A SELF-ADAPTIVE ALGORITHM OF AUTOMATIC INTERIOR ORIENTATION FOR METRIC IMAGES

[1] Wanshou JIANG [2] Guo ZHANG [1] Deren LI

[1] Laboratory for Information Engineering in Surveying, Mapping and Remote Sensing
Wuhan University, #129 Luoyu road, Wuhan, P.R. China
Tel: +86-139-71187089, Fax: 86-27-87863229, E-mail: wsjws@china.com
[2] School of Information Engineering in Remote Sensing, Wuhan University, P.R.China

KEY WORDS: interior orientation, self-adaptive algorithm, softassign, deterministic annealing

ABSTRACT

Automatic interior orientation is one of the key problems in photogrammetric processing of aerial images. In past years, it has been deeply studied, but it is still worth studying, especially when the images with fiducial marks are not good. In this paper, a new self-adaptive algorithm is put forward. It adopts softassign and deterministic annealing technology combined with affine transformation to search fiducial marks in metric images. Even when fiducial marks are not good, the Self-Adaptive Algorithm can still work successfully. Other strategies such as pyramid, automatic determination of searching range are also taken into consideration.

1.INTRODUCTION

Interior orientation is a fundamental problem in photogrammetry. Nowadays, most of the commercial software of DPS will be compelled to apply manual interior orientation if the automatic orientation is failed, which will make the users feel 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 [1]. The pixel coordinate system of the digital image is explicitly given through the matrix of gray values. However, the image coordinate system is only given by the fiducial marks. Therefore, the transformation between pixel and image coordinates by fiducial marks has to be accomplished. 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 found pattern the correct fiducial number.

Listed in Table 1 are several traditional methods of interior orientation [2][3][4][5][6]. In which, interior orientation are divided into three tasks:
1) Approximate positioning of fiducial marks
2) Subpixel positioning of fiducial centers
3) Computation of transformation parameters

Among these tasks, approximate positioning is the most important and the hardest. Gray correlation, binary correlation or other binary image analysis techniques is used in these methods to approximate position of fiducial marks. For the images photographed by RC10, RMK and other aerial cameras, these methods perform well. The fiducial marks of these cameras are distributed on the edges of image. No objects are imaged around the fiducial marks. And so no noise or few noises are assumed in these methods. The target detected by these methods will be only one. And the target is regarded as the fiducial marks wanted.

But in close range photogrammetry, images are photographed with cameras such as P31, UMK etc. The fiducial distribution of P31 is similar to Fig.1, in which the fiducial marks usually merge in the image of objects. Even worse, some parts of the objects (such as a mesh) may have the similar shape as the fiducial marks. Approximate positioning the fiducial marks with these 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 can be very small. In out tests, some are smaller than 0.3. So the orientation of close range photogrammetry remains a problem.

Fortunately, global image matching technique has achieved great successfully. In fact, interior orientation can be regarded as a global matching problem. Firstly we can use gray correlation to find several peaks of correlation coefficient in the predicted searching area. And then determining the fiducial marks from the points of peak is a combination optimization problem. Compared with other image matching problems, searching for the camera fiducial marks is relatively simple, and an affine transformation exists.

There are many algorithms such as genetic algorithm, relaxation algorithm and Hopfield networks, which are usually used to solve combination optimization problem. Relaxation algorithm and Hopfield networks generate local minima and do not usually guarantee that correspondences are one-to-one. Genetic algorithm is time consuming. To overcome these problems, softassign and deterministic annealing technology with affine transformation have been put forward [7][8]. 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 our study, softassign and deterministic annealing are adopted to solve the problem automatic interior orientation.

In order to be more efficient in locating the fiducial marks with less effort, several levels of pyramid images and the original for each patch can be used throughout the template matching processing. The relationship of fiducial marks can be used in determining the searching area of the fiducial marks. When such an area has been determined, we can select several points whose correlation coefficients are locally maximal as candidates of the fiducial marks in the searching area.

Table 1.Methods to automatic interior orientation

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

2.SELF-ADAPTIVE ALGORITHM

Firstly, we demonstrate how we determine the searching area of the fiducial marks by the relationship of fiducial marks in details. Secondly we review affine transformation with an eye toward integrating it with the softassign correspondence engine and deterministic annealing technology proposed by Rangarajan A. et al. [7][8][9]. At last, we develop the full-blown Self-Adaptive Algorithm from the correspondence energy function based on the second step.

2.1 Determining the Searching Area and Candidates

Illustrated in Fig1, 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 determine the searching range of fiducial marks. Suppose the width and height of the rectangle are a and b in mm; the width and height of the image are A, B in pixel. Then for fiducial mark whose coordinates are (x,y), its searching range are:

$$[\frac{A}{2}+\alpha \cdot x - dx, \frac{A}{2}+\alpha \cdot x + dx] \quad for \; x \; direction$$

$$[\frac{B}{2}+\alpha \cdot y - dy, \frac{B}{2}+\alpha \cdot y + dy] \quad for \; y \; direction$$

where.

$$dx = (A - \alpha \cdot a)/2$$
$$dy = (B - \alpha \cdot b)/2$$
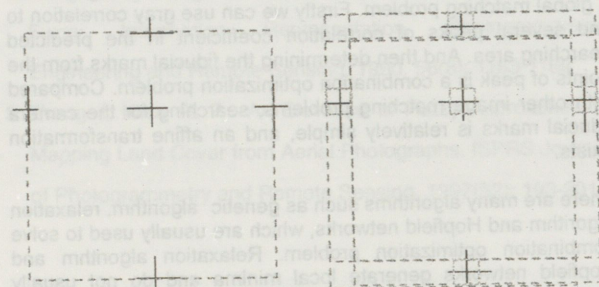$$\alpha \; is \; pixel \; per \; mm$$

Fig.1 Fiducial and image   Fig.2 Searching Range

When the searching areas are determined, we can select several points whose correlation coefficients are locally maximal as candidates of the fiducial marks. And to determine fiducial from the candidates becomes a combination optimization problem.

2.2 Establishment of the Energy Function with Affine Transformation Combining Softassign and Deterministic Annealing Technology

Now the problem is: Given two point-sets {x_i, i=1,2,...,N } and { v_a, a=1,2,...,K}, where {V} denotes the coordinate of fiducial in the image coordinate system and {X} denotes the coordinate of fiducial in the pixel coordinate system. V and X are related by an affine transformation {d, t}. The task is to find the correspondence in the two point-sets. We can define a correspondence matrix {m_{ai}} between the two point-sets at first, such as following:[7][9]

$$m_{ai} = \begin{cases} 1 & if \; point \; x_i \; corresponds \; to \; point \; v_a \\ 0 & otherwise \end{cases}$$

To ensure one-to-one correspondence, each row and each column of M should sum to one. In the case of interior orientation, some candidates have no correspondence. We also put in an extra row and an extra column in M to take care of the outliers so that the row and column summation constraints still work. An example of the correspondence matrix is shown as following: Table 2. Points v_1, v_2 and v_4 correspond to x_1, x_2 and x_3 respectively, and the other points are outliers.

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
v_4	0	0	1	0	0	0
Outlier	0	0	0	1	1	

The energy function with both the correspondence M and the affine transformation (d, t) is the following:

$$E_{2D}(M,d,t) = \sum_{i=1}^{N}\sum_{a=1}^{K} m_{ai}\|x_a - v_a d - t\|^2 + g(d) \quad (1)$$

Subject to $g(d) = \gamma(a^2 + b^2 + c^2)$

Where M always satisfies

$$\sum_{a=1}^{K+1} m_{ai} = 1, \; for \forall_i \in \{1,2,...,N\}$$

and $m_{ai} \in \{0,1\}$.

$$\sum_{i=1}^{N+1} m_{ai} = 1, \; for \forall_a \in \{1,2,...,K\}$$

The v_a is mapped as closely as possible to the x_i by minimizing the first error measurement term. {d} (Composed of four separate parameters { a,Θ,b,c }) is decomposed into scale, rotation, and two components of shear as follows:

$$d = s(A)R(\Theta)Sh_1(b)Sh_2(c)$$

Where

$$s(a) = \begin{pmatrix} e^a & 0 \\ 0 & e^a \end{pmatrix}$$

$$Sh_1(b) = \begin{pmatrix} e^b & 0 \\ 0 & e^b \end{pmatrix}$$

$$Sh_2(c) = \begin{pmatrix} \cosh(c) & \sinh(c) \\ \sinh(c) & \cosh(c) \end{pmatrix}$$

$R(\Theta)$ is the standard 2×2 rotation matrix. $g(d)$ serves to regularize [10] the affine transformation by penalizing large value of the scale and shear components. γ is a constant to adjust regularization effect.

Now the major problem in finding good optimal solutions to the point matching objective (energy function in EQ.1) is to satisfy the two-way constraints, i.e. the row and column constraints on the correspondence matrix together with the constraints that the individual M be either zero or one. Firstly we use deterministic annealing [7][8] methods to turn our discrete problem into a continuous one in order to reduce the chances of getting trapped in local minima. Deterministic annealing is closing related to simulated annealing except that all operations are deterministic. This method consists of minimizing a series of objective function indexed by a control parameter (temperature parameter). As the temperature is decreased the correspondence matrix approaches a permutation matrix. (with binary outlier). An

entropy term $T \sum_{ai} m_{ai} \log m_{ai}$ is added to the energy function to

serve this purpose. The major problem now is the point-matching objective subject to the usual two-way constraints on the matching matrix and the new constraint that the individual entries of M lie in the interval [0,1].

With the deterministic annealing technology, our two-way constraints is that: We are given a set of variables {Q_{ai}} where $Q_{ai} \in R^1$. Then we associate a variable $m_{ai} \in \{0,1\}$ with each

Q_{ai}, such that $\forall_i \sum_{a=1}^{K+1} m_{ai} = 1$ and $\forall_a \sum_{i=1}^{N+1} m_{ai} = 1$. The aim is to find the matrix M that minimizes the following:[7]

$$E(M) = \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai} Q_{ai}$$

This is known as the assignment problem, a classic problem in combinatorial optimization [11]. This problem usually has two good solutions: softmax and softassign. Softassign has clear advantages in accuracy, speed, parallelizabllity and algorithmic simplicity over softmax and a penalty term ($\frac{1.0}{T} \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai}$) in optimization problem with two-way constraints. [12].

Putting everything together, the final energy function that is actually minimized by our algorithm is as follows: [7][9]

$$E(M, d, t) = \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai} \| x_i - v_a d - t \|^2$$
$$+ T \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai} \log m_{ai} - (1.0/T) \sum_{i=1}^{N} \sum_{a=1}^{K} m_{ai} \quad (2)$$
$$+ \lambda trace[(d-I)^T (d-I)] + g(d)$$

Where $m_{ai} \in [0,1]$ satisfies:

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

and

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

Let's briefly go through all the components of the energy function. The first term is just the error measure term .The second term is an $x \log x$ entropy barrier function with the temperature parameter T. The entropy barrier function ensures positivity of M. [7]. The third term with a parameter (1.0/T) is used to guard against null matches. The fourth term is to constrain the affine mapping d by penalizing the residual part .The fourth term is serving to regularize the affine transformation by penalizing large value of the scale and shear components.

2.3 Pseudocode for the Algorithm

The pseudocode for the adaptive algorithm is as follows (using the variables and constants defined below)[7][9]

Initialize d, t, T_0, M, X, V, N, K, T_r

Begin A: Do A until (T>T_f)
  Begin B: Do B until d converges or of iteration >I_0
    Begin C (update correspondence parameters by softassign):

$$Q_{ai} \leftarrow -\frac{\partial E(M, d, t)}{\partial m_{ai}}$$

$$m_{ai} \leftarrow \exp(\frac{Q_{ai}}{T})$$

    Begin D Do D until $\hat{M}$ converges or of iteration > I_1
      Update $\hat{M}$ by normalizing across all rows

$$\hat{m}_{ai}^1 \leftarrow \hat{m}_{ai}^0 / \sum_{i=1}^{N+1} \hat{m}_{ai}^0$$

      Update $\hat{m}$ by normalizing across all columns

$$\hat{m}_{ai}^0 \leftarrow \hat{m}_{ai}^1 / \sum_{a=1}^{K+1} \hat{m}_{ai}^1$$

      End D
    End C
    Begin E (Update pose parameters by coordinate descent)
      Y=MX (calculate current correspondence points)(Pay attention to this)
      Update (d, t) using Least squares for affine transformation with Y and V
    End E
  End B
  $T \leftarrow T * T_r$
End A

Variable and constant definition can be found as following:
X the coordinate of fiducial mark in the pixel coordinate system,
N number of fiducial mark in the pixel coordinate system
V the coordinate of fiducial mark in the image coordinate system
K number of fiducial mark in the image coordinate system
T control parameter of the deterministic annealing method
T_0 initial value of the control parameter T
T_f minimum value of the control parameter T
T_r rate at which the control parameter T decreases (annealing rate)
E (M, d, t) point matching objective function (EQ.(2))
m_{ai} matching matrix variables
Q_{ai} partial derivative of E (M, d, t) with respect to m_{ai}
I_0 Maximum of iterations allowed at each value of the control parameter T
I_1 Maximum of iteration allowed row and column normalizations

The criterion for convergence for step D is

$$\sum_{i=1}^{N} \sum_{a=1}^{K} | m_{ai}^0 - m_{ai}^1 | < \varepsilon_1 , \text{ and } \varepsilon_1 \text{ is a constant close to zero.}$$

The criterion for convergence for step B is $\sum | \nabla d | < \varepsilon_2$, and ε_2 is also a constant close to zero.

3.EXPERIMENTS

3.1 A Real Image Examples

The algorithm is tested on some close-range photographs. These photographs are 6000 pixels×4500 pixels taken by a P31 metric camera. The fiducial marks' distribution is showed in Fig.3. The image window of four fiducial marks of this camera are depicted in Fig.4(a,b,c,d). It can be seen these fiducial marks are not all good. Two of them merge in the objects; one of them is very bad. In this experiment, 12 points (Table 3) are found as candidates of fiducial marks.

The Self-Adaptive Algorithm is set up in the following manner. The T_0 is set so that it is slightly more than twice as long as the longer border of the film to allow all possible matching. T_r (annealing rate) is 0.93. T_f is half of the longer length of the film. The correspondence matrix M is set to zero, and the outliers row and column are endowed with a value proximate to zero, our transformation variables d is a unit matrix and t is zero. The alternating updating of correspondence M and transformation d is repeated for 5 times, which is usually sufficient for convergence after which the temperature (T) decreases with T_r. After T<T_f, the correspondence matrix got is listed in Table 4.

A clean-up heuristic is necessary because the algorithm does not always converge to a permutation matrix. In the test, a very simple heuristic is used. We just set the maximum element in each row to 1 and all others to 0. From table 4, it can be seen that a correct one-to-one correspondence is got with the algorithm.

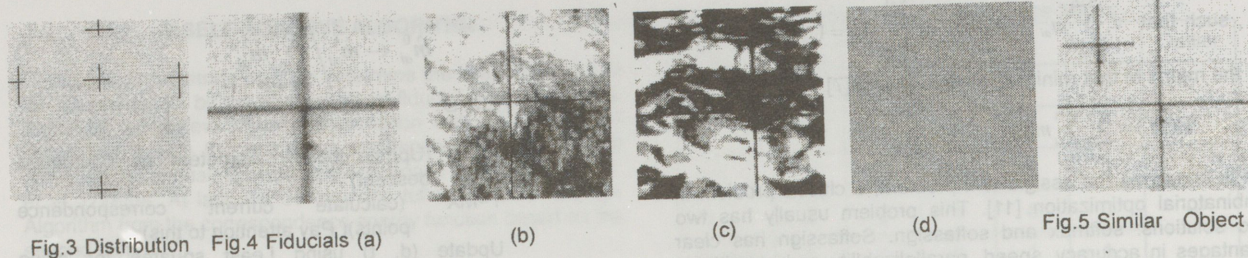### 3.2 Example with Similar Objects Near the Fiducial Mark

Fig.3 Distribution   Fig.4 Fiducials (a)   (b)   (c)   (d)   Fig.5 Similar   Object

Table 3 the candidates of each fiducial mark

Fiducial		X (pixel)	Y (pixel)	Correlation coefficient
1	1	2935	205	0.47895
	2	2935	169	0.42382
	3	2886	205	0.41220
2	4	67	1598	0.55935
	5	68	1655,	0.43236
	6	67	1550	0.41243
3	7	2965	4453	1.00000
	8	2965	4420	0.69096
	9	2965	4508	0.69037
4	10	5817	1560	0.28147
	11	5817	1609	0.22221
	12	5918	1582	0.21994

Fig.4(a) is a good image of fiducial mark. Now one object similar to the fiducial mark is added to generate the image in Fig.5. The new image is used to test the algorithm. The candidates of fiducial mark 3 are listed in Table 5. The point number of added object is 8, whose correlation coefficient is also large. The parameters of the algorithm are set the same as before. After

$T<T_6$, the correspondence matrix is got as listed in Table 6. A correct one-to-one correspondence is got.

Table 5 the candidates of the third fiducial mark

Fiducial		X (pixel)	Y (pixel)	Correlation coefficient
3	7	2965	4453	0.99911
	8	2913	4408	0.99513
	9	2965	4408	0.70765

4. CONCLUSION

The interior orientation becomes much harder when fiducial marks merge in image of objects. The self-adaptive algorithm performs quite well without the usage of correlation coefficient.

ACKNOWLEDGE

Table 4 the correspondence matrix of real image experiment

m_{ai}	1	2	3	4	5	6	7	8	9	10	11	12	Outlier
1	0.463	0.299	0.237	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.482	0.058	0.460	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.499	0.316	0.185	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.551	0.435	0.014	0.000
Outlier	0.537	0.071	0.763	0.518	0.942	0.540	0.501	0.684	0.815	0.499	0.565	0.986	

Table 6 the correspondence matrix of the experiment with outlier

m_{ai}	1	2	3	4	5	6	7	8	9	10	11	12	Outlier
1	0.376	0.298	0.326	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.000	0.000	0.000	0.408	0.184	0.407	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	0.000	0.000	0.000	0.000	0.000	0.000	0.393	0.242	0.365	0.000	0.000	0.000	0.000
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.502	0.372	0.126	0.000
Outlier	0.624	0.702	0.674	0.592	0.816	0.593	0.607	0.758	0.635	0.498	0.623	0.874	

REFERENCES

(1). Zhang Z., Zhang J.. 1996. Digital Photography.   Press of wtusm

(2). Christian Heipke 1997 .Automation of interior , relative , and   absolute   orientation   .ISPRS   Journal   of Photogrammetry & Remote Sensing 52(1997)1-19

(3). Kersten T and Haring T.1995 Automatic interior orientation .Internal report, ETH Zurich

(4). Lue,Y, 1995. Fully operational automatic interior orientation Proceedings   GeoInformatics'95,HongKong,May 26-28,Vol-1,pp.26-35

(5). Schcker.W. 1995. Ein operationelles Verfahren zur automatischen   inneren   orientierung   von luftbildern .Z.Photogramm,fernerkundung,63(3):115-122

(6). Strackbein,H.and   enze,M.,1995.Automatische   innere orientierung.Internal   report   ,Landesvermessungsamt Nordrhein Westfalen

(7). S.Gold, A. Rangarajan, C. P. Lu, S Pappu, and E. Mjolsness. New algorithms for 2-D and 3-D point matching : pose estimation and correspondence . Pattern Recognition, 31(8):1019 1031, 1998

(8). S.Gold, and A. Rangarajan. A graduated assignment algorithm for graph matching. IEEE Trans. Patt. Anal. Mach. Intell., 18(4):377-388,1996.

(9). Haili Chui and Anand Rangarajan 2000 A new algorithm for non-rigid point matching , IEEE Conference on Computer Vision and Pattern Recognition (CVPR),

(10). Girosi, F.,Jones,M.,and Poggio,T.(1995). Regularization theory and neural net work architectures. Neural Computation, 7:219-269

(11). Papadimitriou,   C.   and   Rangarajan,   K.   (1982). Combinatorial Optimization. Prentice-Hall,Inc.,Englewwood Cliffd,NJ.

(12). Gold,S.,Rangarajan,A.(1996).   Softmax to softassign: neural network algorithms for combinatorial optimizations Journal of Artificial Neural Networks, in press