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Automatic Control Point Generation for Satellite Image Registration

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Abstract: Image registration is the process of spatially aligning two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. In this process, two images (the base image and sensed image) are geometrically aligned in order to compare the difference between them. The key operation regarding automatic registration of satellite images is to generate an accurate set of control points and then apply a suitable transformation function to the pair of images to be registered. This paper proposes a fundamentally new approach to automatically generate the control points and based on these points, registration of satellite images is performed. After removing the outliers from the initially generated random set control points, a mapping function is generated as a hypothesis using the proposed method. Parameters of the mapping function are used in the transformation step to align the base image and sensed image. The sampling technique used in this paper is more efficient than the existing methods like RANSAC and LMedS.

Keywords: Image registration; transformation; outliers; mapping function; RANSAC; LMedS

I. INTRODUCTION

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. It is the geometrical alignment of two images (the base image and sensed image) in order to be able to compare and integrate the data obtained from them. Registration process has many applications in remote sensing like weather forecasting and change detection, medical imaging and in computer vision field. In satellite image registration, the main process is to generate an accurate set of control points and based on these points, registration is performed. The main aim of this paper is to propose a new method to automatically generate the control points required for registration. Traditional satellite image registration process required manual selection of control points. It is very time consuming and tedious task especially when considering large volumes of data. Reduction of human involvements in the process of image registration has been a hot research theme.

There are mainly four distinguishable phases in an automatic satellite image registration system. Initial step is the feature detection phase in which distinct objects are automatically detected. These features can be represented using their point representatives (Control Points). In the second step known as feature matching phase, correspondence between base image and sensed image is established. In the third step, parameters of the mapping function are estimated from the feature correspondences. In the final phase, image resampling is done and a suitable transformation is applied.

It is often impossible to generate error free control points in every situation. Matching may fail when images are taken with different viewing conditions or when there are repetitive patterns in them. Hence estimation of accurate set of control points is very important. From the initial random set of control points, a minimal subset containing only inliers of a particular geometric model is selected. In this paper, fundamental matrix (F) is estimated as the geometric model. It is a 3X3 singular matrix of rank 2 which relates corresponding points in stereo images.

Two perspective images of a single scene are related by the so-called epipolar geometry [1], which can be described by the fundamental matrix. The fundamental matrix is independent of scene structure. It can be computed from correspondences of imaged scene points alone, without requiring knowledge of the cameras' internal parameters or relative pose. The proposed automatic satellite image registration system consists of following steps which are shown in figure 1.

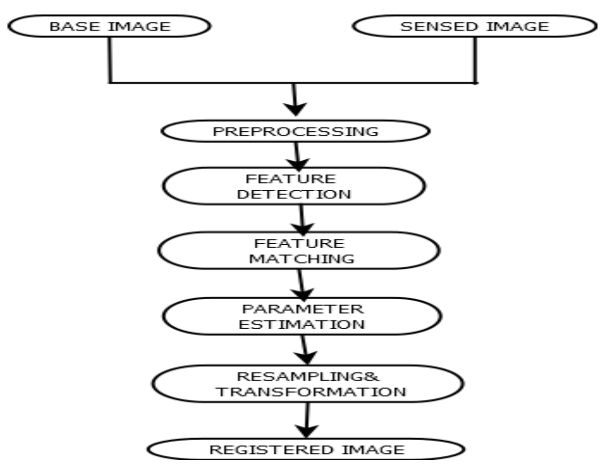


Figure1. Satellite Image Registration System

The rest of the paper is organized as follows: Section 2 surveys related work to put this paper in the right context. Section 3 describes our proposed system of Satellite image registration. Section 4 provides extensive experimental results and Section 5 draws conclusions and discusses future work.

II. RELATED WORKS

A lot of research has been carried out for designing a robust methodology to automatically generate the control points required for satellite image registration. The extraction of inliers from the initially generated random set control points is the most challenging step in the registration process. RANSAC algorithm [2] has been used as a powerful tool for such estimation process due to its ability to handle a tremendous amount of outliers. In practical settings, the data may contain multiple instances of the geometric models or structures. Many innovative methods have been proposed to speed up RANSAC to handle multistructure data. RANSAC algorithm needs the information of the percentage of outliers, which is usually not available. The LMedS [3] estimation does not require such information, but it is very time-consuming.

Matas and Chum [4] design a pre-evaluation stage which attempts to quickly filter out bad hypotheses. One of the consequences of this approach is that it requires many more hypotheses than the original RANSAC. To avoid this disadvantage, in PROSAC algorithm [5], Matas et al. proposed a similarity function based on which inliers are extracted. Tordoff et al. [6] proposed MLESAC algorithm which adopts the same sampling strategy but attempts to maximize the likelihood of the solution. Through preemptive RANSAC algorithm [7], Nister generated a fixed number of hypotheses beforehand, and then compared against each other by scoring them in parallel.

The existing methods consider the inlier probability of a datum to be independent of other data. This is a crucial deficiency of previous methods. Also these methods are based on a false assumption that inlier points appear as clusters. In this paper, we are using a sorting technique based on residual values to determine whether a datum is inlier to the mapping function or not.

Image registration methods can be broadly classified as area based methods and feature based methods [8]. Area-based methods are preferably applied when the images have not many prominent details and the distinctive information is provided by intensity variations. These type of registration methods are used in medical imaging. Feature-based matching methods are typically applied when the local structural information is more significant than the information carried by the image intensities. They allow to register images of completely different nature and can handle complex distortions. Feature-based methods are used in remote sensing and satellite image registration.

III. METHODOLOGY

A prototype of the proposed satellite image registration system is given in fig 1. It mainly consists of five stages: image acquisition and preprocessing, feature detection, feature matching, estimation of parameters of the mapping function, image resampling and transformation.

A. Image Acquisition and Pre-processing:

After acquiring the input satellite images, preprocessing is applied for resolution enhancement. In this paper, we are using a resolution enhancement technique based on the interpolation of the high-frequency subband images obtained by Discrete Wavelet Transform [DWT] [9] and the input image. DWT is used to decompose input satellite image into different subbands. Then, the high-frequency components and the input low-resolution image have been interpolated, followed by combining all these images to generate a new enhanced image by using inverse DWT.

B. Control Point Generation:

After preprocessing, the resolution-enhanced image is used to estimate the control points required for registration. To efficiently fit a geometric model onto the data with minimal loss to accuracy, the inlier points to the geometric model are extracted. Let $X := \{x_i\}_{i=1}^{N}$ be a set of N input data. A series of M geometric models is fitted on randomly selected minimal subsets of the data.

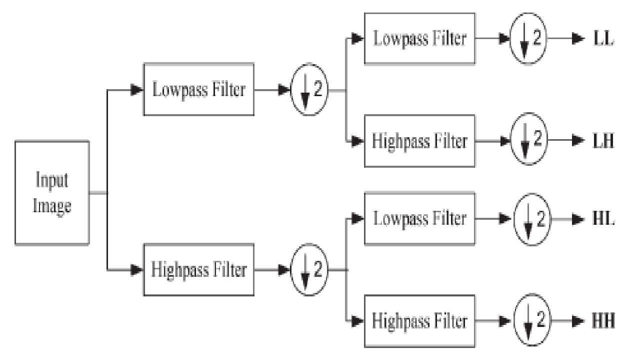


Figure2. Block Diagram of DWT Filter Banks.

The residual values corresponding to each datum with the M geometric models form a vector:

$$a^{(i)} := [a_1^{(i)} a_2^{(i)} ... a_M^{(i)}]. \qquad (1)$$

These residual values indicate the Sampson distance of each datum to the corresponding geometric model. We can form an ordering,

$$b^{(i)} := [b_1^{(i)} b_2^{(i)} ... b_M^{(i)}], \qquad (2)$$

such that the elements in $a^{(i)}$ are sorted as,

$$u < v \Rightarrow a_{b_u^{(i)}}^{(i)} \leq a_{b_v^{(i)}}^{(i)}. \qquad (3)$$

This sorting is used for the extraction of accurate set of inliers from the data. i.e., If a geometric model has a higher position in the sorting, there is a higher probability of x_i being an inlier to that model. The intersection between x_i and x_j,

$$f(x_i, x_j) := \frac{1}{y} | b_{1:y}^{(i)} \cap b_{1:y}^{(j)} | \qquad (4)$$

Specifies if x_i and x_j are inliers of the same structure or not. The window size y with $1 \leq y \leq M$. The value of intersection function ranges between 0 and 1. Window size controls the discriminative power of intersection function.

Let the geometric model to be fitted be determined by the minimal subset

$$S = \{x_{s_1} \ldots. x_{s_p}\} \subset X \quad (5)$$

The first datum x_{s_1} in the model is selected from the uniform distribution,

$$x_{s_1} \sim U(1, N) . \quad (6)$$

To select the second datum x_{s_2}, the following probability distribution is used.

$$P_1(i) := \begin{cases} \alpha_1 f(\boldsymbol{x}_i, \boldsymbol{x}_{s_1}), & \text{if } i \neq s_1, \\ 0, & \text{otherwise}, \end{cases} \quad (7)$$

where α_1 is the normalization constant :

$$\alpha_1 = \frac{1}{\sum_{i \neq s_1} f(x_i, x_{s_1})} \quad (8)$$

The second datum is selected according to P_1 .The intersection values of the first and second data are used to select the third datum, and so on. Thus the information provided by the k data chosen thus far is to sample the $(k+1)$ th datum. The residual vector and window size are updated after a block of hypotheses are generated.

The main steps of control point generation can be summarized as follows:

a. **Input:** Data X , Block size b > 0
b. **Output:** Set θ of *M* tentative geometric models
c. Random sampling of data and store as *S*, until the block size is reached.
d. When *M*=*b*, select at random x_{s_1} .
e. For *k* =1,2,….(*p-1*), construct P_k .
f. Sample S_{k+1} according to P_k .
g. θ = θ U {new tentative geometric model}
h. Update residual vector and window size.
i. Return θ.

C. Control Point Matching and Mapping Function Generation:

After the accurate set of inlier control points are generated, control point matching is established in the base and sensed image pairs using SIFT keypoint matching [10] algorithm. SIFT matching transforms image data into scale-invariant coordinates relative to local features.

Fundamental matrix is generated as the mapping function which can relate the corresponding points in stereo image pairs. Being of rank two and determined only up to scale, the fundamental matrix can be estimated given at least seven point correspondences. The seven parameters of fundamental matrix can be obtained from point correspondences alone.

D. Image Transformation:

After estimating fundamental matrix as a geometric model, projective transformation is applied on the input images based on the parameters of the geometric model. Projective transformation is a transformation that maps lines to lines without preserving parallelism. Projective transformation generates registered image as output.

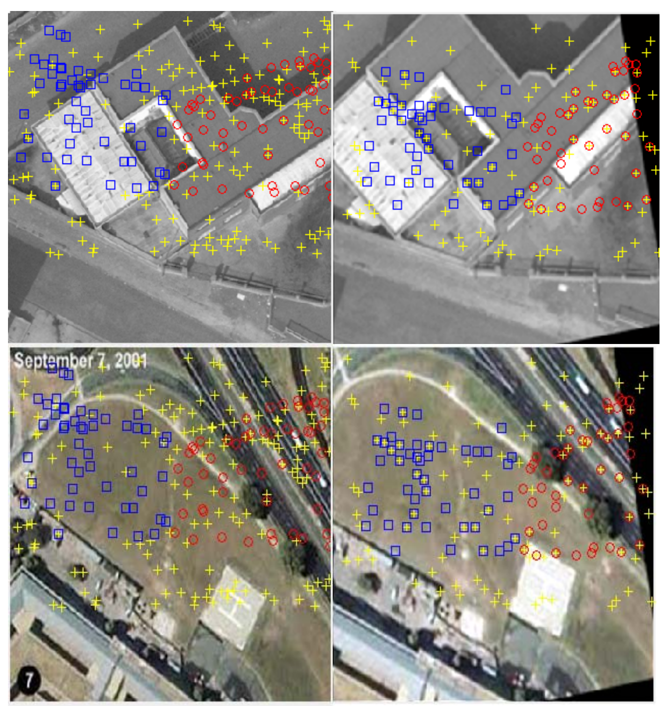
IV. RESULTS AND DISCUSSIONS

After acquiring the input images and applying pre-processing, initial random set of control points are selected. Outlier points are eliminated. The keypoint correspondences and matching scores were obtained by SIFT matching. Hypotheses were generated from 7 keypoint correspondences via the standard 7-point estimation method. For each method, 50 random runs were performed, each for 60 CPU seconds.

The proposed image registration method is implemented on the following satellite images and the results are shown in fig.3,4 and 5. The table summarizes performance of existing methods and the proposed method.

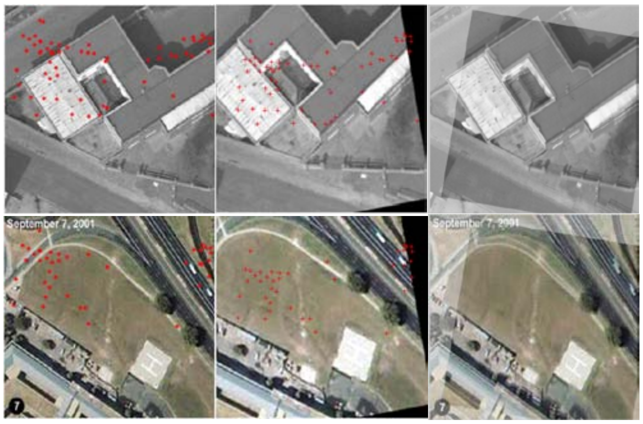
(a) (b) (c)

Figure3. (a)Base Image. (b)Unregistered Image. (c) Enhanced Image



(a) (b)

Figure4. Tentative Set of Control Points. (a)In Base Image. (b)In Unregistered Image.



(a) (b) (c)

Figure5. Inlier Control Points. (a)In Base Image. (b)In Unregistered Image.(c)Image Registration

Table I Performance Measure of Proposed Method

Data		Random	LO-RANSAC	PROSAC	proposed method
image 1	CPU	0.03	0.01	$< 10^{-3}$	0.02
	Iter	11	4	1	8
	I-1 (28, 58%)	1426	1429	1778	184
	Fail	0	0	0	0
image 2	CPU	19.13	18.44	17.41	**0.18**
	Iter	5716	5572	5458	**41**
	I-1 (48, 27%)	7	7	8	**355**
	I-2 (28, 16%)	1	1	1	**175**
	Fail	47	47	44	**0**

Table I shows that the proposed image registration method generates control points more effectively than existing methods.

V. CONCLUSIONS

In the process of image registration, two images are geometrically aligned in order to compare and integrate the data contained in them. To make the two images into the same coordinate system, some control points areto be generated. The proposed satellite image registration system is very efficient compared to the existing systems to generate an accurate set of control points. It dramatically reducesthe number of samples required especially in case of multistructure data.

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