EVOLUTION OF NETWORK ORIENTATION PROCEDURES

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ABSTRACT:

This paper discusses the evolution of algorithms and procedures for network orientation that have accompanied the transition of close-range photogrammetry from a film-based to a digital image-based measurement process suited to partial or full automation. A brief mathematical background to orientation models derived via perspective projection and projective geometry is first presented, and the issue of generating initial values for image orientation parameters is discussed. The potential for employing linear models from projective geometry in the orientation process is also considered. Developments over the past few decades in multi-image network orientation processes are then reviewed, with the current state of the art being indicated by way of the discussion.

1. INTRODUCTION

Digital cameras have had a profound impact upon close-range photogrammetry, not just in terms of CCD cameras replacing metric film cameras. To varying degrees, virtually all off-the-shelf digital cameras can be considered metric. Unmodified SLR-type models can yield 3D measurement accuracy to better than 1:50,000 and now form the data acquisition component of some automated vision metrology systems. Moreover, inexpensive consumer-grade cameras can be employed for a host of lower accuracy multi-image photogrammetric measurement tasks, which may involve either manual image measurement and step-wise data processing, or fully automatic operation in instances where special targetting strategies are adopted. While the photogrammetric community has readily adapted so as to make full use of digital imaging technology, it nevertheless still relies on well-proven mathematical models, the last significant innovations in this area being the bundle adjustment in late 1950s and the concept of camera self-calibration in the early 1970s.

The two underlying models for photogrammetric orientation remain the well-known collinearity and coplanarity models, which form the basis of relative, absolute and exterior orientation. Both are non-linear and initial or 'starting' values are required for the iterative least-squares solution of the parameters. The requirement to determine these starting values has had a considerable influence upon network orientation in close-range photogrammetry. As most photogrammetric triangulation projects culminate in a bundle adjustment, it could be said that the evolution within network orientation has primarily been a story of evolving algorithms and procedures to optimise the automated recovery of the initial values of exterior orientation and object point coordinates, and occasionally interior orientation (IO) parameters as well.

Along with photogrammetry, the disciplines of machine vision and computer vision (CV) maintain a keen interest in 3D scene reconstruction from digital imagery. The models employed in CV are primarily based on projective geometry and they typically do not emphasise rigorous Euclidian reconstruction. Linear models are preferred, in spite of the questionable computational stability and reliability of their application to other than 'ideal' stereo vision geometry (i.e. low or no convergence and a small base/depth ratio). One motivation for direct, linear orientation models is that they circumvent the need to provide initial values for the orientation parameters.

This paper reviews the evolution in algorithms and procedures for close-range photogrammetric network orientation. A brief mathematical background to orientation models based on perspective projection and projective geometry is first offered. This is followed by a review of the different network orientation scenarios that have been employed over the past 25 years, i.e. in the period of development of stand-alone measurement systems designed for a broad range of applications. The potential role of projective geometry models for determining initial values of image orientation parameters is also considered. This paper, which is a modified version of Fraser (2005), also reports on the state of the art in close-range photogrammetry and vision metrology, which is represented by systems ranging from fully automatic to those with on-line orientation to support manual measurement of images recorded with off-the-shelf digital cameras.

2. MATHEMATICAL BACKGROUND

2.1 Collinearity Model

Taking into account that all image points lie within the focal plane and corrections are required to image coordinates for principal point offset and lens distortion, the 7-parameter similarity transformation between the Cartesian image (x, y, z) and object (X, Y, Z) spaces can be recast to the well-known perspective projection form as:

$$\begin{pmatrix} x - x_p + dx \\ y - y_p + dy \\ -c \end{pmatrix} = \lambda R \begin{pmatrix} X - X^c \\ Y - Y^c \\ Z - Z^c \end{pmatrix} = \lambda \begin{pmatrix} X' \\ Y' \\ Z' \end{pmatrix} \quad (1)$$

where λ is a scale factor, c the principal distance and x_p, y_p the coordinates of the principal point. The rotation matrix R is formed as the product of three rotations, identified here as azimuth α, elevation ε and roll κ, and the translation terms X^c, Y^c and Z^c are with respect to the object space system. The terms dx and dy represent the corrections for so-called departures from collinearity, with the principal perturbation to image coordinates being radial lens distortion.

The CV community employs projective geometry, where Eq. 1 can be recast into the following model:

$$\frac{1}{\lambda}\begin{pmatrix}1 & 0 & -x_p\\ 0 & 1 & -y_p\\ 0 & 0 & -c\end{pmatrix}\begin{pmatrix}x\\ y\\ 1\end{pmatrix} = R\begin{pmatrix}1 & 0 & 0 & -X^c\\ 0 & 1 & 0 & -Y^c\\ 0 & 0 & 1 & -Z^c\end{pmatrix}\begin{pmatrix}X\\ Y\\ Z\\ 1\end{pmatrix} \tag{2}$$

or

$$\frac{1}{\lambda}C\begin{pmatrix}x\\ y\\ 1\end{pmatrix} = P\begin{pmatrix}X\\ Y\\ Z\\ 1\end{pmatrix} \tag{3}$$

Here, the 3x4 matrix P is termed the projection matrix and C the 'calibration' matrix, even though it typically does not take into account the lens distortion corrections represented by dx and dy. There is no distinction between the homogenous representation of Eq. 2 and the formulation of Eq.1, except for the lens distortion corrections being absent from the second expression. However, there is a marked distinction between the CV and photogrammetric approaches to solving the image-to-object space transformation.

Starting with the photogrammetric approach, a simple division of the first and second rows of Eq. 1 by the third gives rise to the well-known collinearity equations

$$\begin{pmatrix} x - x_p + dx + c\,X'/Z' \\ y - y_p + dy + cY'/Z' \end{pmatrix} = 0 \tag{4}$$

The solution of the non-linear equation system generated by bundles of intersecting rays from multiple images is via a linear least-squares approach, which requires linearization of Eq. 4 to the general form of the photogrammetric bundle adjustment:

$$-v + A_1\delta_1 + A_2\delta_2 + A_3\delta_3 + w = 0 \tag{5}$$

Here, v is the vector of observational residuals (residuals in image coordinate measurements); A_i are matrices of partial derivatives; w is a discrepancy vector and δ_1, δ_2 and δ_3 comprise the corrections to starting values for the six exterior orientation parameters (α, ε, κ, X^c, Y^c, Z^c), three object point coordinates (X, Y, Z) and the camera calibration parameters. It is not the intention here to develop the bundle adjustment formulation any further, as the reader can find this in modern textbooks on photogrammetry (e.g. Luhmann et al., 2006; Krauss, 2000; Mikhail et al., 2001). Important to this discussion is, firstly, that the solution to Eq. 5 is rigorous in a functional and stochastic sense (it is a maximum likelihood solution) and, secondly, that in order to recover estimates for δ_i, appropriate starting values for the parameters are required. The initial values related to δ_1 and δ_2 will be termed $\underline{O}$ and $\underline{X}$, where

$$\underline{O} = (\alpha_1^0, \varepsilon_1^0, \kappa_1^0, X_1^{c0}, Y_1^{c0}, Z_1^{c0}, ..., Y_m^{c0}, Z_m^{c0})^T$$

and

$$\underline{X} = (X_1^0, Y_1^0, Z_1^0, ..., X_n^0, Y_n^0, Z_n^0)^T$$

for the m images and n points. Of the self-calibration parameters in δ_3, generally only the principal distance requires an initial value other than zero for frame-centred image coordinates.

Practical solutions for Eq. 5 require an efficient means to determine starting values. As will be discussed later, the most common approach has traditionally involved separately solving for δ_1 and δ_2. Under the assumption that a given number of 'control points' (known in XYZ) are available, δ_2 and δ_3 can be suppressed and δ_1 is solved image by image in a series of spatial resections. Having determined the image orientation, δ_1 and δ_3 are suppressed and δ_2 is solved by spatial intersection. With the initial values $\underline{O}$ and $\underline{X}$ in place, a full self-calibrating bundle adjustment solution follows.

The requirement to determine initial values has been viewed outside the photogrammetric community as an impediment to the adoption of rigorous (non-linear) orientation models. This has also been the case with both the explicit requirement for image coordinates referenced to the nominal principal point, and the implicit necessity of accounting for calibration corrections such as lens distortion. Projective geometry formulations, as represented by Eq. 2, have thus appeared as potential alternatives because they can be solved in a linear manner. This assumes that the elements p_{ij} of the projection matrix P are linearly independent, which of course they cannot be if the equivalence of Eqs. 1 and 2 is to hold true. The first proposed linear orientation model, which predated early developments in CV approaches by a decade, was the well-known direct linear transformation (DLT) which was introduced to close-range photogrammetry by Abdel-Aziz & Karara (1971). The DLT modelled the projective geometry relationship between image coordinates (x', y') of arbitrary scale, orientation and origin, and object space coordinates.

Exterior orientation via the DLT is generally a two-step process, equivalent to spatial resection followed by intersection, though a 'bundle adjustment' formulation is possible. Of the 11 parameters involved, only 9 are independent. Difficulties can therefore be expected with certain configurations of camera stations and object points, the most obvious being that the DLT will not accommodate planar or near planar object point arrays. As a consequence of the two non-linear constraints implicit in its formulation being ignored, the DLT has a tendency to be numerically unstable, especially in situations of low observational redundancy, say with 10 or fewer 'known' object points; a minimum of 6 is required. The DLT can accommodate calibration corrections dx and dy, but only where 'true' image coordinates (x, y) are employed, rather than (x', y').

2.2 Coplanarity Model

A second fundamental mathematical model, which has long been the basis of relative orientation (RO) in stereo photogrammetry, is the coplanarity model. This states that the two intersecting rays to an object point from two images must lie in a single plane, the epipolar plane, which also includes the baseline vector between the two perspective centres. The coplanarity condition can again be formulated using Eq. 1, for the case of one image being relatively oriented to a second, as

$$u_1^T\begin{pmatrix}0 & bz & -by\\ -bz & 0 & bx\\ by & -bx & 0\end{pmatrix}R_2^T u_2 = 0 \tag{6}$$

where

$$u_i = \begin{pmatrix} x_i - x_p + dx & y_i - y_p + dy & -c\end{pmatrix}^T$$

Here, the matrix R_2 describes the rotation of the second image with respect to the first and by and bz are translations. The translation bx, which lies in the base line, can be assigned an arbitrary value since scale cannot be recovered from the model. Note also that object coordinates do not explicitly appear.

The coplanarity condition, Eq. 6, can also be recast into homogeneous form, along the same lines as Eq. 2:

$$\begin{pmatrix} x_1 & y_1 & 1 \end{pmatrix} C^T K R_2^T C \begin{pmatrix} x_2 \\ y_2 \\ 1 \end{pmatrix} = 0 \tag{7}$$

where *K* represents the skew-symmetric matrix of Eq. 6 and *C* is again the calibration matrix (without consideration of *dx* or *dy*). Further substitution for matrix products leads to

$$\begin{pmatrix} x_1 & y_1 & 1 \end{pmatrix} C^T E C \begin{pmatrix} x_2 \\ y_2 \\ 1 \end{pmatrix} = 0 \tag{8}$$

and

$$\begin{pmatrix} x_1 & y_1 & 1 \end{pmatrix} F \begin{pmatrix} x_2 \\ y_2 \\ 1 \end{pmatrix} = 0 \tag{9}$$

where *E* is called the essential matrix, and *F* the fundamental matrix. The distinction between them is the assumption that the IO is known for the essential matrix expression (Hartley & Zisserman, 2000; Faugeras & Luong, 2001). The non-iterative algorithm for relative orientation (RO) via the essential matrix, which is widely used in CV, has been attributed to Longuet-Higgins (1981). However, it had already been known to photogrammetrists for at least two decades, as illustrated by Thompson (1959) and Stefanovic (1972).

Once again, the projective geometry models for RO, which centre upon the essential and fundamental matrices, are equivalent to the coplanarity condition, at least when the lens distortion corrections *dx* and *dy* are ignored. However, the solution of Eq. 8 by linear methods, which assume that the elements comprising *E* and *F* are independent, is not at all the same as solving Eq. 6 via a linearized Gauss-Markov model. The linear solution for the three rotations and two translations of RO via the essential matrix, which is more appropriate in a photogrammetric context than the fundamental matrix, is generally a two-step process. The elements e_{ij} of *E* are first solved via the expression

$$A\underline{e} = 0 \tag{10}$$

where

$$A_i = \begin{pmatrix} x_1 x_2 & y_1 x_2 & x_2 & x_1 y_2 & y_1 y_2 & y_2 & x_1 & y_1 & 1 \end{pmatrix}_i$$

and

$$\underline{e} = (e_{11}, e_{12}, e_{13}, e_{21}, e_{22}, e_{23}, e_{31}, e_{32}, e_{33})^T$$

after which *E* is decomposed into its constituent component matrices *K* and R_2.

In much the same way as was previously described for the collinearity equations, the linear least-squares model for the coplanarity condition is given as (Mikhail et al., 2001):

$$Bv + A\delta + w = 0 \tag{11}$$

where *A* and *B* are matrices of partial derivatives with respect to the parameters and image coordinates, respectively; *v* and *w* are as previously defined for Eq. 5; and δ is the vector of corrections to the initial values for the two translations and three rotation angles, taken this time as ω, φ, κ. These initial values are represented by the vector $\underline{\Delta}$:

$$\underline{\Delta} = (\omega^0, \varphi^0, \kappa^0, by^0, bz^0)^T \tag{12}$$

For convergent imaging configurations with arbitrary image orientation (e.g. images orthogonally rotated), determination of appropriate initial values $\underline{\Delta}$ can be very challenging, hence the appeal of linear models such as Eq.10. One can read not only of the recovery of RO parameters from a stereo pair of images via the projective geometry approach, but also of the simultaneous determination of certain IO elements, for example the focal lengths associated with each image. Photogrammetrists would state that this is not feasible, at least in practical and metric terms, in spite of the elegance of the mathematics involved in deriving the solutions for *E* and *F* and subsequently decomposing these matrices to determine the projection matrix *P* in Eq. 2. However, it is widely recognised that 'noisy' data, ie redundant observations and real measurements, can lead to numerically unstable solutions for *E* and *F*, and consequently to unreliable results.

In the two-step solution process for the projection matrix *P*, *E* (or *F*) is typically determined through either a homogenous linear equation solution with normalised coordinates for the 8 or more points involved (Hartley, 1997) or a singular value decomposition (SVD). A RANSAC approach (Fischler & Bolles, 1981) can also be employed in cases where there are many corresponding point pairs available. The rotation matrix and translations are then recovered via SVD (Hartley, 1992), which for the essential matrix of Rank 2 should in theory yield two equal singular values and a third which is zero.

The projective geometry approaches to RO are considered in this discussion not because they present a potential alternative to the coplanarity model, but more because they might appear to offer possible practical approaches to the determination of initial values $\underline{\Delta}$, $\underline{O}$ and $\underline{X}$. The implementation of such an approach has been reported by Roth (2004). One must keep in mind, however, the difficulties associated with the reliable recovery of RO via projective geometry models in cases of 'difficult' (eg highly convergent) imaging geometry. Moreover, like the DLT, these approaches do not work in instances of a near planar array of object points and they can yield ambiguous solutions. The words of Horn (1990a) are worth recalling here: "Overall, it seems that the two-step approach to RO, where one first determines an essential matrix, is the source of both limitations and confusion". Alternative RO algorithms employing closed-form initial parameter determination are available (e.g. Horn 1990b).

The foregoing mathematical background provides an insight into the developments in network orientation for close-range photogrammetry over the past three decades. The common endpoint of the orientation process for metric applications is - and should be - the bundle adjustment model of Eq. 5. Critical to its implementation, however, is the generation of initial values. This aspect has greatly influenced the practical development of close-range photogrammetric systems, especially since the emergence of digital cameras and process automation.

3. NETWORK ORIENTATION SCENARIOS

3.1 Range of Camera Station Configurations

Shown in Figs. 1 to 3 are examples of camera station configurations encountered in close-range photogrammetry. The first exemplifies a mix of 'stereo', implying low convergence or near parallel optical axes, and convergent geometry. A typical multi-station convergent configuration, exemplifying strong network geometry, is shown in Fig. 2. Finally, Fig. 3 represents a photogrammetrically challenging network geometry where the camera stations and most object points are near to being in a single plane. This configuration is very representative of those encountered in traffic accident reconstruction, which is a fast growing application area for digital close-range photogrammetry (Fraser et al., 2005). Reference will be made to these network configurations in the following discussion.

3.2 The Traditional Approach

As analytical photogrammetry evolved, the 'traditional' orientation scenario of analog stereo restitution remained popular. This was a two-step process, appropriate for two-image configurations:

Manual image measurement
↓
Relative Orientation
↓
Absolute Orientation

The RO was via the coplanarity model (Eq. 6) or, less frequently, the collinearity model (Eq. 4). The absolute orientation (AO) was performed with a 3D similarity transformation. Thus, the first issue typically concerned how to determine initial values $\underline{\Delta}$. This is relatively straightforward for stereo geometry. Although certain constraints apply to the degree of convergence between the camera axes, two rotations can be assigned an initial value of zero, and the relative rotation about the optical axis can be estimated from the image point distribution. The initial values for *bx* and *bz* translations are most often taken as zero. For AO, closed-form and quasi least-squares solutions for 3D similarity transformation are well known, and thus computing rigorous AO via a linear least-squares solution does not pose any practical difficulties.

3.3 Early Days with Multi-Image Networks

Given that the approach above was effectively limited to stereo pairs, and that stereo geometry is not optimal from an accuracy standpoint, an alternative was sought to accommodate the convergent multi-image geometry shown in Fig. 2. This gave rise to a second orientation scenario, as follows:

Manual or automatic image point measurement
↓
Resection
↓
Spatial intersection
↓
Bundle adjustment
↓
(Absolute orientation)

A number of object points (minimum of 4) were assigned preliminary XYZ coordinates (measured or arbitrary), and from these, two or more images could be resected via closed-form resection (e.g. Fischler & Bolles, 1981). Thus, $\underline{O}$ was established for these images. Spatial intersection would follow to provide the XYZ coordinates of object points ($\underline{X}$). From the new object point coordinates, further images were resected and further points intersected, until initial values were established for all parameters. Bundle adjustment then followed to refine the approximate values. This process suited the sequential, monoscopic measurement of images, yet it had two main drawbacks – which were not viewed as such at the time. These were that initial XYZ coordinate values for at least 4 points were needed and a careful labelling of image points was required to ensure correct correspondences between images.

This approach was not optimal for all situations, as seen in Fig. 3, where not only would the geometry pose difficulties for resection, but many cycles of resection/intersection would be required to determine all initial values for $\underline{O}$ and $\underline{X}$. Nevertheless, the approach was adopted in the 80s for industrial photogrammetry systems, and it remains in common use today.

At the same time the CV community were engaged in popularising the essential matrix approach, albeit two images at a time. Why, one might ask, were the methods of photogrammetric orientation not adopted in CV? Of the no doubt many contributing factors, five come to mind:

- There was no desire whatever to get involved with manual point labelling; correspondences were to be determined automatically, with a percentage of these accepted as being potentially erroneous.
- The need to assign object point coordinates and determine initial values was to be avoided.
- There was a preference to work with pixel coordinates and to ignore lens calibration.
- Metrically accurate results were not being sought.
- Because of the wide use of zoom lenses, prior estimates of focal length might not be known.

Nevertheless, some developments in CV were curious given the then state of the art in photogrammetry. For example, the camera calibration approach of Tsai (1987) requires not only the provision of an object point array with known XYZ coordinates, but also a multi-stage process involving closed-form solutions and initial value generation for iterative non-linear optimization. Moreover, there were different requirements relating to planar and non-planar 3D object point arrays. At the time, a fully rigorous single or multi-camera self-calibration could be obtained with much less effort and much greater model fidelity and accuracy via a self-calibrating bundle adjustment, Eq. 5.

3.4 The Exterior Orientation Device and Coded Targets

The introduction of digital cameras opened the door to full automation of the exterior orientation (EO) process. Images could be scanned for targets, and after initial resection (computation of $\underline{O}$), a correspondence determination based on, say, epipolar constraints or spatial intersection criteria could be employed to provide initial values for object point coordinates. To facilitate the initial resection, the EO device was introduced (e.g. Ganci & Handley, 1998; Fraser, 1997). The EO device, examples of which are shown in Fig. 4, is a pattern of targets of known 3D coordinates, which is automatically detected and recognized within an image. The scenario for orientation then follows that of the previous section, except that the sequence is automatic.

After resection for the images that 'see' the EO device, intersection follows to determine initial values $\underline{X}$ of object point coordinates. What happens with images in which the EO device does not appear? This is where coded targets come in. These were first proposed for close-range photogrammetry in the late 1980s.

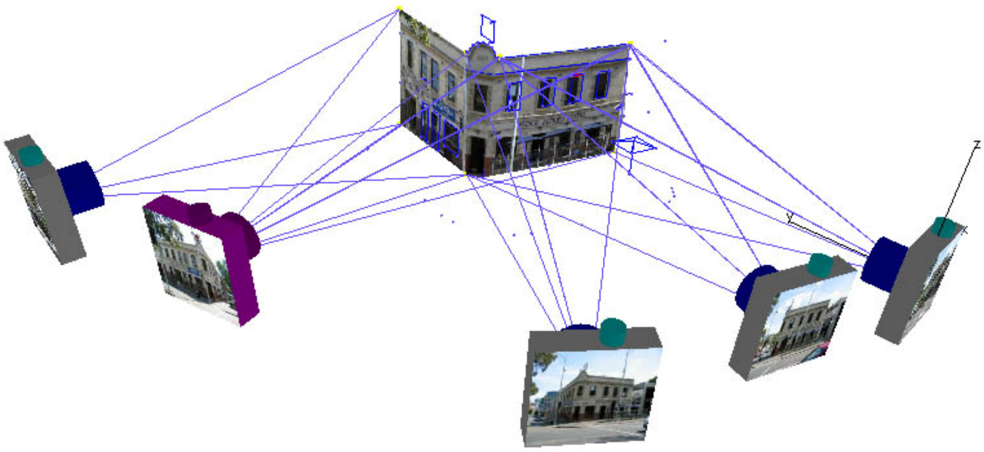

Figure 1: Mixed stereo and convergent image geometry.

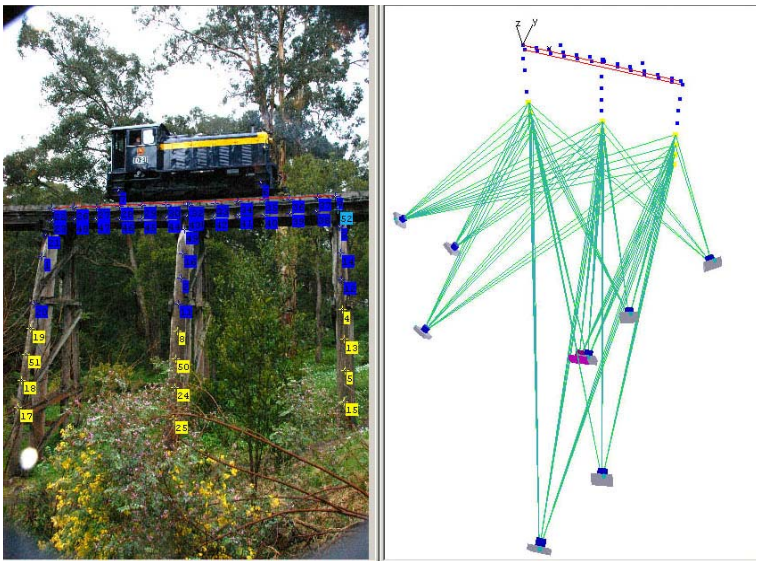

Figure 2: Convergent multi-image network and near-planar array.

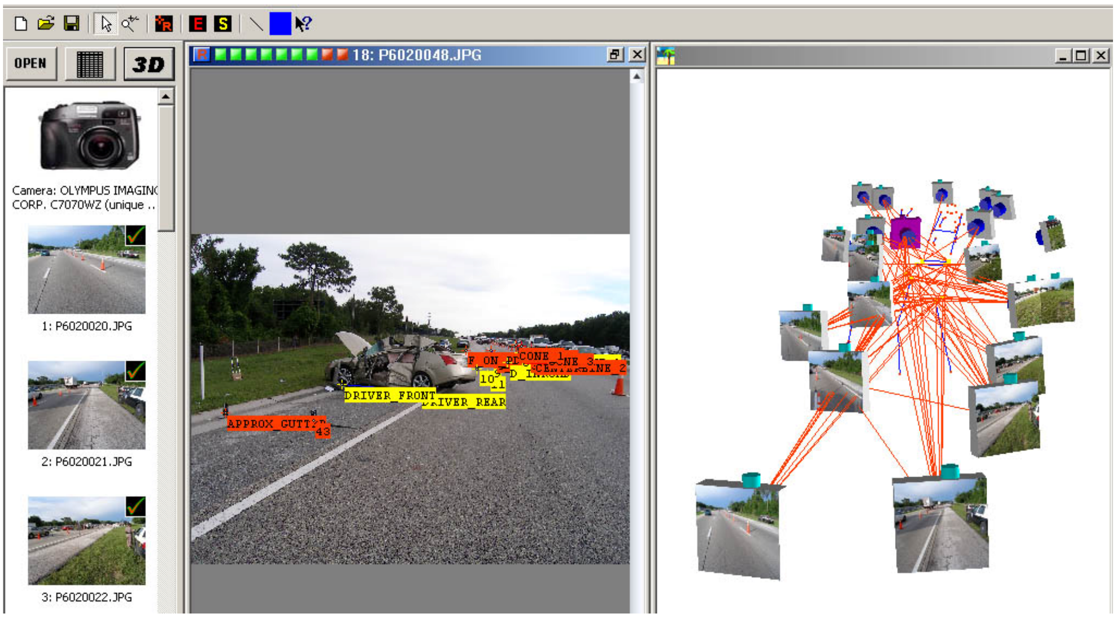

Figure 4: Multi-image geometry with camera stations near to the effective plane of the object, typical in accident reconstruction.

If there are coded targets distributed on the object, which are automatically recognised and triangulated in the initial spatial intersection, then groups of these become, effectively, EO devices. Once again, an iterative process of resection/intersection and possibly initial bundle adjustment is pursued until starting values for all parameters are determined. A final bundle adjustment is then performed.

Figure 4: Examples of EO devices.

This scenario affords fully automatic network orientation and 3D coordinate determination of targeted object points. The word 'target' here is important, for targets are essential, along with favourable illumination conditions (usually provided via a strobe flash) to ensure that the resulting image points will be automatically detected and accurately measured. Whereas from a CV standpoint the provision of targets is something to be avoided, one can surmise that the EO device/coded target approach would go a long way to alleviating camera calibration concerns in applications such as motion tracking and object modelling, since the process is simple, fully automatic and produces an accurate, scene independent calibration.

3.5 Coded Targets Alone

In spite of the benefits of the EO device it does display shortcomings. For very large objects, a physically large EO device is needed to ensure success in the initial closed-form resection. Moreover, the camera station geometry and EO device location must be such that robust detection and measurement is provided in enough images (minimum of two) with suitable geometry to support reliable initial spatial intersection. A scenario in which coded targets are employed, but the EO device is not, is considered.

As with the previous process, the images would be scanned and the coded and uncoded targets measured. Because the coded targets provide point correspondences, there need only be a sufficient number of pairs of homologous points between two images to facilitate RO. This first step in the orientation process now requires a solution of the coplanarity equations (initial values $\underline{\Delta}$), with the full scenario becoming:

Automatic image measurement
↓
RO using coded targets
↓
Resection
↓
Bundle Adjustment
↓
Spatial intersection
↓
Bundle adjustment
↓
Absolute orientation

Following the initial RO, resection follows for those images 'seeing' enough of the codes included in the RO. A bundle adjustment can then be used to refine the network, after which correspondence determination and spatial intersection follow to establish additional object coordinates ($\underline{X}$). This is followed by a final bundle adjustment and AO. There may be a number of resection/intersection stages in the building of the network, though these occur fully automatically and the user can be oblivious to the number of cycles performed. This process is followed, for example, in the ongoing development of the *Australis* software system, and also in *iWitness* (Photometrix, 2006; Fraser et al., 2005) albeit only for sensor calibration in fully automatic form in *iWitness* (Cronk et al., 2006). While the approach has proven to be robust and reliable for providing initial values $\underline{O}$ and $\underline{X}$ for the bundle adjustment, the provision of starting values $\underline{\Delta}$ for the initial RO proved a quite challenging problem.

Given the considerable amount of literature on the essential matrix/fundamental matrix model for image orientation, one would be left with the impression that this was a viable 'working' approach for RO. Experience suggests otherwise, and indeed it is consistent with the observation by Horn (1990a) quoted earlier. Put simply, reliable and reasonably representative values for the five parameters of RO cannot be expected with a sufficient degree of confidence, especially in convergent imaging configurations with a modest number of point correspondences (say 8-10) and object arrays which display limited depth in proportion to their lateral extent. The networks in Figs. 2 and 3 provide examples of such cases.

As an alternative approach to determining initial values $\underline{\Delta}$ for RO, a Monte Carlo type strategy can be adopted in which a very large number of possible RO solutions are assessed for the available image point pairs. The refined solution in each case is obtained via the coplanarity model using combinations of plausible initial values (there could be many of these). From the number of qualifying solutions obtained for the first five point pairs considered, the most plausible are retained. However, RO may not be final at this time, as there could be quite a number of possible solutions in cases of weak geometry. This will be compounded by the presence of random image measurement errors, however small. The entire process takes only a fraction of a second.

3.6 On-line Orientation for Manual Image Measurement

A favourable characteristic of adopting an initial RO in the orientation process, much as is done with stereo model restitution, is that it is quite well suited to on-line initial network orientation. This is where the measurement of image coordinates involves interactively referencing points in image pairs rather than labelling them for later off-line computation of orientation. As soon as enough image points are referenced, RO can automatically take place, in the background. It is quite conceivable that in cases of very poor geometry, such as represented by Fig. 3, there may be multiple plausible solutions to the RO when only 5 to 8 points are available. The RO process must then keep track of these possible solutions and examine every one as each additional point is referenced. The correct solution is generally isolated with no more than ten points, whereas for a strong geometry a successful RO can usually be reported to the operator after 6 points are referenced. The orientation process can then be summarized as:

Mark points of interest in a single image

↓

Reference these to a 2nd image (no point labels necessary); RO automatically computed and updated on-line with each new point after first 5

↓

Reference a new image to any of the referenced images and resect after 4-6 points referenced; bundle adjustment computed and updated on-line with every new point added

↓

Repeat third step; self-calibration can be initiated when the network is judged internally to be geometrically strong enough

↓

Final AO to obtain XYZ coordinates in desired reference system

The on-line network orientation process is a feature of *iWitness*. It also extends to the system's other computational processes related to orientation (resection, bundle adjustment, AO). At no time need the operator select a key such as 'compute'; processing occurs immediately enough information is available. Enhanced error detection is also a feature of this approach since blunders are recognised, and corrected, as they occur.

4. CONCLUDING REMARKS

Underlying the different orientation and sensor self-calibration algorithms and computational procedures in close-range photogrammetry are two basic functional models which have served photogrammetry well: the collinearity and coplanarity models. Although non-linear, both are solved via linear least-squares, thus requiring the determination of initial values for the parameters. The reason for the different computational sequences that have evolved over the years is closely related to the different approaches to initial value determination.

It is also for this reason that one hears justification for the developments of alternative, linear solutions to image orientation. The author has attempted to demonstrate that while generation of initial values may have been viewed as an impediment in the past, it has never been much more than a necessary nuisance. Moreover, with closed-form solutions and alternative approaches to solving RO and EO in an approximate manner, orientation systems requiring neither operator input nor provision of additional object space information are readily realisable. For example, the provision of coded targets, not in any required configuration, is sufficient to enable fully automatic EO and camera calibration, as exemplified by the *iWitness* camera calibration process (Cronk et al., 2006).

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