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A Novel Speed-up Feature Matching Algorithm for Image Registration using SUSAN and RANSAC

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Abstract- A novel feature matching algorithm for image registration is proposed in this paper. The accuracy of a registration process is highly dependent on the feature detection and matching. In this paper, we use a SUSAN (Smallest Univalue Segment Assimilating Nucleus) algorithm to detect features, which is one of the most excellent methods, robust to noise and less affected by rotation. One common approach used for feature matching is correlation between feature points. But in this method much computational time is required to establish the correspondences. In this paper, we overcome this difficulty through our speed-up approach. The basic concept of our approach is to calculate the descriptor values for every feature point which are then stored. These values will finally be used for feature matching. This reduces the number of operations in feature matching step and thus speed-up in matching is obtained. After matching, RANSAC method is used to find the registration transform parameters.

Keywords- Image Registration, SUSAN, Feature Matching, Computation Time, RANSAC.

I. INTRODUCTION

Image registration is a task required in many applications of image processing where one must take measurements that involve multiple images. Registration is the alignment of multiple images so as to either eliminate the differences between them or highlight the salient differences for the purpose of study.

Image registration is a crucial step in all image analysis tasks, in which the final information gains various data sources like image fusion, image mosaic, change detection, and stereo imaging. Image registration is widely used in remote sensing, medical imaging, computer vision etc. Over the recent years, many registration algorithms have been proposed. According to the matching method, image registration algorithms can be broadly classified into two main categories: area based methods and feature based methods [6].

The area-based algorithm obtains the transform parameters of two input images using image intensity, which involves all the pixels in the images [6]. The area-based methods using the similarity measurement of gray value are simple and easy to be implemented, but its computation is huge and susceptible to the light and noise. The template matching is a common area based method. This method uses a distortion function that measures the degree of similarity between the template and the image. Typical distortion measures include Sum of Absolute Differences (SAD), Sum of Squared Differences (SSD), and Normalized Cross Correlation (NCC), etc. Taking into account the robustness, researchers often adopt NCC.

Since the basic template matching algorithm needs to be calculated at each position in the reference image, so the computation time is very long.

The image registration algorithm based on feature extraction utilizes the image features including image edges, image corners to calculate the parameters of the affine transformation equation [6]. The registration accuracy of feature-based approaches is high, but their frameworks are more complex. For feature based methods, registration algorithms can be viewed as combinations of the following three components: feature extraction, feature matching, and finding the transform parameters. Since the advantages of feature point are as follows: low computational complexity, fast calculation, insensitivity to illumination changes and invariant to image rotation and scale, this paper uses image registration based on feature point.

The task of feature extraction is that of extracting a number of feature points from images for further processing. Harris corner [7], SIFT [4] corner are examples of classic point features. However Harris corner is sensitive to scale and hard to establish correspondence between different scale images, whereas, SIFT takes more time to detect feature points. In this paper, features are extracted using SUSAN [1]. SUSAN corner detector has the advantage that it is robust to noise and rotation of the image.

Once a set of feature points are determined, the registration parameters can be determined from these selected feature points. To determine the registration parameters, one commonly adopted approach is to establish complete correspondences and then to use these correspondences to determine the registration parameters; the other is to roughly estimate the registration parameters and then to perform a refining process to obtain more accurate registration results. In the first approach, the most common method used to establish such correspondences is the correlation method. The transform parameters can then be found after feature matching, which help register the images. Common methods include Least Squares and RANSAC [9]. RANSAC being a robust model fitting method is preferred over Least Squares.

This paper is organized as follows. Section II introduces steps in image registration. Section III will introduce our new speed-up approach so that it can overcome the difficulty of correlation approach and greatly improve the performing speed. Section IV gives some results which prove the effectiveness of this new algorithm. The last section of the paper draws conclusions.

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II. STEPS IN IMAGE REGISTRATION

A. Feature Extraction: SUSAN

Smith and Brady proposed the SUSAN algorithm for corner detection. In this algorithm, the concept of USAN was proposed for the first time. The USAN is defined as follows: scanning the whole image by a circular mask, in other words, a circular mask is placed at each point in the image, and for each point, the brightness of each pixel within the mask is compared with that of the nucleus (the center point), if the brightness difference between them is less than a given threshold, the pixel and nucleus are believed with the same brightness. All the pixels satisfying this condition within circular mask constitute a region called USAN (Univalue segment assimilating nucleus).

We depict the size of USAN with USAN's area. Fig. 1 shows different USAN's area gotten by placing a circular mask at different positions of a simple image. In Fig. 1, "a" is circular mask whose center pointed by an arrow is called the nucleus.

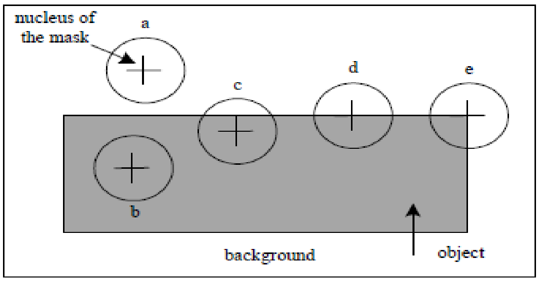

Figure 1: Different USAN area when circular mask is placed at different locations

It is seen from the Fig. 1, USAN area of the flat region point is larger than half of the circular mask's area, USAN area of the edge point is equal to half of the circular mask's area, and USAN area of corner is smaller than half of the circular mask's area. In fact, the sharper the corner is, the smaller the USAN area is. Therefore, corners can be detected by setting brightness difference threshold and USAN's area threshold. The theory of SUSAN operator can be expressed as follows: Setting brightness difference threshold between other pixels and nucleus within mask as *t*, and implementing the following similarity comparison function:

$$c(\vec{r},\vec{r}_0) = \begin{cases} 1 \; when & |I(\vec{r}) - I(\vec{r}_0)| < t \\ 0 \; when & |I(\vec{r}) - I(\vec{r}_0)| > t \end{cases} \qquad (1)$$

Where $I(\vec{r})$ denotes the brightness of mask's nucleus, $I(\vec{r}_0)$ denotes the brightness of mask's non-nucleus, and *t* is similarity threshold for distinguishing the target from the background. Summing up $c(\vec{r},\vec{r}_0)$ within the mask to get USAN's area of nucleus:

$$n(\vec{r}_0) = \sum_r c(\vec{r},\vec{r}_0) \qquad (2)$$

Setting area threshold as *g*, and comparing it with USAN's area to get the initial corner response function:

$$R(\vec{r}_0) = \begin{cases} g - n(\vec{r}_0) & n(\vec{r}_0) < g \\ 0 & otherwise \end{cases} \qquad (3)$$

B. Feature Matching: Correlation Method

This method attempts to establish a correspondence by matching image intensities, usually over a window of pixels in each image. In this method features are matched by finding for each pixel in one image (the reference image) the best match (best correlation) in the other image by comparing a window of pixels in one image with a window of pixels in the other.

The Normalized Cross Correlation (NCC) is given by:

$$\bar{c}(\mathrm{d}) = \frac{\sum_{k=-W}^{W}\sum_{l=-W}^{W}(I_l(i+k,j+l)-\bar{I}_l)(I_r(i+k-d_1,j+l-d_2)-\bar{I}_r)}{\sqrt{\sum_{k=-W}^{W}\sum_{l=-W}^{W}(I_l(i+k,j+l)-\bar{I}_l)^2 \; \sum_{k=-W}^{W}\sum_{l=-W}^{W}(I_r(i+k-d_1,j+l-d_2)-\bar{I}_r)^2}} \qquad (4)$$

where, $\bar{I}_l$ and $\bar{I}_r$ are the average pixel values in the left and right windows.

Drawbacks of Correlation Method:

As seen in Equation (4), for matching features using correlation method, for each feature point in reference image, the correlation is computed for all features points in the other image. For E.g. if the images contain n feature points, then the correlation is to be computed for $n \, \mathrm{x} \, n = \boldsymbol{n^2}$ combinations. This results in much computational time to establish the correspondences. This problem is a time bottleneck in the whole registration process.

C. Finding Transform Parameters: RANSAC

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. A basic assumption is that the data consists of "inliers", i.e., data whose distribution can be explained by some set of model parameters, though may be subject to noise, and "outliers" which are data that do not fit the model. 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.

III. A NOVEL REGISTRATION ALGORITHM TO SPEED-UP FEATURE MATCHING

In this section, we will introduce our new approach for feature matching which reduces the computation time to a great extent, making it possible to be used in real-time applications. This paper focuses on speeding up the feature matching in the registration process.

The basic concept of our approach is to create a descriptor vector table by selecting a window around all the feature points extracted in the images to be registered. Then, for every window considered, the center pixel intensity is subtracted from all its neighbors. This is computed for each feature point in the images along with their average values and is stored for further comparison. This creates a descriptor vector table whose size is the same as number of feature points obtained in the images under consideration. This simplifies feature matching and reduces the computation time.

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A. Steps for measuring similarity or mismatch using our speed-up approach are as follows:

a) Descriptor vector table creation for reference image and image to be registered:

Let I_1 be the reference image and I_2 be the image to be registered.

1. Select a 3x3 or 5x5 window around all the feature points extracted in the images to be registered.
2. For every window considered, its center pixel intensity is subtracted from all its neighbors.

$$f_{11} = \sum_{k=-r}^{+r} \sum_{l=-r}^{+r} (I_1(i+k, j+l) - I_1(i,j)) \quad (5)$$

$$f_{21} = \sum_{k=-r}^{+r} \sum_{l=-r}^{+r} (I_2(i+k, j+l) - I_2(i,j)) \quad (6)$$

where,

$$I_1(i,j) = selected\ feature\ point\ intensities\ in\ ref.image$$

$$I_2(i,j) = selected\ feature\ point\ intensities\ in\ image\ to\ be\ registered$$

$$r = \frac{(w-1)}{2},\ w\ is\ window\ size$$

3. For every window considered, its average value is calculated.

Average value of first image window

$$f_{12} = \frac{1}{n} \sum_{k=-r}^{+r} \sum_{l=-r}^{+r} I_1(i+k, j+l) \quad (7)$$

Average value of second image window

$$f_{22} = \frac{1}{n} \sum_{k=-r}^{+r} \sum_{l=-r}^{+r} I_2(i+k, j+l) \quad (8)$$

4. Store the above values for window considered around each feature points detected in the images. This will generate feature vectors,

$$f_1 = \begin{bmatrix} f_{11} \\ f_{12} \end{bmatrix} \quad (9)$$

$$f_2 = \begin{bmatrix} f_{21} \\ f_{22} \end{bmatrix} \quad (10)$$

b) Feature Matching:

1. Find the Euclidian distance between vectors f_1 *and* f_2 by,

$$d_1 = |f_{11} - f_{21}| \quad (11)$$

$$d_2 = |f_{12} - f_{22}| \quad (12)$$

2. If $d_1 < t_1$ & $d_2 < t_2$

then those feature points get matched.

t_1 = *threshold* for comparing difference of sum

t_2 = *threshold* for comparing difference of avg

IV. RESULTS

We tested our approach proposed above to register a set of images for various rotation angles and noted down the computation time for feature matching based on conventional correlation method and our speed-up approach.

Table I displays results of the registration obtained using our speed-up approach.

Image	**Rotation(angle in degrees)** Actual	Obtained	**Computation time(s)** Correlation Method	Our Speed-up Method
pout.tif (291x240)	10	10.16	0.11	**0.02**
	30	38.8		
	45	46.6		
	90	90.00		
cameraman .tif (256x256)	10	9.90	0.84	**0.21**
	30	32.6		
	45	48.73		
	90	90.00		
empire.jpg (569x800)	10	9.7	24.97	**0.53**
	30	33.90		
	45	50		
	90	86.93		
housefront.jpg (1408x1056)	10	9.99	31.28	**0.82**
	30	34.45		
	45	50.87		
	90	91.11		

Table I: Registration and Computation Time Results using our speed-up approach

V. CONCLUSION

The basic principle behind making image registration faster is to identify certain heuristics which reduces the search space for the algorithm. We have successfully shown that our algorithm is much better for feature matching in terms of computation time. The computational complexity of our speed-up approach is only $O(2n)$ as compared to correlation method which is $O(n^2)$, where n are the number of feature points.

As it was listed in Table I, there is a significant reduction in the computation time to match features between two images by using our approach as compared to the existing correlation approach. Our proposed method shows an overall reduction of **97.22%** computation time, thus making it suitable for real-time applications. It also shows good results in terms of observed rotation.

Compared with conventional correlation method, the proposed scheme is a great improvement in terms of computation time.

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