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An Automatic Registration through Recursive Thresholding-Based Image Segmentation

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ABSTRACT*: Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints. It is used in computer vision, medical imaging, automatic target recognition and compiling and analyzing images and data from satellites. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements. Automatic image registration is still an actual challenge in several fields. Several methodologies have been proposed to tackle this problem, however, two approaches are widely used in this context: edge-based and region-based. In edge-based methods, the local discontinuities are detected first and then connected to form longer, hopefully complete, boundaries. In region-based methods, areas of an image with homogeneous properties are found, which in turn give the boundaries. The two methods are complementary, and one may be preferred to the other for some specific applications like document image analysis. Although several methods for automatic image registration have been proposed in the last few years, it is still far from a broad use in several applications, such as in remote sensing. In this paper, a method for automatic image registration through recursive threshold-based image segmentation is proposed.*

Index Terms— *Binary image , Image Registration, Image Wrapping, Segmentation.*

I. INTRODUCTION

Image registration is the process of transforming different sets of data into ones Coordinate system. Data may be multiple photographs, data from different sensors, from different times, or from different viewpoints. It is the process of spatially aligning two or more images of a scene. The process in effect establishes point-by-point correspondence between the images. The basic input data to the registration process are two images: Reference or source image and Target or sensed image. Registration is treated as an optimization problem with the goal of finding the spatial mapping that will bring the images into alignment with the fixed image. Generally the steps involved in image registration are:

- ***Preprocessing:***

Image smoothing, deblurring, image segmentation, edge detection.

- ***Feature extraction and selection:***

Extracting points, lines, regions, templates, etc. from images and selecting some.

- ***Correspondence:***

Determining the correspondence between selected features in images.

- ***Determining the transformation function:***

From the corresponding feature points determining the transformation parameters.

- ***Re-sampling:***

Re-sampling the sensed image to the geometry of the reference image using the transformation.

Many papers are published to illustrate the techniques for image registration. In the literature we found different image registration techniques namely image registration based on hierarchal approach [1], image registration techniques based on segmentation [2], [3], [4] and image registration technique based on multiple feature extraction and matching[5]. In this paper we are proposing the technique for automatic image registration through Recursive Threshold-Based Image Segmentation.

II.METHODOLOGY

In principle, the image registration technique proposed here consists of following steps:

- Read the input image and Convert it into binary image.
- Segmenting only one bright object from an image to an approach that recursively segments the brightest object at each recursion, leaving the darkest object in the given image.

- Find corner points set using Harris, find the correlation for each block with other Image and find maximum correlation points.
- Fit to homograph using RANSAC and Wrap image.
- Image is registered.

The block diagram for our proposed method is as shown in Fig.1.

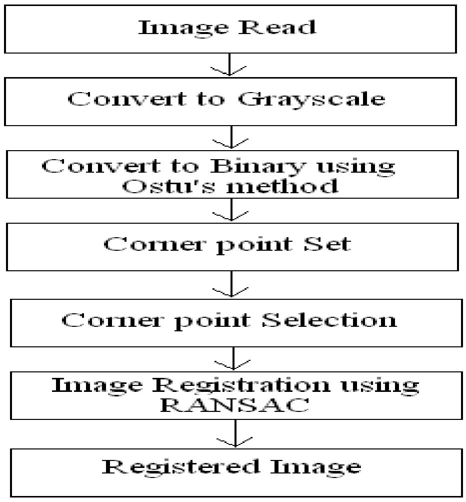

Figure 1.Block Diagram for Our Proposed Method

It mainly consists of following key steps: Preprocessing, Binary image conversion, segmentation, correlation, Harris corner point, RANSAC, Image wrapping and finally Image Registration. At first we consider one image convert it into grayscale and then to Binary. We segment given image and we find the corner points then we find correlation for each block with all blocks of other image. Fit to homograph using RANSAC. Finally we wrap image and Register.

The data flow diagram and flowchart of proposed method is as shown in Fig.2 and Fig. 3 respectively.

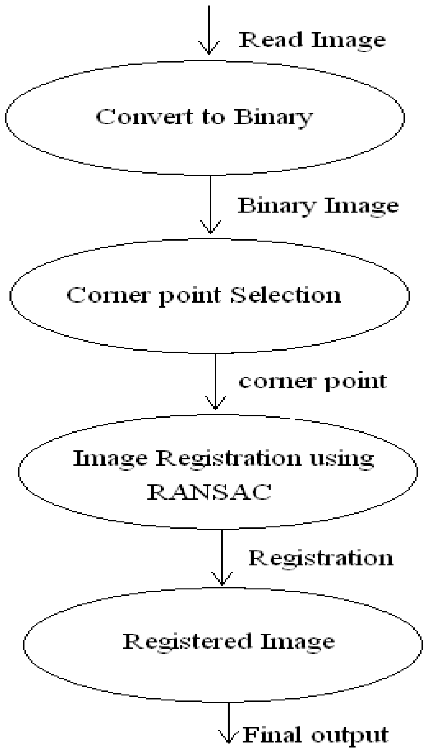

Figure 2.Data Flow Diagram of Proposed Method

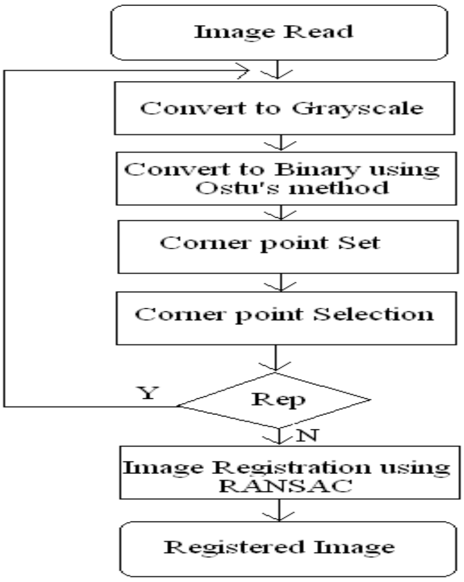

Figure3.Flow chart Diagram of Proposed Method

The algorithm for Corner Detection using Harris and algorithm for image registration is shown below:

2.1 Algorithm for Corner Detection using Harris

Step1: Read image a
Step2: Divide image a into 20*20blocks and segment image
Step3: Find Correlation for each block with all block of other image
Step4: Find Max Correlation points using 3*3 window
Step5: Select first 100 points in whole image
Step6: Return to Harris Corner points x, y

2.2 Algorithm for Image Registration using RANSAC

Step1: Find distance between set of all points x and y, distance matrix 100*100
Step2: Fit to homograph using RANSAC, select best 50 match of control points of both images
Step3: Find rotation, shift and scale of image
Step4: Wrap Image 2 according to transformation
Step5: Merge Image 2 with Image 1

III. IMPLEMENTATION

The implementation phase involves the actual materialization of the ideas, which are expressed in the analysis document and developed in the design phase. It involves:

- Convert image to binary image.
- Image Segmentation using Recursive Thresholding.
- Corner detection using the Harris Corner Detector.
- Fit to homography using RANSAC.
- Image warping and Registration.

3.1 Convert image to binary image

Read the input image and Convert it into binary image.

BW =im2bw (I, level)
BW =im2bw(X, map, level)
BW =im2bw (RGB, level)

BW = im2bw (I, level) converts the grayscale image I to a binary image. The output image BW replaces all pixels in the input image with luminance greater than level with the value 1 (white) and replaces all other pixels with the value 0 (black). Specify level in the range [0, 1]. This range is relative to the signal levels possible for the image's class. Therefore, a level value of 0.5 is midway between black and white, regardless of class. To

compute the level argument, you can use the function gray threshold. If you do not specify level, im2bw uses the value 0.5.
BW = im2bw(X, map, level) converts the indexed image X with color map to a binary image.
BW = im2bw (RGB, level) converts the true color image RGB to a binary image.
If the input image is not a grayscale image, im2bw converts the input image to grayscale, and then converts this grayscale image to binary.
3.2 Image Segmentation using Recursive Thresholding Here two approaches are widely used in this context: edge-based-like and region-based-like. In edge-based methods, the local discontinuities are detected first and then connected to form longer, hopefully complete, boundaries. In region-based methods, areas of an image with homogeneous properties are found, which in turn give the boundaries. It beyond segmenting only one bright objects from an image to an approach that recursively segments the brightest object at each recursion, leaving the darkest object in the given digitized image. The recursive methodis developed without any constraints on the number of objects in the digitized image.
3.3 Dynamic Thresholding

We propose thresholding recursively and proceed in the following way: according to a global threshold value is evaluated for a given image. A new image with one object (the brightest) being threshold is produced. Now, the regions, as in Fig. 3, are considered as the given image and the process of histogram, peak selection, and thresholding is recursively repeated until no new peaks can be found or regions become too small. In this sense, an effective recursive segmentation technique that segments the brightest object at each recursion can be achieved.
3.4 Corner detection using the Harris Corner Detector
Harris determines the average variation in intensity that results from shifting the window by a small amount in different directions. Letting I denote the image intensities and W specify the current image window, the change E produced by a shift (x, y) is given by equation 1:

$$E_{xy} = \sum_{u,v} W_{u,v}[I(u+x, v+y) - I(u,v)]^2 \qquad (1)$$

An expansion about the shift origin is then performed as shown in equation 2:

$$E_{xy} = \sum_{u,v} W_{u,v}\,[(xI_x + yI_y + O(x^2, y^2)]^2 \approx (x,y)M(x,y)^T \quad (2)$$

Where,

$$M = \begin{pmatrix} I_x^2 \otimes W & (I_x I_y) \otimes W \\ (I_x I_y) \otimes W & I_y^2 \otimes W \end{pmatrix} \qquad (3)$$

Ix and Iy are the first order derivatives of the intensity function in the x and y directions respectively, O(x2, y2) represent higher order properties, and W is defined as the Gaussian function for a smooth circular window. The detection process used in this research may be summarized as consisting of the following stages:

1. The calculation of the image gradients Ix and Iy
2. Convolution of the image gradients Ix and Iy, and their product, IxIy with a smooth circular Gaussian convolution mask
3. Calculation of the corner responses from the smoothed gradients, and
4. Thresholding the corner responses and applying non-maximum suppression process to eliminate multiple candidates for a corner point. Find correlation for each block with all blocks of other images. Find maximum correlation points using 3*3 windows. Select 100 points among them then return to corner points.

3.5 Fit to homography using RANSAC

In this work Random Sampling Consensus (RANSAC) is used to automatically compute a homography between two images. The input to the RANSAC algorithm is the estimated feature correspondences in the images, and the output is the estimated homography with a set of interest points in correspondence, no other a priori information is required. The support for each sample set is measured by applying the homography to all the points in the initial match set, and then counting the number of matches within a distance threshold (in our case the symmetric transfer error). For the RANSAC algorithm, a decision needs to be made regarding the number of samples and the type of sample selection taken. Firstly, degenerate samples in which three of the four points are collinear are discarded, because a homography cannot be generated from them. Next, samples that consist of points with a good spatial distribution over the images are sought. As revealed in, the estimated homography maps a region straddled by the computation points, but the accuracy generally deteriorates with distance from this region. This is known as the extrapolation problem and hampered our early attempts to estimate a homography. This problem is dealt with by ensuring that the images used are well textured so that the detected corners have a good spatial distribution over both images.

3.6 Image warping and Registration

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. Once the homography has been found it may be applied to one of the images to align it with the other. The task of applying a known transformation to an image is known as image warping. Transforming each pixel from the first image using the estimated homography would result in holes and or overlaps in the output image due to discretization and rounding. The backward approach is therefore usually taken. First, the inverse mapping is applied to the output sampling grid, projecting it onto the input. The result is a resampling grid specifying the location at which the input is to be resampled. The input image is then sampled at these points and the values assigned to their respective output pixels. Finally automatic registration is made.

IV.EXPERIMENTAL RESULTS

All experiments were carried out using Matlab 7.9. It mainly consists in combining several segmentations of the pair of images to be registered, first we convert it in to binary then we make registration. The application of the proposed methodology is illustrated to simulated rotation and translation. The first dataset consists in a photograph and a rotated and shifted version of the same photograph, with added noise. It was also applied to a pair of satellite images with different spectral content and simulated translation, and to real remote sensing examples comprising different viewing angles, different acquisition dates and different sensors.

Figure 4.Image A

Figure 5. Image B

Figure 6.Registered image

V.CONCLUSION AND FUTURE WORK

Here we take two images for registration. We register by joining these two main areas of image processing. Since it does not require any manually selected points either for rotation or translation, it is a fully automatic procedure. The proposed method is based upon detecting closed similar blocks in both images. Taking into account that the pair of images to be registered presented limited differences regarding their spectral content, it will usually be possible to detect similar regions in both images, even for regions with low contrast. The proposed image registration technique work well for well defined pairs of points, mainly on tilted, blur and noisy images.

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