MODEL-BASED AUTONOMOUS INTERIOR ORIENTATION

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ABSTRACT

The model-based approach to autonomous interior orientation is an entirely novel approach. It is driven by the simple structural description that one can build for a fiducial mark. In this research we have focused on recognizing and measuring the fiducial marks automatically. This is motivated by the desire to establish an automation chain in digital photogrammetry, starting with the interior orientation. We benefit from a simple fact that fiducial marks are artificial objects projected onto the film during exposure time. Most every fiducial has a simple, regular shape. This invites us to represent the fiducial marks as a structural description and to detect the structural elements in the image. The CAD design of the fiducial mark and the optical parameters of the projection lens are used to build a geometric model for the fiducial mark. Edge detection is performed to generate image primitives. The Hough Transform is executed over the edge image for identification and approximate localization. Least Squares Adjustment is used for precise localization and the affine transformation is used to compute the transformation parameters. The results of the Hough Transform, represented in the accumulator array, are analyzed via quadratic conic section fitting. The analysis of the fitted conic section renders valuable information regarding the surface complexity in terms of noise and the surrounding structures to the fiducial mark. A fast version of the Hough Transform, for the peak detection, is implemented via histogram peak detection. The developed technique is capable to handle noisy and partially detected or missing information of the fiducial mark. The collected evidence in terms of hypothesis generation, verification, and validation allows us to define a percept sequence to reason about the recognition of the fiducial mark.

1 INTRODUCTION

1.1 Photogrammetric Tasks

The main task of photogrammetry-analog and digital alike-is to reconstruct the object space from images. This reconstruction can be considered as the inverse process of image formation. The latter proceeds from the scene to the image while reconstruction begins with images and ends with a suitable description and representation of the scene. One task of reconstruction deals with determining positions of features in the object space from known quantities in the image space. Before computing positions in the object space, two major tasks must be solved, however. For one we need to determine the exterior orientation of the camera- its position and attitude referenced in the object space. The other prerequisite is the interior orientation, the subject of this study.

Image orientation is a prerequisite for any task involving the computation of three-dimensional coordinates. Image orientation refers to the determination of parameters describing specific photogrammetric models for mapping geometric primitives such as points, lines, and areas from one coordinate system to another. A coordinate system relevant to photogrammetry is the object, the model, the image, and the pixel or stage coordinate system (Heipke, 1997). Due to their importance, image orientation has always been a focus of attention in the photogrammetric community. The interior orientation is the starting point in image orientation.

1.2 Anatomy of a Fiducial Mark

The fiducial marks are located on the upper surface of the inner cone of an aerial camera. They are located either at the four corners of the format opening and/or in the center of the four sides. Fiducial marks are registered onto the film by projecting an image of the mark through a small lens housed inside the cone (Schenk, 1999). Since each fiducial is designed and projected separately, small variations may occur.

Fiducial marks have typical patterns, made up of geometrical structures including straight-line segments, crosses, solid squares and circles, and annulus, see Fig. (1). Most of the structures serve the identification process and lend themselves as suitable candidates for a Hough Transform. The actual fiducial center, whose coordinate is known from camera calibration, is a small disc, just slightly bigger than the measuring mark of the analytical plotter (Schenk, 1999).

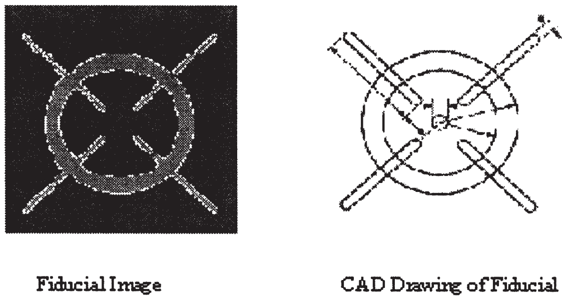

Fig. 1: A portion of a fiducial image and its CAD design provided by the manufacturer.

1.3 Overview of Automatic Interior Orientation

The automation of the interior orientation needs to concentrate primarily on recognizing and measuring the fiducial marks. In general there are many different ways to automatically or semi-automatically locate the fiducials on the digital images, such as manual identification or providing an approximate position of the fiducial and then determine its center by using an automatic mensuration technique e. g. mathematical morphology or fully automatic fiducial identification and mensuration (Lue, 1997). Interior orientation in most existing softcopy workstations requires at least one or two fiducials to be measured manually before the remaining fiducials can be automatically determined. In general, interior orientation is approached as a template-matching problem augmented with least squares matching (Lue, 1997) or with a modified Hough Transform for rough localization (Kersten and Haering, 1997). Also interior orientation is solved via binary correlation with a hierarchical approach for rough localization and gray level correlation for subpixel accuracy (Schickler and Poth, 1996).

In this study, we benefit from the fact that fiducial marks are artificial objects projected onto the film during the exposure time. Based on this fact, the interior orientation problem is approached as a model-based object recognition task utilizing most of the available prior knowledge regarding the fiducials, in terms of providing the CAD design data, their shape, their location, the camera optics e. g. the projection factor of the fiducials and the pixel size of the image. At the identification level the interior orientation is solved as an object-recognition problem, and at the precise localization level it is solved as an ordinary least-squares adjustment problem.

1.4 Objective of Autonomous Interior Orientation

A system is autonomous to the extent that its behavior is determined by its own experience. In the context of this research and our view of digital photogrammetry we are going to use Schenk's (1999) definition of autonomous "as if the process is really 100% automatic and does not require human intervention- sort of a black-box- then the word autonomous can be used to describe the system".

The objective of autonomous interior orientation can be summarized in the following points. The main objective is the identification and approximate localization, subpixel localization of fiducial centers, and computation of the transformation parameters between the pixel coordinate system and the photo coordinate system. Identification includes the task of determining which of the fiducial marks is detected. Subpixel localization is required because the pixel size is most likely larger than the expected precision of the fiducial centers. Another objective is the requirement for a general, fast, accurate, reliable, and robust solution accommodating different types of fiducial marks. A system is general if it can cope with different problems as they may occur in the production environment. A third objective is the system should cope with image resolution where the fiducial centers have been lost; as long as the fiducial mark is still identifiable, the location may be determined from the features that describe the fiducial mark (Seedahmed and Schenk, 2000).

2 MODEL-BASED RECOGNITION OF FIDUCIAL MARKS

The object recognition problem in general, can be defined as a labeling problem based on models of known objects. Formally, given an image containing one or more objects of interest and a set of labels corresponding to a set of models known to the object recognition system, the system should assign correct labels to regions, or a set of regions, in the image.

An object recognition system must have the following components to perform the task: Model-database, feature detector, hypothesizer, and hypothesis verifier (Theodoridis and Koutroumbas, 1999). The model database contains all the models known to the system. The information in the model database depends on the approach used for recognition. It can vary from a qualitative or functional description to precise geometric information. In this study the model database contains information about the CAD design of the fiducial mark, its optical projection factor onto the film, and the pixel size of the image.

3 HOUGH TRANSFORM

The basic idea behind any transform-based features is that an appropriately chosen transform can exploit and remove information redundancies, which usually exist in the set of samples obtained by any measurement techniques. If the transform is suitably chosen, transform domain features can exhibit information-packing properties compared with the original input samples (Theodoridis and Koutroumbas, 1999).

The last few years have seen an increasing use of parameter estimation techniques that use a voting mechanism. One of the most popular voting methods is the Hough Transform (HT). The HT is considered as a parameter estimation strategy based on the statistical mode. More common strategies such as least- squares error fitting are based on the statistical mean. The HT has achieved engineering importance in several areas of image understanding (Brown, 1986), (Leavers, 1992). Since its early formulation, the Hough Transform (Hough, 1962) has undergone intense investigation, which have resulted in several generalizations and a variety of applications. The basic mechanism is a voting scheme in the parameter space. The parameters that receive a higher vote are declared winners, followed by a de-Houghing to find the required curve at the image space using the detected parameters.
In order to gain a basic understanding of HT we will describe the straight-line algorithm. A straight-line in the sense of HT is a set of collinear points, see Fig. (2). The HT is a mapping h from R^2 into the function space defined by:

$$h:(x,y)\rightarrow p = x\cos\theta + y\sin\theta \tag{1}$$

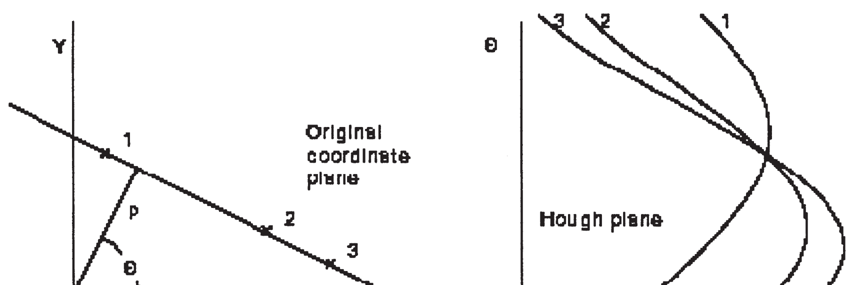

Fig. 2: The polar representation of a line and its Hough space.

The HT takes each of the points (x_i, y_i) to a sinusoidal curve in the (p,θ) plane. The property that the Hough algorithm relies on is that curves that have common intersection points in the (p,θ) plane belong to the same line in the (x,y) plane and they form a peak. This peak should be detected with its associated parameters (p,θ). These parameters are used in a de-Houghing step in order to trace a line associated with these parameters. The polar representation is preferred over the slope-intercept to avoid the difficulties in vertical line detection.

The HT can be implemented easily for any analytic curve by interchanging the role of the observations and parameters. For a circle with a known radius, the observations are the coordinates along the circumference and the parameters are the circle centroid.

4 PRECISE LOCALIZATION

The previous section addresses the problem of identification and approximate localization of analytical curves. With the HT technique we know where it is, but we have not made any effort yet to determine its position as accurately as possible. The success with identifying the major structures of the fiducial mark suggests taking a different approach to determine its center. That is, we compute the center from the structural elements rather than directly from the center pixels. In our implementation we used two concentric circles to indicate the center. The center will be determined by Least Squares adjustment (Schaffrin, 1997). The mathematical model for the two concentric circles is:

$$\begin{aligned} (x_i - x_o)^2 + (y_i - y_o)^2 - R_1 &= e_i \\ (x_j - x_o)^2 + (y_j - y_o)^2 - R_2 &= e_j \end{aligned} \tag{2}$$

where (x_i, y_i) are the pixels on the outer circle with known radius R_1, (x_j, y_j) are the pixels on the inner circle whose radius is R_2, and e_i, e_j are random errors.
The proper handling of the stochastic properties of the model will be via condition equations with parameters. The model of condition equations with parameters states:

$$B_{m+r\times 2(m+r)}(y_{2(m+r)x1} - e_{2(m+r)\times 1}) = A_{m+r\times m}\xi_{m\times 1} \qquad e \sim (0, \sigma_0^2 P^{-1}) \tag{3}$$

with rank (A) ≤ min (m+r, m)=m.

- B: this matrix contains the partial derivatives with respect to the observations.
- y: the observed pixel coordinates.
- e: the true error vector.
- A: this matrix contains the partial derivatives with respect to unknown parameters.
- ξ: the vector of the true unknown parameters (fiducial center).
- P: weight matrix of the observations.

For the above-mentioned stochastic model we need to introduce an estimation based on geometric or stochastic approach, such as least-squares adjustment to find an estimate for the unknown parameters.

5 ALGORITHM

Before the identification of the fiducial marks (FM), image patches of reasonable size that contains the FMs are extracted using a priori knowledge about their expected locations in the image, see Fig. (3). The process starts by running an edge operator over the image patches, e.g., Canny's edge algorithm with its associated parameters. For our experiments we use aerial photographs acquired by *Wild RC10*. Since the circular elements of the FMs are unique compared to their linear elements, the Hough space for the two circles using their known radii is generated first. After generating the Hough space for the two circles, a peak detection process is performed for the identification and an approximate localization, and then this step is followed by a de-Houghing to trace the pixels which belong to each circle in the edge image. Simply substituting the parameters of each circle in their corresponding equation does the tracing, and every pixel in the edge image satisfying these equations will be reported as a potential pixel candidate. Based on the detected FM centers, a window is opened in the edge image to restrict the search area for linear structural elements of the fiducials. The Hough space is generated for the linear elements followed by peak detection and pixel tracing. Since the linear elements are known with specified orientation, the peak search in its Hough space is restricted to a predetermined range of orientation, namely, 35-55 degrees. and 125-145 degrees. The linear elements of the fiducials support only the identification process and not the precise localization of the FM. Precise localization of the fiducial centers is based on least-squares adjustment using the two radii and the pixels along the circumferences of the two circles as observations.

When two fiducial marks have been successfully recognized, a similarity transformation can be performed to establish an approximate relationship between the pixel coordinates and the camera coordinates. This approximate transformation is generally very helpful in defining the search area for the third fiducial if we have a difficulty in its identification using the HT. By using the similarity transformation with the developed techniques we benefit from the available strategies to come up with an intelligent solution.

The peak searching in the Hough space is implemented via histogram searching, and this casts the HT as a fast version in terms of peak detection. Also the histogram provides an elegant mechanism of multiple peak detection without any further search. The histogram memory allocation is determined during the run time based on the expected feature size.

6 EXPERIMENTS

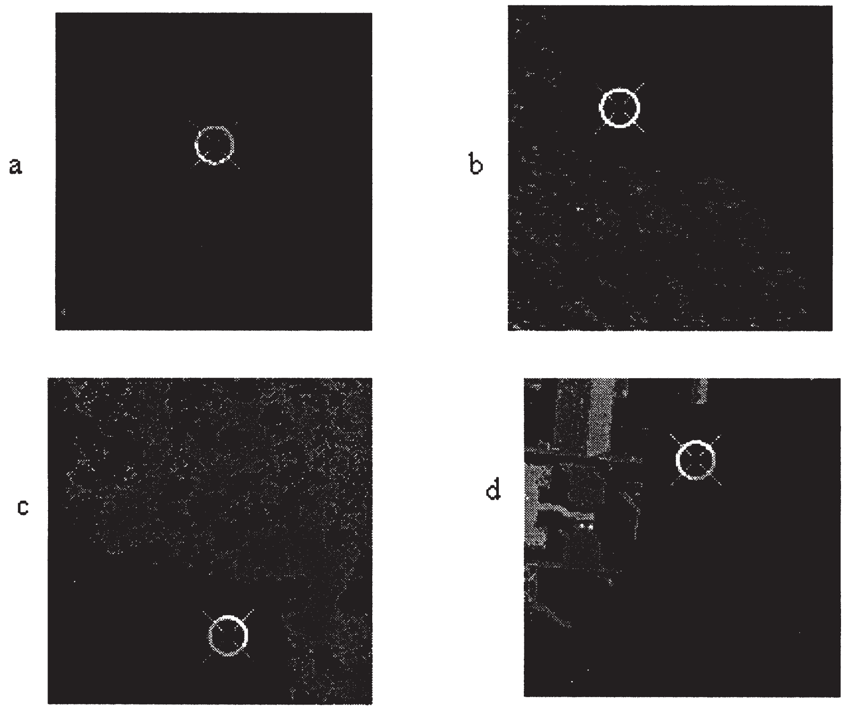

Fig. 3: a, b, c, and d are fiducial patches belong to the upper left corner (UL), upper right (UR), lower left (LL) and lower right lower (LR) corners of 8k x8k image.

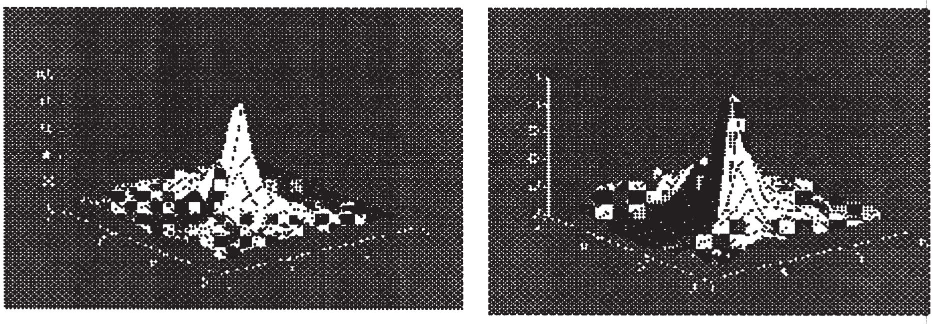

Fig. 4: The detected peaks for the Inner and Outer Circles respectively.

Location	Radius in pixels	i_center	j_center	Traced Perimeter	Analytical Perimeter	Success
UL	Inner 26	214	258	156	163.38	Yes.
UL	Outer 33	214	257	198	207.37	Yes.
LL	Inner 26	405	284	158	163.38	Yes.
LL	Outer 33	405	284	185	207.37	Yes.
UR	Inner 26	162	177	127	163.38	Yes.
UR	Outer 33	162	177	183	207.37	Yes.
LR	Inner 26	132	280	143	163.38	Yes.
LR	Outer 33	132	279	203	207.37	Yes.

Table 1:The results of HT for the FM with their pixel tracing.

Results of Precise Localization:

UL

j=257.245 i=213.872
Dispersion Matrix:
$$\begin{bmatrix} 0.002 & -1.1e-5 \\ -1.1e-5 & 0.002 \end{bmatrix}$$
Redundancy=352
$\sigma_o^2 = 0.356$

UR

j=176.974 i=161.98
Dispersion Matrix:
$$\begin{bmatrix} 0.003 & 4.5e-5 \\ 4.5e-5 & 0.003 \end{bmatrix}$$
Redundancy=308
$\sigma_o^2 = 0.551$

LL

j=284.007 i=405.034
Dispersion Matrix:
$$\begin{bmatrix} 0.003 & 4.5e-5 \\ 4.5e-5 & 0.003 \end{bmatrix}$$
Redundancy=341
$\sigma_o^2 = 0.486$

LR

j=279.362 i=132.275
Dispersion Matrix:
$$\begin{bmatrix} 0.002 & 1.0e-5 \\ 1.0e-5 & 0.002 \end{bmatrix}$$
Redundancy=344
$\sigma_o^2 = 0.342$

The identified and precisely localized FM are used with their calibrated FM to determine the affine transformation parameters, which relate the pixel, coordinates with the photo coordinates. The affine transformation can be represented by:

$$\begin{aligned} X_{Pixel} &= a_1 + b_1 X_{Calibrated} + c_1 Y_{Calibrated} + e_x \\ Y_{Pixel} &= a_2 + b_2 X_{Calibrated} + c_2 Y_{Calibrated} + e_y \end{aligned} \quad (4)$$

The above representation of the affine transformation will allow treating the calibrated FM as error free observations, and the stochastic property of the model can be handled via Gauss-Markov model.

Calibrated Fiducial Coordinates in mm are:
[x=-105.993, y=106.00], [x=-106.001,y=-106.008], [x=106.006,y=-106.008], [x=106.016,y=105.997].

The Transformation Parameters are:
a_1=4267.915 b_1=35.706 c_1= -0.2471.
a_2=4173.123 b_2= -0.2471 c_2= -35.709

Residuals in Pixel:
[Rx=0.1897,Ry=-0.1918],[Rx=-0.1897,Ry=0.1918],[Rx=0.1897,Ry=-0.1918],[Rx=-.1897,Ry=0.1918].

The estimated variance component is:
$\sigma_o^2 = 0.1456$

7 HOUGH SPACE ANALYSIS

The Hough space is analyzed via a quadratic surface. This surface is centered at the detected peak in the Hough space, see Fig. (4). After determining the coefficients of the surface much valuable information can derived from this surface, like translation, rotation, and stationary point classification (Strang, 1988), (Leon, 1998). The quadratic surface equation is:

$$F(i,j) = k_1 + k_2 i + k_3 j + k_4 i^2 + k_5 ij + k_6 j^2 \tag{5}$$

The computed coefficients of this surface render valuable information in the following format:

- This surface has been translated vertically from the standard position if the coefficients of i^2 and i are both nonzero.
- This surface has been translated horizontally from the standard position if the coefficients of j^2 and j are both nonzero.
- This surface has been rotated from the standard position by an angle θ that is not a multiple of 90° when the coefficient of ij is not zero.
- By computing the first and the second derivative of the surface we can build the Hessian matrix, from which we can compute the eigenvalues (λ_1, λ_2). The eigenvalues can be used to classify the surface at the critical points e.g. the origin.

Circle	K_1	K_2	K_3	K_4	K_5	K_6	Orient	λ_1	λ_1	SurDsp
Inner	9.08	-.0369	.374	-.0093	.0042	.001	-11.1°	-.0196	.0029	Saddle
Outer	10.63	.0135	-.693	-.020	-.0004	-.0328	178.8°	-.0418	-.0658	Max

Table 2: Surface parameters and its derived properties for UL FM of the 8k x 8k image.

Circle	K_1	K_2	K_3	K_4	K_5	K_6	Orient	λ_1	λ_1	SurDsp
Inner	8.08	.025	.354	.0004	.0027	.042	1.844°	.0009	.0853	Min
Outer	10.147	-.069	-.6235	-.0129	-.0086	-.040	171.1°	-.0245	-.0817	Max

Table 3: Surface parameters and its derived properties for LL FM of the 8k x 8k image.

Circle	K_1	K_2	K_3	K_4	K_5	K_6	Orient	λ_1	λ_1	SurDsp
Inner	8.194	.0064	.300	.0105	.00605	.0169	111.8°	.0187	.0362	Min
Outer	10.364	.0319	-.6016	-.0226	-.0030	-.0359	186.4°	-.0450	-.0721	Max

Table 4: Surface parameters and its derived properties for UR FM of the 8k x 8k image.

Circle	K_1	K_2	K_3	K_4	K_5	K_6	Orient	λ_1	λ_1	SurDsp
Inner	8.3	.0247	.348	-.0005	-.0029	.0218	3.8°	-.0014	.0439	Sadlle
Outer	10.56	-.107	-.586	-.021	-.0023	-.0377	176.1°	-0418	-.0757	Max

Table 5: Surface parameters and its derived properties for RL FM of the 8k x 8k image.

8 ANALYSIS AND DISCUSSION

The proposed algorithm is tested over three images scanned at three different resolutions of 2k, 8k, and 18k (pixel size 111.05 μm, 27.37 μm, and 12.56 μm). The algorithm is successfully identifying and localize the FM at the three different resolutions. The 2k resolution is too coarse to detect the structural elements of the FM. At the 8k and 18k resolutions the precise localization of the fiducial mark yields an accuracy of $1/20^{th}$ and $1/30^{th}$ of the pixel size respectively. This excellent accuracy is obtained because all the pixels that have been identified as structural elements of the FM contribute to the precise localization. The precise localization at the 18k moves the precision from sub-pixel to sub-micron. Since the end product of the interior orientation is the transformation parameters between the pixel coordinates and the photo coordinates, the results of the proposed algorithm and the calibrated fiducial marks are successfully determine these parameters with a variance component corresponding to 0.15 of the pixel size.

The Hough space analysis via quadratic conic section renders valuable information in terms of surface properties. For instance, the shift parameters generated from different fiducial marks, which belong to the same image, reflect the similarity of the fiducial marks structures. Also the orientation of the surface and the eigenvalues of the Hessian matrix reflect the surface complexity. For the orientation part, deviation from multiple of 90° reflect the complexity in terms of missing edge information, noise effects, and/or the contribution from the surrounding structures to the fiducial mark, see tables (2), (3), (4) and (5).

The hypothesis of the fiducial mark consists of many features, which can be realized, in a unary and binary constraints. The two centroids define a binary constraint, see table (1). Pairs of lines with 45° and 135° define unary and binary constraints. Also the shift parameters (K_1) resulted from the conic section fitting they can define a measure of similarity between the fiducial structures which can be considered as a global constraint, see tables (2), (3), (4) and (5). For a detailed discussion see (Seedahmed and Schenk, 2000).

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