Fast Image Registration Based on Features Extraction and Accurate Matching Points for Image Stitching

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Abstract

The image registration is one step of the image stitching technique. This step plays an important role in the resulted stitch image. The image registration depends on the accuracy of its basics that is the feature detection and feature matching.
This work is present an automatic algorithm to get a good final stitched image. The work main aim is to achieve a good quality stitched image obtained in less time.
In this work, to reduce the time for feature detecting, SURF technique is mostly used algorithm as it is the fastest descriptor. RANSAC is applied for outlier elimination and to robustly estimate the best fitting homography, and at end homography transformation is used as transformation model to warp image with inverse warping. Good results are obtained after applying the presented method. The results are examined visually.

Keywords: *Registration, stitching, homography, SURF, RANSAC.*

1. Introduction

Registration and stitching of images play an important role in the field of Computer Vision. Image registration and stitching has found its place in many industrial and scientific applications. Some of the popular applications are registering aerial photographs of cities and conducting more complex cases of registering images of the earth's surface generated by geo-satellites. Most of these applications focus on the accuracy rather than the performance. However, some of these applications need the algorithm to work faster [1].

Image Registration is an essential task in image processing used to match two or more pictures taken, For example, at different times, from different sensors, or from different viewpoints [2].

Image registration process attempts to discover corresponding points between two images and spatially align them to reduce difference among the two images from a geometrical standpoint, it aligns two images: the first is called the reference which is kept unchanged and is used to warp the second image, the second image is called the sensed image which is transformed to aligned with the target image. The image registration can performed either manually or automatically [3].

Image registration is an intermediate step in many operations that need the correction of images. Also it is regarded an important component in many systems ,such as matching a target with a real-time image of a scene for target recognition, monitoring global land usage using satellite images to find changes, matching stereo images to recover shape for autonomous navigation, and aligning images from different medical modalities for diagnosis to integrate information. It is a prerequisite step prior to image fusion or image mosaic. [3][4]

in 2014 P. Subha proposed an approach to identify some visual objects or "Landmarks" in an image and generate relevant images in matching probability order using "IMA GE REGISTRATION" Methods by combines scale interaction of Discrete wavelets for feature extraction, Scale Invariant Feature Transform (SIFT) for feature matching and Normalized 2D Cross-Correlation for obtaining maximum positive matches [5]. In 2012 Amaury and Ericpresent develop a direct image registration approach that uses Mutual Information (MI) as a metric for alignment use to registration in image sequences or direct tracking they propose a new optimization method that is adapted to the MI cost function and gives a practical solution for real time tracking [6]. in 2014 Selva Raj K and Poovendran proposed a method for automatic image registration through histogram-based image segmentation (HAIRIS). HAIRIS allows for the registration of pairs of images (multitemporal and multisensor) with differences in rotation and translation, with small differences in the spectral content, leading to a subpixel accuracy[7].

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2. Image stitching

Image stitching is the process that combines two or more overlapped images from the same scene, to form a single mosaic image with a wide field of view [8].
Image mosaicing can be used in many fields like, medical imaging, computer vision, data from satellites, military automatic target recognition [9].Image registration efficiency play important role in the steps of the image stitching [8].
Problems with existing algorithms for image stitching are that the existing image registration and stitching algorithms are designed to be universally applicable to registering images in any orientation[10].Most of the algorithms that are found in this area can be categorized into two classes which are direct stitching and feature based stitching which is based on extracting features of the two images and matching the features across the two images[10].An Image Mosaic is a synthetic composition generated from a sequence of images and it can be obtained by decided the geometric relationships between the input images. This relation is used to transform the images to one coordinate system [9].

3. The presented work:

The general steps require registering and stitch a set of generic digital images are, see figure 1[3] [4]:
1. Preprocessing
These operations are performed on images and they improve the registration performance. Like (edge detection, smoothing, deblurring, Noise filtering, Region extraction, segmentation, etc.). In the presented work, the applied image didn't need the prepress step because it is captured by good resolution camera.
2. Feature detection
Choosing the more invariant features, like (interest points, lines, regions, templates. . .)
3. Feature matching
Discovering the corresponds of feature pairings and avoiding outliers.
4. Transformation estimation
Constructing the mapping function to transform the sensed image to the reference.
5. Resampling
Using the transformation to warp sensed image to the reference.

3.1 Feature detection

The first step in image mosaic process is feature detection. Features should be Special elements in the two images to be matched [9]. A robust algorithm was needed that should be able to detect the same features in the two images at different projections of the same scene.

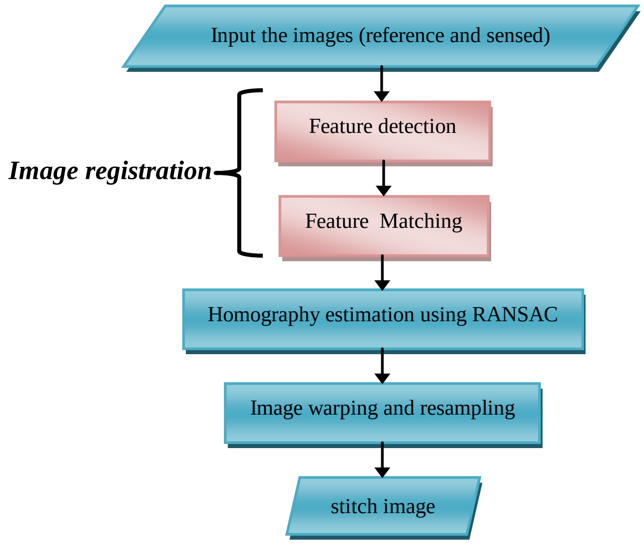

Fig. 1 Image stitching model

The correct result of this step reflects on reliability of the next step in matching correspondence features [3]. There many algorithm for features detection (closed-boundary regions, edges, contours, line intersections, corners, control point, etc.)[4].
Some of the popular algorithms which have been used for the purpose: Harris corner detection method is accurate, and rotationally invariant. But, it is scale variant. The FAST algorithm is both rotation and scale invariant with improved execution time. But, its performance is poor in presence of noise. SIFT algorithm is robustness; it is rotation, scale invariant and more effective in presence of noise. It has highly distinctive features (sum of Eigen values after PCA). but, it suffers from illumination variation and it is suffered with speed. Therefore it is not applicable to the real-time problems. The algorithm, SURF proves it is the best in terms of execution time, illumination invariance property, and good performance. [9][11][12]
SURF Algorithm:
The SURF (Speed Up Robust Features) algorithm is a robust and fast feature detector ;therefore , it is mostly used in the computer vision applications[12].
It is based on multi-scale space theory and the feature detector is based on Hessian matrix. Since Hessian matrix has good performance and accuracy. In image I, x = (x, y) is the given point, the Hessian matrix H(x, σ) in x at scale σ, it can be defined as:

$$\mathbf{H}(\mathbf{x},\sigma)=\begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{yx}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \quad \text{……. (1)}$$

Where $L_{xx}(x, \sigma)$ is the convolution result of the second order derivative of Gaussian filter with the image I in point x, and similarly for $L_{xy}(x, \sigma)$ and $L_{yy}(x, \sigma)$.

SURF creates a “stack” without 2:1 down sampling for higher levels in the pyramid resulting in images of the same resolution. Due to the use of integral images, SURF filters the stack using a box filter approximation of second –order Gaussian partial derivatives as shown in figure (2). Since integral images allow the computation of rectangular box filters in near constant time.

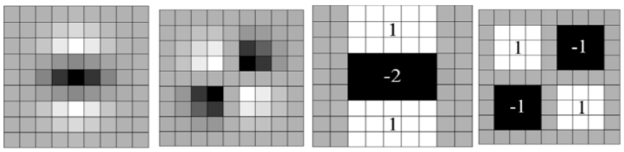

Fig. 2 the second orders Gaussian partial derivatives in y-direction and xy-direction.

The proposed SURF descriptor is based on properties. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. And second construct a square region aligned to the selected orientation, and extract the SURF descriptor from it. In order to be invariant to rotation, it calculate the Haar–wavelet responses in x and y direction as shown in figure (3) [11][13].

Fig. 3 Haar wavelet types used for SURF

3.2 Feature matching

After the features are detected using SURF method, the feature correspondences between given image pairs are matched by using the Sum of Absolute Difference (SAD) as a metric search over all features that are detected to determine the best match pairs with a sufficiently less score are collected to form a set of candidate matches.

Descriptors usually consist of feature vectors that are used for distance calculation. Euclidean distance or L2-norm is typically used but also other measures like L1-norm, Sum of Absolute Difference (SAD), and Hausdorff distance can be utilized. There are several strategies that can be applied to point pairing. For example, the greedy method, where the best match is always paired, can be used [14]. The greedy method has that each decision is locally optimal. These locally solutions will finally add up to globally optimal solution.

3.3Homography estimation using RANSAC

The third step of image stitching is a homography estimation. To decrease the computation time through the homography estimation, the RANdom Sample Consensus (RANSAC) is used. It eliminates the outliers (undesired features which do not belong to the overlapping area) from the extracted points. RANSAC is a resampling technique that generates candidate solutions by using the minimum number observations (data points) required to estimate the model parameters, not similar to conventional sampling techniques that use as much of the data as possible to obtain an initial solution .[15][9][12]
After this elimination process, only matching inlier points are remaining. According to these points, transformation model can be estimated, which is Homography transform.

RANSAC Algorithm

1. Select randomly the minimum number of points required to determine the model parameters (in stitching image we select 4 features correspondences)
2. Solve for the parameters of the model.
3. Determine how many points from the set of all points fit with a predefined to toleranceϵ.
4. If the fraction of the number of inliers over the total number points in the set exceeds a predefined threshold τ, re-estimate the model parameters using all the identified inliers and terminate.
5. Otherwise, repeat steps 1 through 4 (maximum of N times). [15]

Homography:

Before we register images, we need to establish the mathematical relationships that map pixel coordinates from one image to another [1].The geometric relation between two views is modeled by a homography, Homography is mapping between two images planes of the same scene. It’s widely useful for images where multiple images are taken from the same position but through different camera angles and then warped together to produce a panoramic view[9] .
The homography is also known as a *projective* or *perspective transform*, operates on homogeneous coordinates $\tilde{x}$and$\tilde{x}'$,

$$\tilde{x}' \sim \tilde{H}\tilde{x} \quad \ldots\ldots\ldots (2)$$

Where $\sim$denotes equality up to scale and $\tilde{H}$ is an arbitrary 3×3matrix. Note that $\tilde{H}$ is itself homogeneous, i.e., it is only defined up to a scale. The resulting homogeneous coordinate$\tilde{x}'$must be normalized in order to obtain an inhomogeneous result$\tilde{x}'$, i.e.,

$x' = \frac{hoox+h01y+h02}{h20x+h21y+h22}$ and $y' = \frac{h1ox+h11y+h12}{h20x+h21y+h22}$.....(3)

The Perspective transformations preserve straight lines [1].

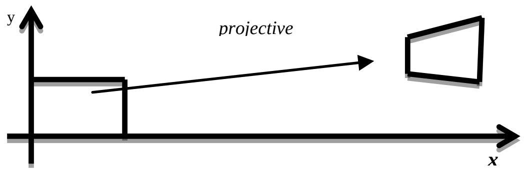

Fig. 4 2D planar projective transformation.

3.4 Image warping and resampling

In this step we use the mapping function which is found in the previous step to warp the sensed image and then to register with reference image. Warping can be done in a forward or backward manner. In the sensed image, each pixel can be directly transformed using the estimated mapping functions. This approach, called a forward method, is complicated to implement, because it can produce holes and/or overlaps in the output image (due to the discretization and rounding).Therefore, the backward approach is usually chosen[3].The images are placed properly on the bigger canvas using registration transformations to get the output resulted stitched image[9].

The registered image data from the sensed image are determined using the same coordinates of the reference pixel. In the inverse estimated mapping function, the image interpolation takes place in the sensed image on the regular grid. In this way neither holes nor overlaps can occur in the output image because missing values are interpolated from the ones already present. The nearest neighbor function, the bilinear and bicubic functions are the most widely used, but also quadratic splines, cubic B-splines, higher-order B-splines, Catmull_ Rom cardinal splines, Gaussians and truncated sinc functions are applied in some cases [3].We use the bilinear interpolation which is considered to be higher-order methods in terms of accuracy and visual appearance of the transformed image and therefore it has become the most commonly used approach [3].

4. Conclusions and results:

In this paper, we present anew automatic fast method to estimate accurate fit transform motion parameters which helps good matching for image registration step by considering the relationships between the matched feature points in the two input images. In figure (5) we input two images the reference image and the sensed image. Then, in figure (6) we detect features points using SURF algorithm in the two images. In figure (7) after features extraction we associated features points between the two images. First we compute the fit score between two features, scores features based on Sum of Absolute Difference (SAD). Then by using the greedy algorithm object is associated with whichever object has the best fit score and every possible combination is examined .if an association is found from the first image to the second image, then the best fit in second image is associated with feature in first image. In figure (8) show the final stitch image after warping the image by using Homography estimation using RANSAC then resampling the two images to one image using bilinear interpolation. Figure (9-10-11-12) shows another example.

(a) (b)

Fig. 5 input two images (a) is the refrence image, and (b) is the sensed image.

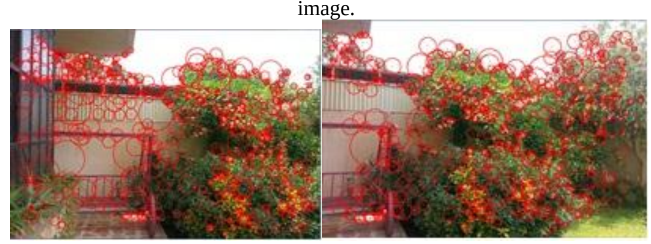

Fig. 6 detected features using SURF in the two images.

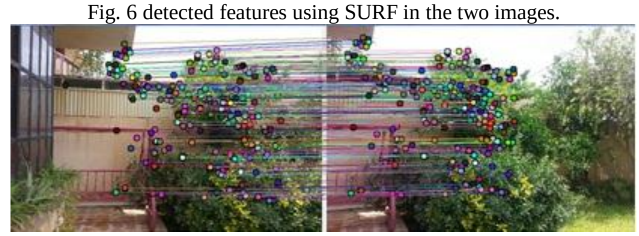

Fig. 7 associated features between the two images.

Fig. 8 the resulte image ,stitched image (a) and (b) together.

(c) (d)

Fig. 9 input two image (c)is the refrence image , and (d) is the target image.

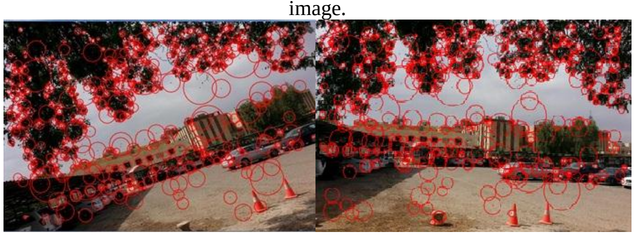

Fig. 10 detected features using SURF in the two images.

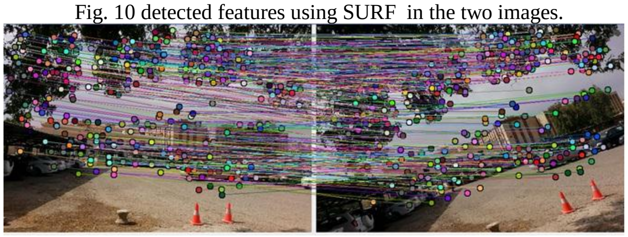

Fig. 11 associated features between the two images.

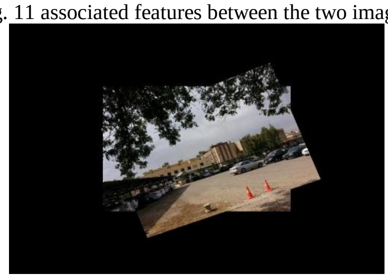

Fig. 12 the resulte image ,stitched image (c) and (d) together.

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