A Self-Adaptive Algorithm of Automatic Interior Orientation for P31 Images

Wanshou Jiang¹, Guo Zhang² and Deren Li¹

¹Laboratory for Information Engineering in Surveying, Mapping and Remote Sensing

²School of Information Engineering in Remote Sensing,
Wuhan University, #129 Luoyu road, Wuhan, P.R. China

Abstract

Though automatic interior orientation has been deeply studied, it still remains problem for close range images photographed by P31 camera, in which fiducial marks merge in images of objects. In this paper, automatic interior orientation is regarded as a global image matching problem, which can be processed in two steps. Firstly, several possible fiducial marks are extracted with straight-line extraction by template matching and Hough transformation. Secondly, the unique fiducial marks are determined by softassign and deterministic annealing technology combined with affine transformation from the candidates fiducial marks. Experiments and discussions of parameter are also presented. It is confirmed that the fiducial marks can be determined reliably and gross error can be detected. Other strategies such as automatic determination of the minimum searching range are also taken into consideration.

I. INTRODUCTION

Interior orientation is a fundamental problem in photogrammetry. Nowadays, most of the commercial software of DPS includes automatic interior orientation function. For most metric images, interior orientation can be finished automatically. If automatic interior orientation fails, manual operation has to been included, which is very inconvenient.

Interior orientation is usually referred to reestablishing the relationships between the pixels and the image coordinate system. We are concerned with the relationship of a set of (usually six affine) parameters for the transformation from pixels to image coordinates. Additionally, it will correct the possible image deformations. The image coordinate system is determined by the fiducial marks. However, the pixel coordinate system of the digital image is explicitly given through the matrix of gray values. Therefore, the transformation between pixel and image coordinates by fiducial marks has to be accomplished via the fiducial as identical points. The reestablishment of the interior orientation can be considered as a pattern recognition problem: one has to find the center of the pattern representing the fiducial marks and ascribe each founded pattern the correct fiducial number.

Table 1 shows several traditional methods of interior orientation [1]. In which, interior orientation are divided into three tasks:

- · Approximate positioning of fiducial marks
- Subpixel positioning of fiducial centers
- Computation of transformation parameters

Among these tasks, approximate positioning is the most important and the hardest one. Gray correlation, binary correlation or other binary image analysis techniques are used in these methods to approximate the position of fiducial marks. For

aerial images photographed by RC10, RMK and other aerial cameras, on which fiducial marks distribute on edges or corners with no objects around, these methods perform well. And each fiducial mark can be extracted individually.

But for images photographed with P31 camera, fiducial marks merge in the image of objects. Even worse, some parts of the objects (such as a mesh) may have the similar shape to the fiducial marks. The former methods may fail in such cases. If similar objects exist near a fiducial mark, several targets will be detected. Even if no similar targets exist, it is very hard for binary analysis to detect fiducial marks in complex gray images. As for gray correlation, the coefficient on fiducial marks may be very small. In our tests, some are even smaller than 0.3. For P31 images, the automation of interior orientation remains a problem.

In this paper, a new algorithm is put forward. In our algorithm, the fiducial marks are determined simultaneously with combination optimization technique. At first, the fiducial marks of P31 camera are crosses that merge in objects' image. So fiducial marks can be regarded as intersections of two perpendicular lines. Generally it is difficult to extract the unique straight lines of fiducial marks. So for each fiducial mark, the intersections points may be more than one. Secondly, the fiducial marks and their image are one-to-one correspondence with affine transformation. So the correspondence relation between the fiducial marks and the candidates can be regarded as a combination optimization problem. The energy function of the problem should reach minimum with the correct one-to-one correspondence.

There are many algorithms such as genetic algorithm, relaxation algorithm and Hopfield networks, which are usually used

1082-4006/00/0702-113\$5.00 ©2001 The Association of Chinese Professionals in Geographic Information Systems (Abroad)

Reference	Approximate fiducial positioning	Accurate fiducial positioning	Pose estimation					
Kersten and Haring (1995)	Modified Hough transform	Least-squares matching	Depends on camera type					
Lue (1995)	Grey value correlation hierarchy	Least-squares matching	Manual					
Schickler (1995)	Binary correlation hierarchy	Grey value correlation	Automatic					
Strackbein and Henze (1995)	Binary image analysis, no hierarchy	Fitting of parabolas to gray value function	Manual					

Table 1. Methods for automatic interior orientation [1]

to solve combination optimization problem. Relaxation algorithm and Hopfield networks generate local minima and do not usually guarantee that correspondences are one-to-one, and genetic algorithm is time consuming. To overcome these problems, softassign and deterministic annealing technology with affine transformation have been put forward [2,3,4]. This algorithm solely makes use of point location information, but it can supply an access to one-to-one correspondence and reject a fraction of points as outliers. In [2], though outliers exist, it's almost still one-to-one correspondence. In our example, the candidates for one fiducial mark sometimes reach 10. So for most candidates, no correspondence exists, and has to be rejected as outliers.

II. EXTRACTION OF FIDUCIAL MARKS

Minimum searching range

Illustrated in Figure 1, we can obtain the smallest rectangle area that contains all the fiducial marks according to camera calibration data. Normally, the rectangle is smaller than the image. When the rectangle is moved along the border of image, the traces of fiducial marks will determine the searching range of fiducial marks (Figure 2). Suppose the width and height of the rectangle are a and b in mm, the width and height of the image are A and B in pixel. Then for fiducial mark whose image coordinates are (x,y), its searching range are



Figure 1. Fiducial marks and image

$$x \in [\alpha \cdot x - dx, \alpha \cdot x + dx], \quad dx = (A - \alpha \cdot a)/2$$

 $y \in [\alpha \cdot y - dy, \alpha \cdot y + dy], \quad dy = (B - \alpha \cdot b)/2$ (1)
Where, α is the number of pixels per mm.

Extraction of the possible fiducial marks

For each fiducial mark of P31, its center is the intersection of two perpendicular lines. The segment of the straight line on fiducial mark can be modeled with horizontal and vertical templates (Figure 3, Figure 4). Its profiles are parabolas. Straight lines are extracted in following four steps:

Step 1, template matching of horizontal or vertical is done in the whole searching area to generate a matrix of coefficients. Local maximums of coefficients that are greater than given threshold are regarded as centers of straight segments.

Step 2, gray profile perpendicular the straight segment is fitted with parabola, from which the sub-pixel position t_{max} of straight segment is computed (EQ.2).

$$g(t) = g_0 + g_1 t + g_2 t^2$$
, max $g(t) \Rightarrow t_{\text{max}} = -\frac{g_1}{2g_2}$

Step 3, Hough transformation is done with centers of straight segments to detect the proximate parameter of straight lines.

$$x\cos\theta + y\cos\theta = \rho$$
 (3)
Step 4, straight lines are fitted with least square adjustment



Figure 2. Searching range



Figure 3. horizontal template

Figure 4. vertical template

with points near the proximate straight lines by step3.

III. COMBINATION OPTIMIZATION

For each fiducial mark, there are several intersection points as candidates. And only one candidate can be the identical point. Denote the set of fiducial marks as $X=\{x_i, i=1,2...N\}$, the set of candidate points as $V=\{v_a, a=1,2...K\}$. V and X are related by an affine transformation EQ (4),

$$v_a = t + x_i d$$
 $i = 1,..., N, a = 1,...K$ (4)

Where $\{d, t\}$ is the parameter of affine transformation.

A matrix $M=\{m_{ai}\}$ can be defined to indicates the point correspondence as following:

$$m_{ai} = \begin{cases} 1 & if \text{ point } x_i \text{ correspond to point } v_a \\ 0 & \text{otherwise} \end{cases}$$
 (5)

Where M always satisfies:

$$\sum_{a=1}^{K+1} m_{ai} = 1, \quad i = 1, 2, ..., N$$

$$\sum_{i=1}^{N+1} m_{ai} = 1, \quad a = 1, 2, ..., K$$
(6)

A possible correspondence matrix is as Table2. Point v_1 , v_2 and v_4 correspond to x_1 , x_2 and x_3 respectively, and the other points are outliers.

Energy function with affine transformation

According to TPS-RPM algorithm put forward in [2]. The energy function can be written as EQ.7:

$$E(M,d,t) = \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai} \| v_a - x_i d - t \|^2$$

$$- \varsigma \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai} + T \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai} \log m_{ai}$$
(7)

Where,
$$(m_{ai} \in [0,1])$$

The first term is just the error measure term of affine transformation by least square. The second term is used to guard against null correspondence. The third term is an $x \log x$ entropy barrier function with the temperature T. The entropy function ensures positivity of M. m_{ai} are relaxed to be continuous from binary-valued, while normalization constrains (EQ.6) are still satisfied. When affine transformation is solved, m_{ai} are used as weight.

By making the correspondence continuous, the correspondence can be "soft" instead of "hard". The energy function becomes better behaved because the correspondence is able to improve gradually and continuously during the optimization without jumping around in the space of binary permutation matrices (and outliers). More details and discussion can be found in [2,3,4].

Softassign and deterministic annealing technology

With the currently estimated transformation (d, t), the first step is to update the correspondence. Differentiating energy function E in (7),

$$\frac{\partial E}{\partial m_{ai}} = \|v_a - x_i d - t\|^2 - \zeta + T(\log x + 1)$$

$$= 0 \Rightarrow m_{ai} = \frac{1}{e} \exp\left(-\frac{\|v_a - x_i d - t\|^2 - \zeta}{T}\right)$$
(8)

Where constant 1/e can be omitted.

And then the Sink horn balancing technique of alternating row and column normalizations is used to satisfy the row and column constraints. When the correspondences are held fixed, a least-square approach is used to solve the affine transformation parameters (d, t).

For every temperature, these steps are repeated until affine transformation parameters are held fixed. Figure 5 illustrates the flow chart of whole process.

IV. EXPERIMENTS

The algorithm is tested on some close range photos of a building taken by a P31 metric camera. These photos are scanned on Vexcel3000 scanner. Image size is about 6000×4500 pix-

Table 2. An example of correspondence matrix

m_{ai}	x_1	x_2	x_3	x_4	x_5	Outlier	
v_1	1	0	0	0	0	0	
v_2	0	1	0	0	0	0	
v_3	0	0	0	0	0	1	
Outlier	0	0	0	1	1		

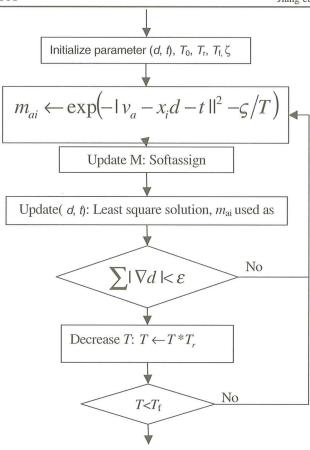


Figure 5. The flow chart of whole process

els. Pixel size is 25μ . The fiducial marks' distribution is showed in Figure 1. In Figures 6, 7, and 8 are some searching areas extracted based on the predicted range according to EQ.1. It can be seen that fiducial marks merge in the image of objects and some crosses similar as fiducial marks exist.

Extraction of candidate fiducial marks

In Figure 6, (a) is searching area of a fiducial mark, white pixels in (b) are the extracted points on horizontal lines with horizontal template, white pixels in (c) are the extracted points on vertical lines with vertical template. Hough transformation is done based on points in (b) and (c). Two horizontal lines and one vertical line are detected and fitted by least square. The two crosses in (d) are intersection points of the three lines.

(a) (b)

Crosses in Figure 7 and Figure 8 are candidate points of two other images.

Combination optimization

After the candidate points are extracted, combination optimization is adopted to determine the unique correspondence. Two results of experiments are showed in Figure 7 and Figure 8. In the two experiments, several fiducial marks have six candidates. That means many candidates have no correspondence and will be outlier. It's very different from the experiment in [2], in which correspondence is almost one-to-one.

In the case of interior orientation, the parameters are set in the following manner:

- (1) The initial temperature T_0 is set the square of searching range diameter.
- (2) The decrease rate of temperature $T_{\rm r}$ (annealing rate) is 0.93,
- (3) $T_{\rm f}$ is set 1
- (4) If the measurement error is denoted as σ_0 and outlier (gross error) is supposed to be $3\sigma_0$, and then the outlier for T_f will be:

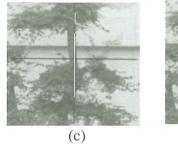
$$outlier = \exp\left\{-\left((3\sigma_0)^2 - \varsigma\right)/T_f\right\}$$
 (9)

In our case σ_0 is supposed to be 0.5 pixels.

- (5) If the coordinate of fiducial marks has been scaled to image and shifted to the bottom left corner, then the initial parameter *t* of affine transformation is set to be zero and d is set to be an identical matrix.
- (6) Parameter ε for convergence is set to be 10e-6.

Table 3 shows the interior result of image 1. From Table 3, it can be seen the initial m_{ai} for every candidate is almost same. After 148 times repetition, an affine transformation and correspondence M results is got. The residual errors and RMS is small enough. It can seen the algorithm does not always converge M to a permutation matrix. So a clean-up heuristic is necessary. In our test, we just set the maximum element in each row to be 1 and all others to be 0. The identical points are marked with a small circle in Figure 7.

Figure 8 is the test result of image 2. When affine transformation is used, correspondences are right. But the RMS is some-



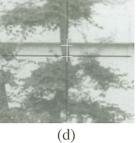


Figure 6. Extraction of candidate points. (a). Searching area; (b) Points on horizontal lines; c) Points on vertical lines; and (d) Candidate points

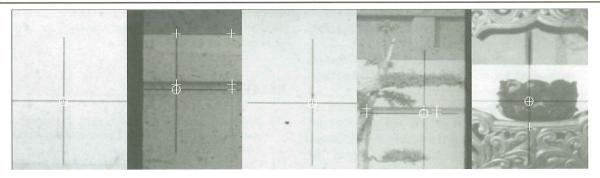


Figure 7. candidates and result of image 1

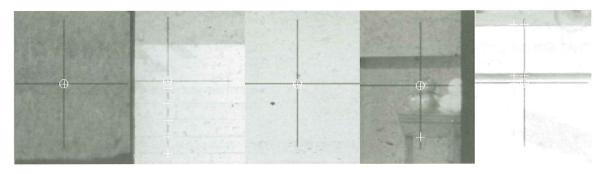


Figure 8. candidates and result of image 2

Table 3. Test of image 1(coordinate in pixels)

Fiducial marks Candidates points			Initializations			After 148 times repetition				
		Candidates points		Errors			Errors			
Χ	Υ	Х	У	Vx	Vy	m _{ai}	VX	Vy	m ai	
2874.7	0	2939.1	107.2	-2.1	-1.2	0.872	-0.2	0	0.902	•
		76.8	1500	-32	-10.3	0.236	0.1	0.1	0.904	
		163.7	1499.6	54.9	-10.7	0.152	87	-0.3	0	
	4075.0	76.8	1509.3	-31.9	-1.1	0.224	0.1	9.4	0	
0	1375.2	163.6	1508.9	54.9	-1.4	0.144	86.9	9	0	
		77.4	1588	-31.3	77.7	0.125	0.7	88.1	0	
		163.4	1587.7	54.6	77.3	0.081	86.7	87.8	0	
2874.8	4250.1	2969	4353.3	-1	-0.6	0.862	-0.1	0	0.905	
		5821.4	1462.3	29	8.6	0.163	0.1	0.1	0.904	0
5749.5 1375.2		5730.9	1462.4	-61.4	8.7	0.18	-90.4	0.2	0	
	40750	5840.5	1462.3	48.2	8.5	0.152	19.2	0.1	0	
	13/5.2	5821.4	1468.3	29.1	14.6	0.159	0.1	6.1	0	
		5731	1469.6	-61.4	15.9	0.175	-90.4	7.4	0	
		5840.5	1468	48.2	14.3	0.149	19.2	5.9	0	
2874.7 13	1075.0	2949.1	1480.8	-1.4	-1.3	0.433	0.2	-0.2	0.898	•
	1375.2	2948.8	1440.6	-1.7	-41.5	0.502	-0.1	-40.5	0	
				R	$MS = \pm 0.20$	08	1			'

Affine transformation parameter:
$$t = \begin{pmatrix} 67.103 \\ 126.021 \end{pmatrix}$$
 $d = \begin{pmatrix} 0.999143 & 0.006973 \\ -0.006556 & 0.999050 \end{pmatrix}$

what bigger. If affine transformation is replaced with similarity transformation, fiducial mark 2 gets null correspondence. It can be seen from Table 4 the error reach 3.5 pixels.

V. CONCLUSIONS

From the formerly descript experiments and other experiments not presented here, some conclusions can be drawn.

(1) Although fiducial marks of P31 camera merge in images

- of objects, their possible position can be extracted with line extraction technique by template matching and Hough transformation.
- (2) Combination optimization technique such as softassign and deterministic annealing can be used to find the unique fiducial marks from several candidates.
- (3) Similarity transformation is more robust than affine transformation to be combined with softassign and deterministic annealing. We suggest that similarity transformation is used to determine the correct correspondence at first. And at last affine transformation is used to determine the relationship of interior orientation for both robustness and precision.

ACKNOWLEDGEMENTS

This research was supported by the National Natural Science Foundation of China (Grand number: 40023004, 40001018). The authors would like thanking Dr. GUO Bingxuan and Dr. HU Xiangyun of

the Laboratory for Information Engineering in Surveying & Mapping and Remote Sensing in Wuhan University for helpful discussions and encouragement.

REFERENCES

- [1] Heipke, Christian, 1997, Automation of interior relative, and absolute orientation, *ISPRS Journal of Photogrammetry & Remote Sensing*, 52:1-19.
- [2] Chui, Haili, A. Rangarajan, 2000, A new algorithm for nonrigid point matching, in *Proceedings, IEEE Conference on Computer Vision and Pattern Recognition*, Volume: 2, pp. 44-51.
- [3] Gold, S. and A. Rangarajan, 1996, A graduated assignment algorithm for graph matching, *IEEE Trans. Patt. Anal. Mach. Intel.*, 18(4):377-388.
- [4] Gold, S. A. Rangarajan, C. P. Lu, S. Pappu, and E. Mjolsness, 1998, New algorithms for 2-D and 3-D point matching: pose estimation and correspondence. *Pattern Recognition*, 31(8):1019 -1031.

Table 4. Effects of transformation type (coordinate in pixels)

Fiducial	Affine	transformati	on	Similarity transformation			
marks	Correspondence		rror	Correspondence	Err	or	
1	1	0.802	-0.14	1	0.086	-0.168	
2	2	-1.098	0.051	Null	-3.546	0.001	
3	8	0.359	-0.063	8	0.046	-0.026	
4	9	-1.098	0.051	9	-0.054	0.087	
5	15	0.796	0.113	15	0.094	0.106	
RMS	± 0.982 pixel			0.107 pixel			
	$t = \begin{pmatrix} 57.905 \\ 138.816 \end{pmatrix} d = \begin{pmatrix} 1.000444 & 0.001518 \\ -0.001368 & 0.999853 \end{pmatrix}$			$t = \begin{pmatrix} 60.538 \\ 138.887 \end{pmatrix} d =$	$ \begin{pmatrix} 0.999837 \\ -0.001383 \end{pmatrix} $	0.001383 0.999837	