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DESIGN OF AN IMAGE MOSAICING TECHNIQUE

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Abstract - *Image mosaicingalgorithm based on SIFT(Scale Invariant Feature Transform)method is proposed. Image Mosaicing is the process of reconstructing or stitching a single, continuous image from a set of separate or overlapped sub-images. Research in computer vision and related fields has produced a variety of methods for stitching two or more images into mosaics. In this paper we are using three step image mosaic methods. The first step is taking two input images and finding out the keypoints in both the images, second step is removing out the bad keypoints in both the images and then by using SIFT we find its matched keypoints pair and then blending is applied for seamless image mosaicking.we get final output mosaic. The experimental results show the proposed algorithm produces an improvement in mosaic accuracy, efficiency and robustness.*

Keywords: *Blending, Homography, Image, Registration, Stitching, Warping.*

1. INTRODUCTION

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. An image is also defined as a two dimensional function (x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. The mosaic as an art form is defined in the Merriam-Webster dictionary as "a surface decoration made by inlaying small pieces of variously coloured material to form pictures or patterns." The mosaic dates to the 4th century B.C., and is generally associated with the Greeks. In fact, the word mosaic is of Greek origin, meaning "patient work of art, worthy of the muses".
Image mosaicing is the process of combining multiple overlapping images of same scene into a larger image. The output of image mosaicing operation will be the combination of input images. Image mosaicing is an effective means of constructing a single panoramic image from a series of snapshots taken in different viewing angles. 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 coordinate transformations that relate the different image coordinate systems. By applying the appropriate transformations via a warping operation and merging the overlapping regions of warped images, it is possible to construct a single image indistinguishable from a single large image of the same object, covering the entire visible area of the scene.
Various steps in mosaicing are feature extraction and registration, stitching and blending. Image registration refers to the geometric alignment of a set of images. The set may consist
of two or more digital images taken of a single scene at different times, from different sensors, or from different viewpoints. 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. This is of practical importance in many fields, including remote sensing, medical imaging, and computer vision [1]. Registration methods can be loosely divided into the following classes: algorithms that use image pixel values directly, e.g., correlation methods [2]; algorithms that use the frequency domain, e.g., fast Fourier transform based (FFT-based) methods [1] algorithms that use low-level features such as edges and corners, e.g., feature based methods [3]; and algorithms that use high-level features such as identified (parts of) objects, or relations between features, e.g., graph-theoretic methods.
The next step, following registration, is image stitching. Image integration or image stitching is a process of overlaying images together on a bigger canvas [4] & [5]. Image Blending is the technique which modifies the image grey levels in the terms of a boundary to obtain a smooth transition between images by removing these seams and creating a blended image.

2. DESIGN METHODOLOGY

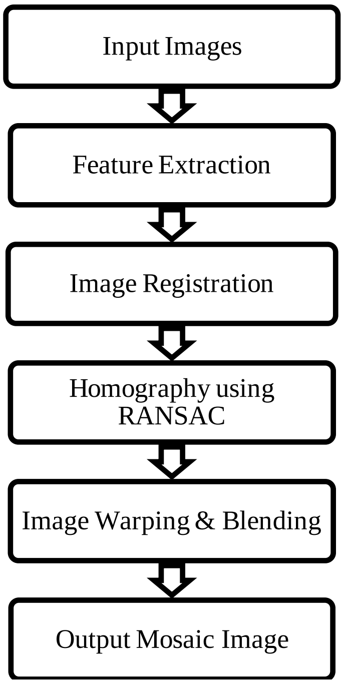

Fig 1: Existing framework for image mosaicking

3. SIFT BASED FEATURE IMAGE MATCHING METHOD

Scale-invariant feature transform (or SIFT) is analgorithm in computer vision to detect and describe localfeatures in images. The algorithm was published by DavidLowe in 1999[13]. The invariant features extracted fromimages can be used to perform reliable matching betweendifferent views of an object or scene because the SIFT isinvariant to image translation, rotation, and partiallyinvariant to illumination changes and scale across asubstantial range of affine distortion or 3D projection. SIFTconsists of four major stages : scale-space peak selection,keypoint localization, orientation assignment, keypointdescriptor. Its essential is to construct a Gaussian pyramidand searching for local peaks in a series of difference-of-Gaussian (DoG) images, which make the computation andoperation speed improved greatly.

A. Scale-space Peak Selection

Feature detection is performed using a stagedfiltering approach, according to the theoretical andexperimental results in [14]. It has been proved by [15] thatunder a varitey of reasonable assumption the only possiblescale-space kernel is the Gaussian funtion. A 2D image indifferent scale space is defined as the convolution of an inputimage and a variable-scale Gaussian kernel :

Wherever Times is specified, Times Roman or TimesNew Roman may be used. If neither is available on yourword processor, please use the font closest in appearance toTimes. Avoid using bit-mapped fonts if possible. True-Type1 or Open Type fonts are preferred. Please embed symbolonts, as well, for math, etc.

$$L(X,Y,\sigma) = G(X,Y,\sigma) * I(X,Y) \quad (11)$$

where$L(x, y,\sigma)$ is the scale space of an image, $I(x, y)$is 2D gray input image, $G(x, y,\sigma)$ is variable-scale Gaussian kernel funtion, * is the convolution operation, and

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)} / 2\sigma^2 \quad (2)$$

For finding stable keypoints within the scale space of animage, Lowe[6] presents Difference-of-Gaussians (DoG)scale-space $D(x, y,\sigma)$. $D(x, y,\sigma)$ can be computed fromthe difference of two nearby scaled images separated bya multiplicative factor k:

$$\begin{aligned} D(x,y,\sigma) &= (G(x,y,k\sigma) - G(x,y,\sigma)) * I(x,y) \\ &= L(x,y,k\sigma) - L(x,y,\sigma) \end{aligned} \quad (3)$$

DoG operator is the replacement of the scale-normalizedLaplacian of Gauss because of less computational cost, andthe value of k is selected so that a fixed number of blurredimages are generated per octave, such as k*2 .During the practical Scale Invariant Feature extracts,image pyramid is introduced into scale-space. By building animage pyramid with resampling between each level, SIFTmethod locates key points at regions and scales of highvariation, making these locations particularly stable forcharacterizing the image. In order to detect the local maximaand minima of $D(x, y,\sigma)$, each sample point is compared toits eight neighbors in the current image and nine neighbors inthe scale above and below (26 neighbors in 3x3 regions atthe current and adjacent scales). If the pixel is a localmaximum or minimum, it is selected as a candidate keypoint.The processing is showed in Fig.2.

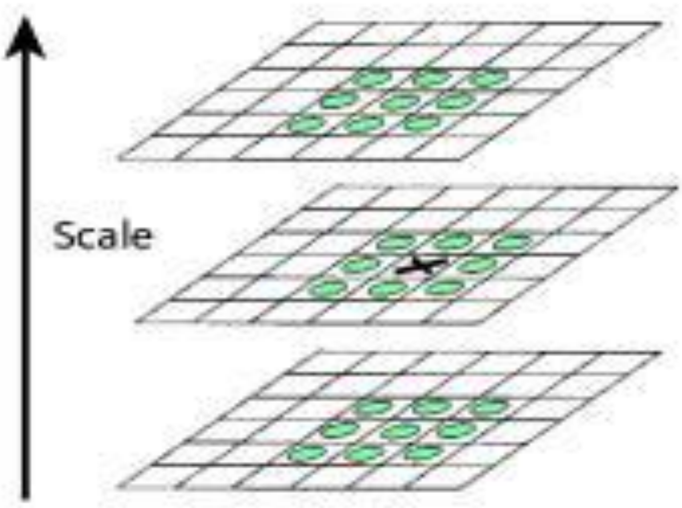

Figure 2. Detect the keypoins of DoG scale-space.

B. Keypoint Location and Processing

In order to make the descriptor invariant to rotation, eachkeypoint is assigned an orientation. the gradient magnitude$m(x, y)$ and orientation $\theta(x, y)$ of the image are computedby pixel differences.

An orientation histogram is formed from the gradientorientations of sample points within a region around thekeypoint. The orientation histogram has 36 binscovering the 360 degrees of major orientation bins.

Each point is added to the histogram weighted bythe gradient magnitude $m(x, y)$ and by a circular Gaussianwith σthat is 1.5 times the scale of the keypoint. Peaks inthe orientation histogram correspond to dominant directionsof local gradients. To every keypoint, Keypoint Descriptor isused to describe all information of the keypoint, and theprocess of constructing descriptor is indicated in Fig.3.

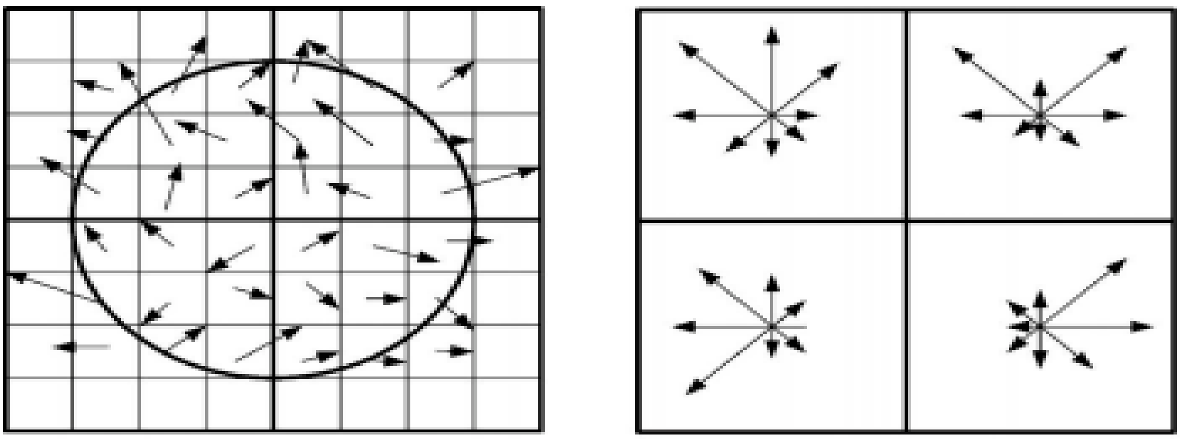

Figure 3. Construct keypoint descriptor

The descriptor is a n-dimensional vector whichsummarizes the gradient magnitude and orientation trend in aregion around the keypoint location. In implementation, the region is divided into 4x4 subregions.
Therefore, the descriptor has a dimension of 128 Theresulting feature vectors are 128 elements[7].

4. HOMOGRAPHY COMPUTATION

4.1 Homography

It is mapping between two spaces which is often used to represent the correspondence between two images of the same scene. It is widely used for the project where multiple images are taken from a rotating camera center ultimately warped together to produce a panoramic view
The steps for homography detection algorithm using RANdom Sample Consensus (RANSAC)[9] scheme is
1. Firstly, corners are detected in both images.
2. Variance normalized correlation is applied between corners, and pairs with a sufficiently high correlation score are collected to form a set of candidate matches.
3. Four points are selected from the set of candidate matches, and a homography is computed.
4. Pairs agreeing with the homography are selected. A pair (p, q), is considered to agree with a homography H, if for some threshold: Dist(Hp, q) < €
5. Steps 3 and 4 are repeated until a sufficient number of pairs are consistent with the computed homography.
6. Using all consistent correspondences, the homography is recomputed by solving step 4.

4.2 RANSAC Algorithm

RANSAC, is a method to calculate the parameters of a mathematical model from a set of observed data.. Input of RANSAC algorithm is a set of observed data, a parameterized model which can explain or fit to the observations, along with some confidence parameters. RANSAC achieves its goal by iterative selection of a random subset of the original data.
Given a fitting problem with parameter x, it estimates the parameters considering the following assumption:
1. Parameter can be estimated from N data items.
2. Available data items are totally M
3. The probability of a randomly selected data item being part of a good model is Pg
4. The probability that the algorithm exit without finding a good fit if one exists is Pf
Then the algorithm is:
1. N data items at random are selected.
2. Parameter x is estimated.
3. Number of data items which fit the model with parameter vector x are found out within a user defined tolerance. Let it be K. 4. If K is large enough, it is accepted and exit with success.
5. The process is repeated 1.4 L times
6. The process is failure if it again enters the loop.
Value of L is found by the following formulae:
Pfail= Probability of L consecutive failures
= Probability that a given trial is a failure) L
= (1 **-** (Probability that a random data item fits the model)N)L

5. IMAGE WARPING & BLENDING

5.1 Image warping

Image warping is the process of digitally employing an image such that any shapes represented in the image have been significantly distorted. Warping can also be used for correcting image distortion as well as for inventive purposes. Basically we can simply warp all the input images to a plane defined by one of them known as reference image. The two images that will form the mosaic are warped, by using the geometric transformation. While an image can be reconstituted in various ways, pure warping means that points are mapped to points without changing the colors. It can be mathematically based on any function from the plane to the plane. If the function is injective then the original can be reconstructed.

5.2 Image Blending

The final step is to blend the pixel 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 at least two image overlap occurs in an output mosaic we will use the alpha values as follows to compute the color at a pixel in there, suppose there are 2 images, $I1$, $I2$, overlapping in the output image; each pixel (x, y) in image Ii is represented as $Ii(x, y) = (\alpha iR, \alpha iG, \alpha iB, \alpha j)$ where (R, G, B) are the color values at the pixel. We will compute the pixel value of (x, y) in the stitched output image as $[(\alpha 1R, \alpha 1G, \alpha 1B, \alpha 1) + (\alpha 2R, \alpha 2G, \alpha 2B, \alpha 2)] / (\alpha 1+\alpha 2)$.

6. EXPERIMENT

The algorithm proposed here has been implemented in Matlab R2010a and has been executed in system with configuration i5 processor, 4 GB RAM, 2 GB cache memory and 2.8GHz processor. Fig 4 is the original input images and it provides the keypoints by using SIFT. Fig 5show the result of keypoints by using SIFT. Fig 6 shows the removing of bad keypoints. Fig 7drawing lines between matched keypoints. Fig 8 the output image mosaic is obtained.

7. RESULTS

We are comparing the original algorithm and the improved algorithm. Fig 4 is two groups of the original images.

Fig 4: The original input images

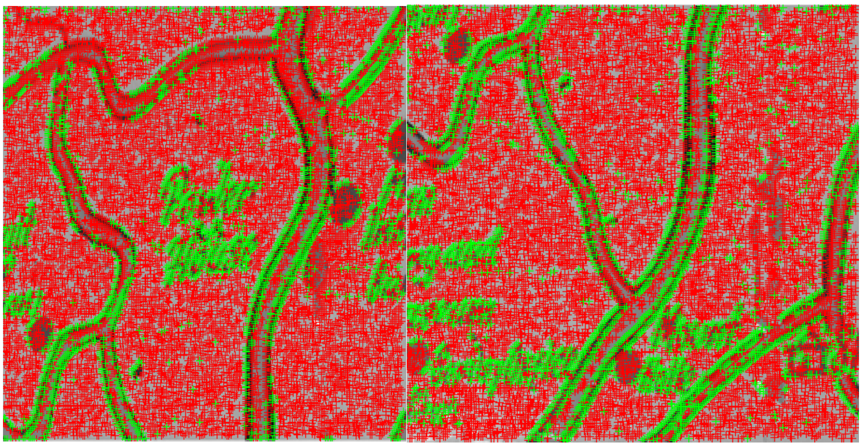

Fig 5: Finding the keypoints

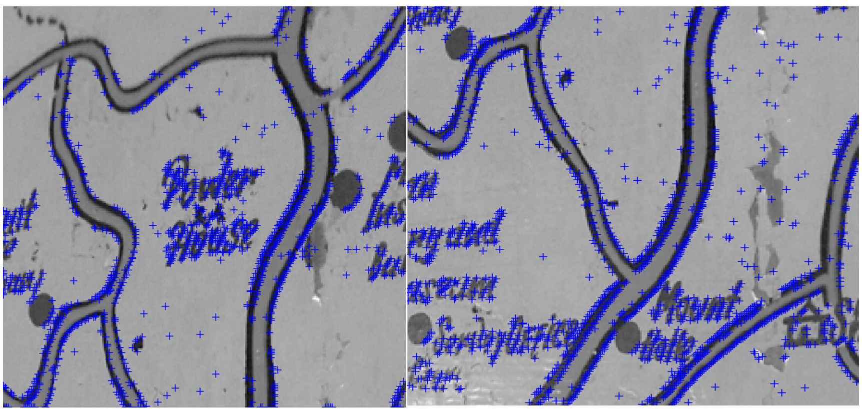

Fig 6: Removing bad keypoints

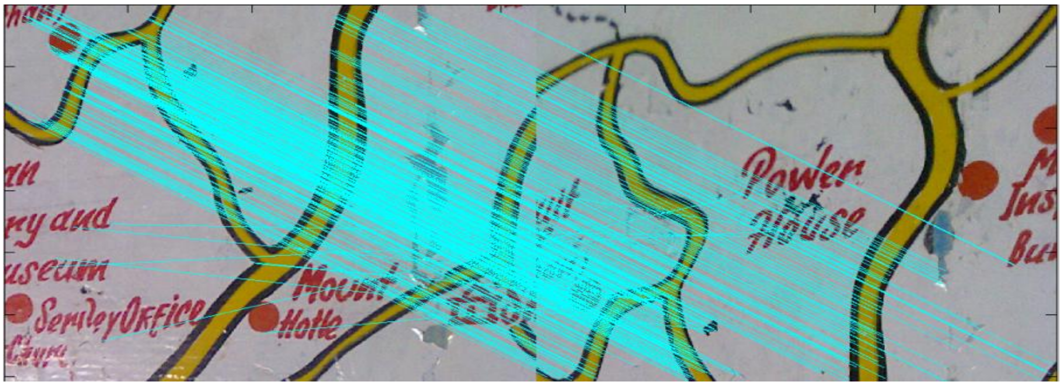

Fig 7: Drawing line between matched keypoints

Fig 8: output image

8. CONCLUSION

The proposed method applies the corner detector technique to extract feature points from a partially overlapping image pair. By defining a similarity measure metric, the two sets of feature points can be compared, and the correspondences between the feature points can be established by using Normalized Cross Correlation Method. Once the set of correctly matched feature point pairs between two images are found, the registration parameters can be derived accordingly. Hence the registered image of two input images can be obtained. Finally we got Seamless Mosaic Image. In future image inpainting is included for good result.

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