

Implementation of RANSAC Algorithm for Feature-Based Image Registration

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ABSTRACT

This paper describes the hardware implementation of the RANdom Sample Consensus (RANSAC) algorithm for featured-based image registration applications. The Multiple-Input Signature Register (MISR) and the index register are used to achieve the random sampling effect. The systolic array architecture is adopted to implement the forward elimination step in the Gaussian elimination. The computational complexity in the forward elimination is reduced by sharing the coefficient matrix. As a result, the area of the hardware cost is reduced by more than 50%. The proposed architecture is realized using Verilog and achieves real-time calculation on 30 fps 1024 * 1024 video stream on 100 MHz clock.

Keywords: RANSAC; Image Registration; VLSI; Image Processing

1. Introduction

Image registration is the process of precisely overlaying two (or more) images of the same area through geometrically aligning common features (or control points) identified in the images [1,2]. Image registration can be more generalized as a mapping between two images both spatially and with respect to intensity [3]. The images can be taken at different times, from different viewpoints or by different sensors. Therefore, image registration techniques normally can be grouped into four categories: multi-modal registration, template registration, multiviewpoints registration and multi-temporal registration [3,4].

The registered images can be used for different purposes, such as (1) integrating or fusing information taken from different sensors, (2) finding changes in the images taken at different times or under different conditions, (3) inferring three-dimensional (3-D) information from images in which either the camera or the objects in the scene have moved and (4) for model-based object recognition [3].

Normally, image registration consists of four steps: (1) feature detection and extraction, (2) feature matching, (3) transformation function fitting and (4) image transformation and image resampling [2,4]. For the robust estimation of transformation function, RANdomSAmple Consensus (RANSAC) algorithm [5] has been used to handle mapping features in presence of outliers successfully. It

also has been showed that it works for robust estimation of mapping functions in the automated image registration [6-8].

This paper proposes a hardware architecture for the RANSAC algorithm. The design adopts the Multipleinput signature register (MISR) and the index register to achieve the effect of random sampling. The matrix triangularization of the forward elimination is realized by systolic array. Sharing the coefficient matrix not only reduces the computational complexity but also saves the area of hardware cost.

2. Main Stages of RANSAC Algorithm

This section briefly introduces the RANSAC algorithm and previous work for hardware implementation. **Figure 1** shows the computational flow of the RANSAC algorithm. The source images need to be registered together after feature detection and matching. The RANSAC algorithm can be applied to get the homography of each image pair. Four initial putative feature matches are selected in the random selection step of each iteration in RANSAC [5], and a correct homography can be got after the final iteration if they are the real inliers. Each RAN-SAC iteration works in the following three steps:

- Select a random sample of four feature matches.
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- Compute the number of inliers consistent with Hby a distance threshold.

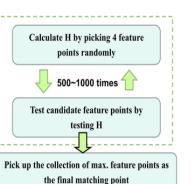


Figure 1. RANSAC algorithm.

Then, H with the largest number of inliers is selected after many iterations and the final homography H can be recalculated with the inliers consistent with the selected H.

Considered mappings between image pair in this paper include scaling + rotation and affine transformation, as most distortions present in natural-world images can be sufficiently accurately approximated (at least locally) by such mappings. Since perspective distortions are locally approximated well enough by affine functions, affine transformations are considered the distortion model for images matching (even though RANSAC can be applied to more complex transformations).

An affine transformation is a linear mapping followed by a translation. In case of images, we are interested in affine functions in two-dimensional spaces, *i.e.* transformations are defined by six parameters. Four of the parameters form the linear part, while the remaining two specify the translation vector. If (x,y) are the source image I coordinates, and (u,v) represent the destination image J coordinates, the affine transformation is represented by a homogeneous matrix A:

$$\begin{bmatrix} U \\ v \\ 1 \end{bmatrix} = A \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \text{ where } A = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix}$$
(1)

where a, b, d, e are elements of the linear part, and c, f are elements of the translation vector.

A 2D affine transformation has six parameters so that we need a non-singular system of six linear equations to reconstruct the transformation. Using the third principle (triangles are mapped into triangles) we can form such a system of equations from three matched pairs of noncolinear keypoints. Consider three points (x1, y1), (x2, y2) and (x3, y3) in the source image I, and their counterparts (u1, v1), (u2, v2) and (u3, v3) in the destination image J. To reconstruct the affine transformation from these triangles, we solve the following system of equations:

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ x_2 & y_2 & 1 & 0 & 0 & 0 \\ x_3 & y_3 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ 0 & 0 & 0 & x_2 & y_2 & 1 \\ 0 & 0 & 0 & x_3 & y_3 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ v_1 \\ v_2 \\ v_3 \end{bmatrix}$$
(2)

Considering the coefficient matrix in (2), this paper makes the equation solving easier by the following set of equations:

$$\begin{bmatrix} \mathbf{x}_1 & \mathbf{y}_1 & \mathbf{1} \\ \mathbf{x}_2 & \mathbf{y}_2 & \mathbf{1} \\ \mathbf{x}_3 & \mathbf{y}_3 & \mathbf{1} \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix}$$
(3)

$$\begin{bmatrix} x_{1} & y_{1} & 1 \\ x_{2} & y_{2} & 1 \\ x_{3} & y_{3} & 1 \end{bmatrix} \begin{bmatrix} d \\ e \\ f \end{bmatrix} = \begin{bmatrix} v_{1} \\ v_{2} \\ v_{3} \end{bmatrix}$$
(4)

For reducing the computational complexity and saving the hardware cost, this paper shares the same coefficient matrix in (3) and (4).

3. Proposed Hardware Architecture

In this section, hardware architecture for the implementation of the RANSAC algorithm applied on the featurebased image registration is presented.

Figure 2 shows the architecture of the RANSAC hardware module, which is composed of three function units: Save and load the matching feature point coordinates, Calculate the homography matrix, and Examine the homography matrix. Details of the architecture are explained next in this section.

3.1. Save and Load the Matching Feature Point Coordinates

Figure 3 shows the internal organization of the save and load the matching feature point coordinates block. In this organization, the input coordinates of matching feature

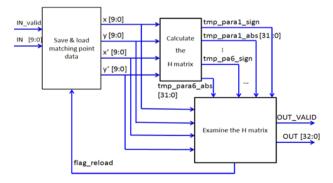


Figure 2. Overall structure of RANSAC.

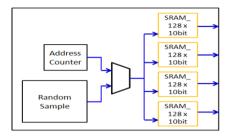


Figure 3. Structure of save and load the coordinates module.

points are separately stored in the SRAMs. These stored coordinates are read for computing the transformation matrix randomly or examining the correctness of the parameters in order. The address generating from the random sample block is used to read coordinates randomly. The address counter increases address progressively for testing the temporary homography matrix.

The random sample scheme is realized by interleaving and permutation. This paper switches the data in the index register instead of switching the coordinates stored in the SRAMs. The method of the random sample circuit is showed in Figure 4. In the interleaving method, we shuffle the data in the index registers by dividing the data exactly in half, and then interleave the two halves in strict alternation to combine the two stacks together. In the permutation step, we choose four data as a group for data rearrangement. Then the switch circuit does the permutation in the index register according to the number generating from random number generator (RNG) and the table in the Figure 4(b). This paper adopts the multiple input signature register (MISR) [9] as the RNG scheme. We load a coordinate data from SRAM and use the 4 least significant bits as the input of MISR.

3.2. Calculate the Homography Matrix

The block diagram of Calculate the homography matrix is showed in **Figure 6**. To initialize the coefficient matrix and the constant matrix 3 matching features are used in serial order. The initialized data are sent to Gaussian elimination block for calculating the temporary parameters of homography matrix. The forward elimination block is realized by systolic array architecture [9]. The designed structure and the input sequence are showed in **Figure 7**.

The array consists of twelve processing elements, three buffer registers and five multiplexers, arranged as shown. There are two types of PEs; namely circular and square PEs. The buffers (ellipsoidal shape in **Figure 7**) are merely to introduce delays. Their inclusion is aimed at avoiding costly inter-iteration I/O. By inserting the correct number of delays in different data paths, it is possible to feed the data back to the triangular PE array without any need for temporary storage of intermediate

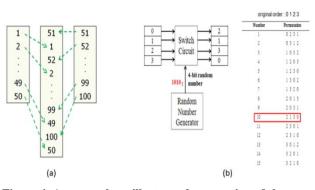


Figure 4. An example to illustrate the operation of the random sample: (a) Interleaving; (b) Permutation.

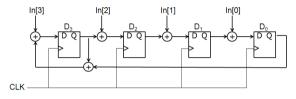


Figure 5. Structure of MISR.

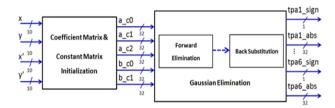


Figure 6. The homography matrix calculation module.

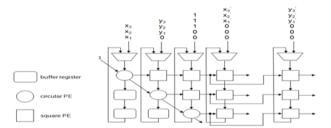


Figure 7. Systolic array of forward elimination.

data. Of course, at the cost of increased memory I/O one could do without the buffer registers. Comparing the design in **Figure 7** with original architecture without sharing the coefficient matrix in **Figure 8**, this paper reduces 29% (2/7) 2-to-1 MUX, 80% (12/15) Buffer registers, 50% (3/6) Circular PEs and 40% Rectangular PEs.

This paper uses the divider showed in the **Figure 9** to realize the ratio computation in the Circular PE. The divisor is entered into the mapping modules. Then we can get the new signal with 10 bits in the range [512,1023]. Next, the new signal is mapped into the reciprocal by the usage of the lookup table. The temporary quotient is generated by the product of the dividend and the reciprocal produced before. Finally, we shift the signal from

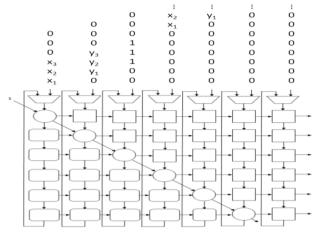


Figure 8. Systolic array of the forward elimination without sharing the coefficient matrix.

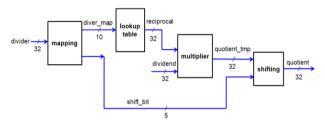


Figure 9. Divider with the circular PE.

the multiplier according to the signal (shift_bit) from the mapping module and generate the correct quotient without iteration.

3.3. Examine the Homography Matrix

Figure 10 shows the organization of the Examine the homography matrix block. The inputted coordinates from matching features are entered into the matrix multiplication module. The coordinates in the reference image are theoretically converted to positions (x'', y'') in the sensed image. We use the coordinate to compute the sum of the squared difference (SSD) with data(x, y) in the reference image. If the calculation result of SSD is lower than 25, the number of inliers will increase by 1. After examining the all remaining data in the SRAMs, the current iteration is finished. The output PE will record the parameters with the maximum number of inliers and output the data after 500 times of iteration.

4. Results and Conclusions

The development environment on software is Visual Studio C++ 2009. CPU is Intel Core i3 I3-2100 3.1 GHz. **Figure 11** shows the simulation waveform resulted from the pair of testing images in **Figure 12**. Comparing with the outcome of software simulation, we can find that the error rate of the calculation result is less than 1%.

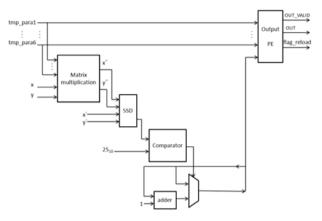


Figure 10. The homography matrix examination module.

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Figure 11. Simulation results of RANSAC implementation.



Figure 12. Testing image pair of the hardware simulation.

In this paper, a practical hardware architecture and organization of the RANSAC algorithm for feature-based image registration applications are proposed and its implementation in Verilog is presented. The architecture adopts systolic array for realizing the Forward elimination module. The computational complexity in the forward elimination is reduced by sharing the coefficient matrix. As a result, the hardware cost is reduced by more than 50%. This paper uses the look-up table for the divider circuit implementation of the circular PE, so the calculation can be done in a single clock cycle without any iteration. The system is able to compute the homography between images up to 30 frames per second (1024 \times 1024 pixels).

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