot{g}(u,\sigma)$,

$\ddot{Y}(u,\sigma) = y(u) \otimes \ddot{g}(u,\sigma)$, and

$\otimes$ is the convolution operator while $g(u,\sigma)$ denotes a Gaussian function with derivation σ

And $\dot{g}(u,\sigma)$, $\ddot{g}(u,\sigma)$, are the 1st and 2nd derivatives of $g(u,\sigma)$ respectively.

CSS algorithm has the following six steps:

a. Obtain a binary edge map by applying canny edge detection to the gray level image.

b. Find the edge contours, fill the gaps and find the T junctions

c. Compute curvature at a high scale for each edge contour.

d. The contours having absolute curvature greater than threshold is considered as local maxima and twice as much as one of the neighboring minima.

e. Track the corners from the highest scale to the lowest scale to improve localization.

f. Compare T junction to other corners and remove one of the two corners which are very close. The CSS detector has been carried out for both edge detection and corner detection explicitly. The Curvature Scale Space (CSS) operator detects corners by directly looking for local maxima of absolute curvature.

D. Drawback:

The obvious drawback in CSS is difficult to find corners in convex objects. Convex objects cannot be represented due to missing inflection points.

III. HOMOGRAPHY USING RANSAC

Calculating homography is the next step of image registration. In homography undesired corners which do not belong to the overlapping area are removed. RANSAC algorithm is used to perform homography. 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. Homography hasbeen estimated using many geometrical primitives.Researches on wide baseline matching [8-10], object recognition [11-12] and image/video retrieval [13] shows that feature matching is improved by spatial consistency which means the match features of each feature and its every neighbouring feature should have the same spatial arrangement.J Sivic and Andrew Zisserman[13] used each region match in the neighborhood of each feature match to count this feature match. The algorithm was first published by Fischler and Bolles. RANSAC algorithm is used for fitting of models in presence of many available data outliners in a robust manner. Given fitting problem with parameters considering the following assumptions.

Fig: 2. Images after execution of RANSAC

a. Parameters can be estimated from N data items.

b. Available data items are totally M.

c. The probability of a randomly selected data item being part of a good model is Pg.

d. The probability that the algorithm will exit without finding a good fit if one exists is Pfail.

Then, the algorithm:

1. Selects N data items at random.
2. Estimates parameter x.
3. Finds how many data items (of M) fit the model with parameter vector x within a user given tolerance. Call this K.
4. If K is big enough, accept fit and exit with success.
5. Repeat 1.4 L times.
6. Fail if you get here.

How big K has to be depends on what percentage of the data we think belongs to the structure being fit and how many structures we have in the image. If there are multiple structures than, after a successful fit, remove the fit data and redo RANSAC.

We can find L by the following formulae:

Pfail= Probability of L consecutive failures.

Pfail= (Probability that a given trial is a failure) L.

Pfail= (1 -Probability that a given trial is a success)L.

Pfail= (1-(Probability that a random data item fits the model)N)L.

$P_{fail} = (1-(Pg)^{N})^{L}$

$L = \log(P_{fail}) / \log(1-(Pg)N)$

IV. IMAGE WARPING AND BLENDING

Image Warping is the process of digitally manipulating an image such that any shapes portrayed in the image have been significantly distorted. Warping may be used for correcting image distortion as well as for creative purposes (e.g., morphing). While an image can be trans formed in various ways, pure warping means that points are mapped to points without changing the colors. This can be based mathematically on any function from part of the plane to the plane. If the function is injective the original can be reconstructed. If the function is a bijection any image can be inversely transformed. The last step is to warp and blend all the input images to an output composite mosaic. Basically we can simply warp all the input images to a plane defined by one them known as composite panorama.

The final step is to blend the pixels colors in the overlapped region to avoid the seams. Simplest available form is to use feathering, which uses weighted averaging color values to blend the overlapping pixels. We generally use alpha factor often called alpha channel having the value 1 at the center pixel and becomes 0 after decreasing linearly to the border pixels. Where atleast two images overlap occurs in an output mosaic we will use the alpha values

V. EXPERIMENTAL RESULTS

Now that all the steps and relevant details of the mosaicing operation have been carefully described, some of the mosaics created will be presented.

The algorithm proposed here has been implemented in MATLAB® version 7.11.0584 (R2010b) 32-bit and has been executed in system with configuration i4 processor, 4 GB RAM, 2 GB cache memory and 2.8GHz processor

Following results (fig 1,2,3,4) shows overall time taken for RANSAC and Warping operation for different images such as Hall image, Home image, Car image and Bridge Image.

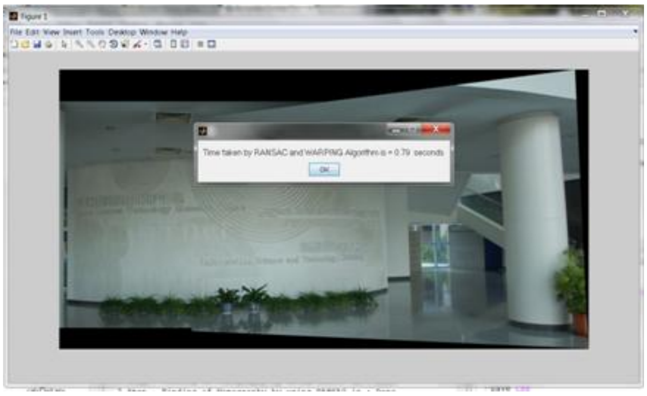


Fig (1) : Hall image

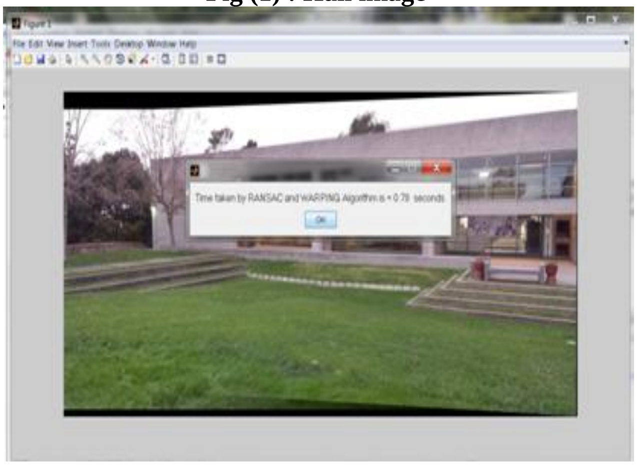


Fig (2): Home image

Fig (3): Car image

Fig (4): Bridge Image

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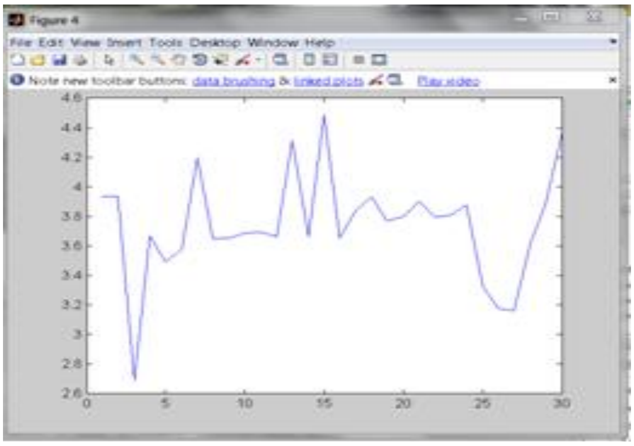
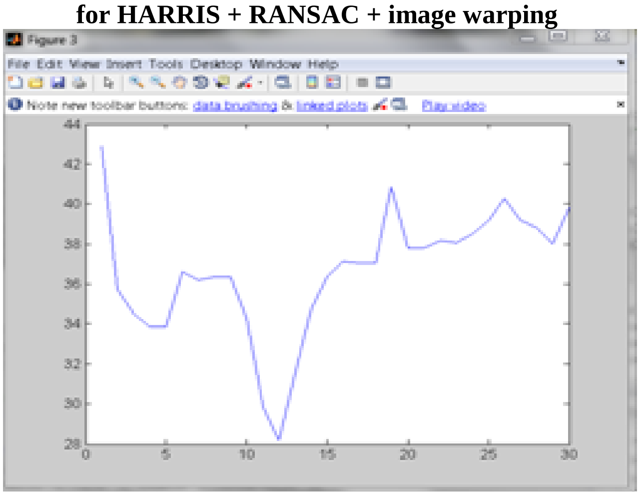
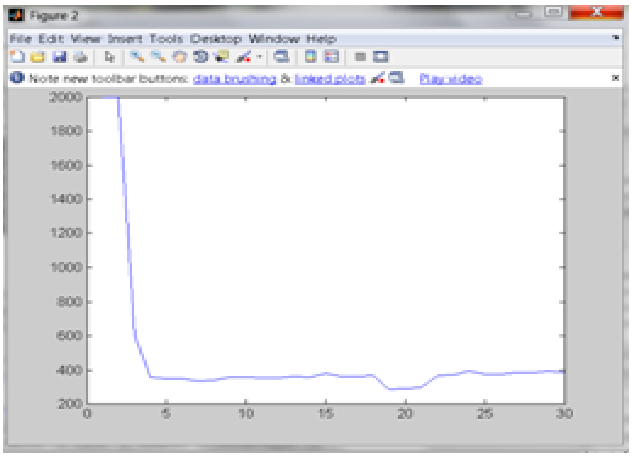


This graph indicates number of iteration Vs time elapsed for HARRIS + RANSAC + image warping

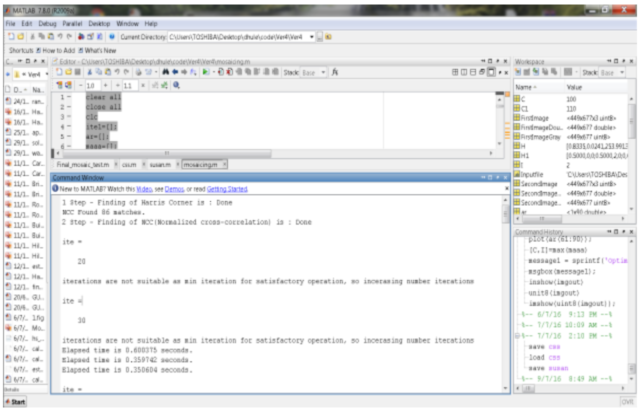


This graph indicates number of iteration Vs time elapsed for SUSAN + RANSAC + image warping



This graph indicates number of iteration Vs time elapsed for HARRIS + RANSAC + image warping

For some iteration, Hessian matrix calculated becomes zero because of less number of iteration for the pair of images so it is invalid to use and the minimum range is identified by number of experimentation. The sample showing the iterations having unsatisfactory results are shown in following result.



VI. CONCLUSION

Standard Mosaicing algorithm for stitching two or more algorithm is implemented and tried to speed up the system by reducing the iterations required by sub-algorithm called RANSAC algorithm. The system requires various sub algorithms like corners detection, HARRIS, SUSAN and CSS. We tested all the sub algorithms by varying its various parameters so that smooth and error free mosaic created with minimum elapsed time. Various corners detection algorithms are tested like Harris corner detection, Susan corner detection and CSS corner detection. We got results by incorporating all corners detection algorithms individually. So we tried to test its performance using elapsed time. Experimental results show that the Harris corner detection is better than the Susan and CSS algorithm for mosaic creation. RANSAC algorithm is also tested by varying its parameters like number of iterations. Basically iteration required for algorithm should be as less as possible for speed up the system but result must be satisfactory. So, by varying number of iterations, RANSAC algorithm is tested and found that at lower iteration, Hessian matrix calculated becomes zero and due to this, algorithm doesn't give satisfactory mosaic. Excluding this iterations, minimum number of iteration is decided as optimized number of iteration. Using this optimized iteration, final mosaic images are created for all data set satisfactorily

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