PHOTOGRAMMETRY-DERIVED NAVIGATION PARAMETERS FOR INS KALMAN FILTER UPDATES

F. A. Bayoud, J. Skaloud, B. Merminod

Geodetic Engineering Laboratory (TOPO), Swiss Federal Institute of Technology/Lausanne (EPFL)
Bât. GR, CH 1015, Switzerland – (fadiatef. bayoud, jan.skaloud, bertrand.merminod)@epfl.ch

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ABSTRACT:

In this paper, a GPS-independent mobile navigation and mapping system is introduced. This system employs the photogrammetric intersection to determine the coordinates of the surrounding objects and then it uses these newly known objects to compute its own position, when it moves, by the photogrammetric resection. The photogrammetric resection output – the exterior orientation parameters – is then used as external measurements in an INS Kalman Filer to compute the filtered exterior orientation parameters to do the intersection. This methodology of navigation and mapping is applied in the robotics community using different sensors and methods, where it is called Simultaneous Localisation And Mapping (SLAM); SLAM is the problem of mapping an area and at the same time using the map to locate the robot. In this paper, the solution for SLAM by integrating photogrammetry resection output and INS via a Kalman Filer is described.

1. INTRODUCTION

It is fundamental that mobile mapping systems use two independent components; one is for positioning, and the other is for mapping. Looking closely at the mapping component, one can find that it might also be used for positioning. This idea is extensively used in the robotics community.

Robotics Simultaneous Localisation And Mapping (SLAM) is the problem of mapping the environment surrounding the robot and at the same time using this map to determine the location of the robot (Csorba, 1997; Newman, 1999). Currently, indoor robotics SLAM is solved using LASER scanners to locate the robot relative to the structured environment and at the same time to map this environment. LASER scanners showed to be a very good tool where the accuracy of localisation is within the centimetre level for short distances and favourable geometry. Outdoors robotics SLAM is not feasible with LASER scanners due to the absence of simple geometric environment. Therefore, different tools have to be used.

Recently, the use of visual methods, integrated with Inertial Measurement Units (IMU), has gained interest. These visual methods rely on one or more cameras (or video). Yet, no clear indication about the mapping methods and integration algorithms is clearly illustrated in the relevant literature (Journal of Robotics Systems; V. 21; Issues 1 and 2).

In Geomatics Engineering, navigation and mapping have been two central research topics for decades. A classical tool for mapping is Photogrammetry, where sequence of stereo-images are captured and analysed. As for navigation systems, the coupling of inertial sensors and Global Navigation Satellite Systems is indispensable. In addition, photogrammetric resection can also be used for positioning.

In this paper, a mobile mapping system is introduced – independent of the GPS/INS integration – by employing two CCD cameras and one IMU (Figure 1). The two CCDs will be used for mapping through photogrammetric intersection, and for positioning through photogrammetric resection. The presence of an IMU is significant in cases where images cannot be used for reasons of visibility and when certain manoeuvres do not guarantee knowledge of the environment; e.g. when the robot or vehicle captures images of an unknown environment.

Thus, The relation between photogrammetry and SLAM is, analysed in this study. This relation has not gained much attention due to the fact that SLAM requires full automation, which until recently was far from photogrammetry. Many attempts were directed towards the full automation of photogrammetry. This goal has been still falling short due to the need of high level of artificial intelligence. Having in mind that it is only a matter of time to reach full automation, an investigation on SLAM from the Geomatics point of view using navigation and mapping modus operandi is essential.

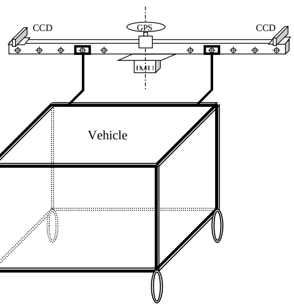

Figure 1: The system

The integration concept between an IMU and photogrammetry via a Kalman Filter (KF) is the central topic of this paper. Section 2 briefly discusses the photogrammetric mathematical model and its two problems: resection and intersection. Section 3 examines the solution of SLAM using photogrammetry in a sequential Least-Squares Adjustment (LSA) mode. Section 4 examines the integration of photogrammetry and INS in a KF. Conclusions are finally drawn in the last section.

2. MATHEMATICAL MODEL OF PHOTOGRAMMETRY

Equations (1) are the co-linearity equations in photogrammetric mapping. They reveal the relationship between the image and the object coordinate systems:

$$F(x) \equiv -x + x_0 - c\frac{R_{11}(X - X_0) + R_{12}(Y - Y_0) + R_{13}(Z - Z_0)}{R_{31}(X - X_0) + R_{32}(Y - Y_0) + R_{33}(Z - Z_0)}$$

$$F(y) \equiv -y + y_0 - c\frac{R_{21}(X - X_0) + R_{22}(Y - Y_0) + R_{23}(Z - Z_0)}{R_{31}(X - X_0) + R_{32}(Y - Y_0) + R_{33}(Z - Z_0)} \quad (1)$$

where x, y = Photo-coordinates
X, Y, Z = Coordinates in the object frame
c = Focal length
X_0, Y_0, Z_0 = Coordinates of projection centre
x_0, y_0 = Photo-coordinates of the projection of the projection centre to the image plane
R_{ij}'s = Elements of the rotation matrix between the image and object frames

With this model, one can solve the basic problems of photogrammetric mapping, namely: resection and intersection:

1. *Resection*, whereby the position and attitude of an image (exterior orientation parameters – EOP, $X_0, Y_0, Z_0, \omega, \varphi, \kappa$) are determined by having at least three points with known coordinates in the object frame as well as in the image frame (Figure 2)
2. *Intersection*, whereby two images, with known positions and attitudes, are used to determine the coordinates (X_i, Y_i, Z_i) of points found on both images simultaneously, employing the principle of stereovision (Figure 3).

Therefore, the right combination of these two problems yields to navigation and mapping at once. Chaplin, 1999, studied the motion estimation from stereo image sequence during GPS outages. Our study stems from the same source but differs in concept, where a KF is used to merge the outputs of a resection and an IMU to perform the intersection.

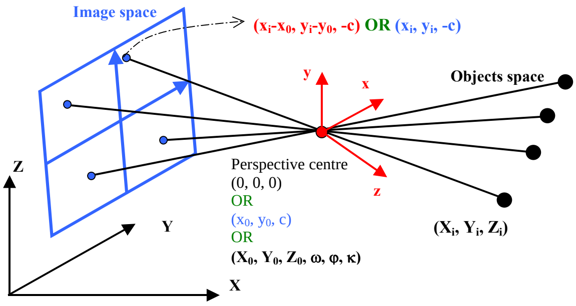

Figure 2: Resection Problem

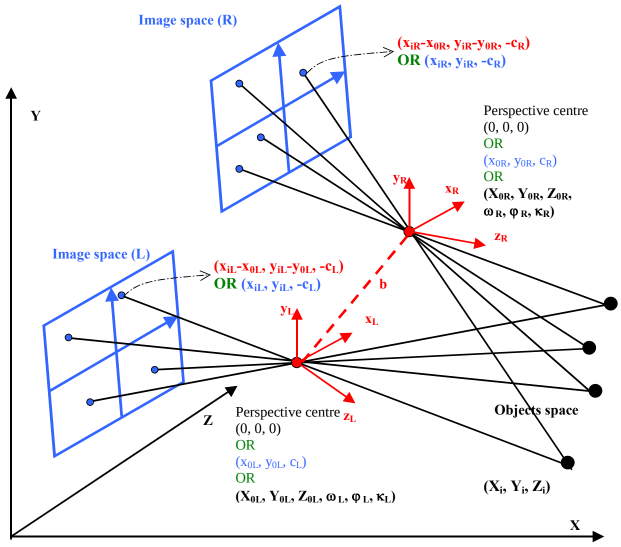

Figure 3: Intersection Problem

3. PHOTOGRAMMETRY AS SLAM

Photogrammetry by itself can be considered as a solution for the Simultaneous Localisation And Mapping (SLAM) problem, provided all necessary measurements can be obtained automatically. Considering the initial position as known, intersection is used to map a number of features; then the vehicle moves and captures images. The features measured from the previous position are taken as Ground Control Points (GCP) in the current stage to compute the EOPs of the cameras.

This procedure requires certain points to consider:

- Recursive LSA: the LSA solution of the epoch $k-1$ is used as observations for epoch k,
- Correlations between measurements and unknowns are carried from one epoch to the other.

This section illustrates the operation of SLAM with resection and intersection in a recursive approach, with the embedding of the time index k. To start with, the initialisation has to be performed by determining the initial EOP of the two cameras. The initialisation can be done in two ways:

1. Initialisation with GPS/INS, which demands open skies for the GPS signal, or

2. Initialisation with resection, which demands the existence of sufficient GCPs at the beginning of the survey.

In the first case, open sky for the GPS is vital. The GPS/INS (Grewal et al., 2000) gives us the position and attitude of the IMU, which – after applying the lever arm and angles transformation – yield the EOP of the two cameras.

As for the second case, at least three GCPs are required for the determination of the position and attitude of the two cameras by resection.

After the initialisation, intersection starts to map (more) features. The vehicle moves and captures a pair of images, and so on and so forth. The flowchart of this procedure is laid out in Figure (4). Its algorithm will be discussed in the following.

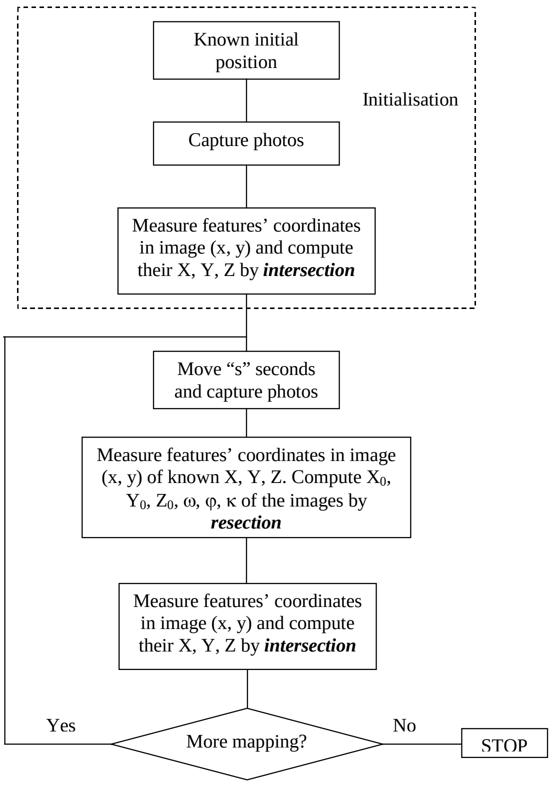

Figure 4: Flowchart of the Photogrammetric SLAM

To simplify the notation, we suppose that at each image-acquisition epoch, n features are mapped. In this way, the vectors and matrices used in the LSA are (L/R = Left/Right images):
Vectors and matrices headed by a prime (e.g., $\mathbf{X}'$) refer to the **resection** and those headed by two primes (e.g., $\mathbf{X}''$) refer to the **intersection**.

Resection unknowns:

$$\boldsymbol{\delta}\mathbf{x}'_{(\mathbf{L,R})} = \left[\delta X_0 \quad \delta Y_0 \quad \delta Z_0 \quad \delta\omega \quad \delta\varphi \quad \delta\kappa\right]^T_{(L,R)}$$

Intersection unknowns:

$$\boldsymbol{\delta}\mathbf{x}'' = \left[\delta X_1 \quad \delta Y_1 \quad \delta Z_1 \quad \cdots \quad \delta X_n \quad \delta Y_n \quad \delta Z_n\right]^T$$

Resection measurements:

$$\mathbf{y}'_{(\mathbf{L,R})} = \left[x_i \quad y_i \quad X_i \quad Y_i \quad Z_i\right]^T_{(L,R)}$$

Intersection measurements:

$$\mathbf{y}'' = \left[x_{Li} \quad y_{Li} \quad X_{L0} \quad Y_{L0} \quad Z_{L0} \quad \omega_L \quad \varphi_L \quad \kappa_L \quad x_{Ri} \quad y_{Ri} \quad X_{R0} \quad Y_{R0} \quad Z_{R0} \quad \omega_R \quad \varphi_R \quad \kappa_R\right]^T$$

Resection first design matrix:

$$\mathbf{A}'_{(\mathbf{L,R})} = \begin{bmatrix} \frac{\partial F(x)}{\partial x'} & \frac{\partial F(y)}{\partial x'} \end{bmatrix}^T_{(L,R)}$$

Intersection first design matrix:

$$\mathbf{A}'' = \begin{bmatrix} \frac{\partial F(x)}{\partial x''} & \frac{\partial F(y)}{\partial x''} \end{bmatrix}^T$$

Resection second design matrix:

$$\mathbf{B}'_{(\mathbf{L,R})} = \begin{bmatrix} \frac{\partial F(x)}{\partial y'} & \frac{\partial F(y)}{\partial y'} \end{bmatrix}^T_{(L,R)}$$

Intersection second design matrix:

$$\mathbf{B}'' = \begin{bmatrix} \frac{\partial F(x)}{\partial y''} & \frac{\partial F(y)}{\partial y''} \end{bmatrix}^T$$

Starting at epoch k with known coordinates, **intersection** takes over:

$$\boldsymbol{\delta}\mathbf{x}''_\mathbf{k} = \mathbf{N}''^{-1}_\mathbf{k}\mathbf{U}''_\mathbf{k} \quad (2)$$

$$\mathbf{N}''_\mathbf{k} = \mathbf{A}''^T_\mathbf{k}\left(\mathbf{B}''_\mathbf{k}\mathbf{C}''_\mathbf{y/k}\mathbf{B}''^T_\mathbf{k}\right)^{-1}\mathbf{A}''_\mathbf{k} \quad (3)$$

$$\mathbf{U}''_\mathbf{k} = \mathbf{A}''^T_\mathbf{k}\left(\mathbf{B}''_\mathbf{k}\mathbf{C}''_\mathbf{y/k}\mathbf{B}''^T_\mathbf{k}\right)^{-1}\mathbf{w}''_\mathbf{k} \quad (4)$$

$\mathbf{C}''_\mathbf{y/k}$, defined in Equations 12 and 13, is the measurements co-variance matrix. $\mathbf{w}''_\mathbf{k}$ is the misclosure vector in LSA. The elements of $\mathbf{x}''_\mathbf{k}$ are used as GCPs at epoch $k+1$ to solve **resection**:

$$\boldsymbol{\delta}\mathbf{x}'_\mathbf{k+1} = \mathbf{N}'^{-1}_\mathbf{k+1}\mathbf{U}'_\mathbf{k+1}\Big|_{(L,R)} \quad (5)$$

$$\mathbf{N}'_\mathbf{k+1} = \mathbf{A}'^T_\mathbf{k+1}\left(\mathbf{B}'_\mathbf{k+1}\mathbf{C}'_\mathbf{y/k+1}\mathbf{B}'^T_\mathbf{k+1}\right)^{-1}\mathbf{A}'_\mathbf{k+1}\Big|_{(L,R)} \quad (6)$$

$$\mathbf{U}'_\mathbf{k+1} = \mathbf{A}'^T_\mathbf{k+1}\left(\mathbf{B}'_\mathbf{k+1}\mathbf{C}'_\mathbf{y/k+1}\mathbf{B}'^T_\mathbf{k+1}\right)^{-1}\mathbf{w}'_\mathbf{k+1}\Big|_{(L,R)} \quad (7)$$

$\mathbf{C}'_\mathbf{y/k+1}$, defined in Equation 8, is the measurements co-variance matrix. The elements of $\mathbf{x}'_\mathbf{k+1}\big|_{(L,R)}$ are used in a stereo-model at epoch $k+1$ to map n new features, $\mathbf{x}''_\mathbf{k+1}$. These n new features at epoch

$k+1$, $\mathbf{x}''_{k+1}$, are used at epoch $k+2$ to compute $\mathbf{x}'_{k+2}$. The procedure continues until the end of the survey.

It is important to note that not only $\mathbf{x}'$ and $\mathbf{x}''$ are used from one epoch to its successive, but also the variances and co-variances via the matrices $\mathbf{C}'_{\mathbf{y}}$, $\mathbf{C}''_{\mathbf{y}}$, $\mathbf{C}'_{\mathbf{x}}$, and $\mathbf{C}''_{\mathbf{x}}$.

Considering firstly the $\mathbf{C}''_{\mathbf{y/k=0}}$, it is given together with the initial camera's position at epoch $k=0$. As stated before, this is then used to find the object coordinates of n new features by **intersection** in order to compute the EOP of the two cameras at epoch $k+1=1$.

Secondly, considering the $\mathbf{C}'_{\mathbf{y/k+1}}$ (measurements co-variance for the **resection**), it is computed as:

$$\mathbf{C}'_{\mathbf{y/k+1}} = \begin{bmatrix} \boldsymbol{\Sigma}_{\mathbf{1}}^{2}\big|^{\text{photo}} & 0 & \cdots & 0 & 0 \\ 0 & \boldsymbol{\Sigma}'^{2}_{\mathbf{1}}\big|^{\text{object}}_{\text{k+1}} & \cdots & 0 & \boldsymbol{\Sigma}'_{\mathbf{1}}\boldsymbol{\Sigma}'_{\mathbf{n}}\big|^{\text{object}}_{\text{k+1}} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{\Sigma}_{\mathbf{n}}^{2}\big|^{\text{photo}} & 0 \\ 0 & \boldsymbol{\Sigma}'_{\mathbf{n}}\boldsymbol{\Sigma}'_{\mathbf{1}}\big|^{\text{object}}_{\text{k+1}} & \cdots & 0 & \boldsymbol{\Sigma}'^{2}_{\mathbf{n}}\big|^{\text{object}}_{\text{k+1}} \end{bmatrix} \tag{8}$$

where $\boldsymbol{\Sigma}_{\mathbf{i}}^{2}\big|^{\text{photo}}$ is the 2×2 co-variance matrix of the photo-coordinates. $\boldsymbol{\Sigma}'^{2}_{\mathbf{i}}\big|^{\text{object}}_{\text{k+1}}$ and $\boldsymbol{\Sigma}'_{\mathbf{i}}\boldsymbol{\Sigma}'_{\mathbf{j}}\big|^{\text{object}}_{\text{k+1}}$, on the other hand, are the 3×3 co-variance matrix of feature i-th and j-th object coordinates. These will be taken from the output of the **intersection** of epoch k, specifically from matrix $\mathbf{C}''_{\mathbf{x/k}}$ that is equal to:

$$\mathbf{C}''_{\mathbf{x/k}} = \mathbf{N}''^{-1}_{\mathbf{k}} = \left(\mathbf{A}''^{\mathrm{T}}_{\mathbf{k}}\left(\mathbf{B}''_{\mathbf{k}}\mathbf{C}''_{\mathbf{y/k}}\mathbf{B}''^{\mathrm{T}}_{\mathbf{k}}\right)^{-1}\mathbf{A}''_{\mathbf{k}}\right)^{-1} = \begin{bmatrix} \boldsymbol{\Sigma}''^{2}_{\mathbf{1}}\big|^{\text{object}}_{\text{k}} & \cdots & \boldsymbol{\Sigma}''_{\mathbf{1}}\boldsymbol{\Sigma}''_{\mathbf{n}}\big|^{\text{object}}_{\text{k}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{\Sigma}''_{\mathbf{n}}\boldsymbol{\Sigma}''_{\mathbf{1}}\big|^{\text{object}}_{\text{k}} & \cdots & \boldsymbol{\Sigma}''^{2}_{\mathbf{n}}\big|^{\text{object}}_{\text{k}} \end{bmatrix} \tag{9}$$

where

$$\boldsymbol{\Sigma}'^{2}_{\mathbf{i}}\big|^{\text{object}}_{\text{k+1}} = \boldsymbol{\Sigma}''^{2}_{\mathbf{i}}\big|^{\text{object}}_{\text{k}} = \begin{bmatrix} \sigma^2_{X_i} & \sigma_{X_i}\sigma_{Y_i} & \sigma_{X_i}\sigma_{Z_i} \\ \sigma_{Y_i}\sigma_{X_i} & \sigma^2_{Y_i} & \sigma_{Y_i}\sigma_{Z_i} \\ \sigma_{Z_i}\sigma_{X_i} & \sigma_{Z_i}\sigma_{Y_i} & \sigma^2_{Z_i} \end{bmatrix} \tag{10}$$

and

$$\boldsymbol{\Sigma}'_{\mathbf{i}}\boldsymbol{\Sigma}'_{\mathbf{j}}\big|^{\text{object}}_{\text{k+1}} = \boldsymbol{\Sigma}''_{\mathbf{i}}\boldsymbol{\Sigma}''_{\mathbf{j}}\big|^{\text{object}}_{\text{k}} = \begin{bmatrix} \sigma_{X_i}\sigma_{X_j} & \sigma_{X_i}\sigma_{Y_j} & \sigma_{X_i}\sigma_{Z_j} \\ \sigma_{Y_i}\sigma_{X_j} & \sigma_{Z_i}\sigma_{Z_j} & \sigma_{Y_i}\sigma_{Z_j} \\ \sigma_{Z_i}\sigma_{X_j} & \sigma_{Z_i}\sigma_{Y_j} & \sigma_{Z_i}\sigma_{Z_j} \end{bmatrix} \tag{11}$$

As for $\mathbf{C}''_{\mathbf{y/k+1}}$ (measurements co-variance used in the **intersection**), it is computed in a similar way as follows:

$$\mathbf{C}''_{\mathbf{Ly/k+1}} = \begin{bmatrix} \boldsymbol{\Sigma}^{2}_{\mathbf{i}}\big|^{\text{photo}} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}''^{2}_{\mathbf{L\_EOP}}\big|_{\text{k+1}} \end{bmatrix} \tag{12}$$

$$\mathbf{C}''_{\mathbf{Ry/k+1}} = \begin{bmatrix} \boldsymbol{\Sigma}^{2}_{\mathbf{i}}\big|^{\text{photo}} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\Sigma}''^{2}_{\mathbf{R\_EOP}}\big|_{\text{k+1}} \end{bmatrix} \tag{13}$$

where $\boldsymbol{\Sigma}''^{2}_{\mathbf{L\_EOP}}\big|_{\text{k+1}}$ and $\boldsymbol{\Sigma}''^{2}_{\mathbf{R\_EOP}}\big|_{\text{k+1}}$ are the measurement co-variance matrices of the Left and Right EOP that are needed to compute new n features at epoch $k+1$. These are found from the output of the **resection** epoch $k+1$ as follows ($\mathrm{j = L, R}$):

$$\boldsymbol{\Sigma}''^{2}_{\mathbf{j\_EOP}}\big|_{\text{k+1}} = \mathbf{C}'_{\hat{\mathbf{x}}\mathbf{/k+1}} = \mathbf{N}'^{-1}_{\mathbf{k+1}} = \left(\mathbf{A}'^{\mathrm{T}}_{\mathbf{k+1}}\left(\mathbf{B}'_{\mathbf{k+1}}\mathbf{C}'_{\mathbf{y/k+1}}\mathbf{B}'^{\mathrm{T}}_{\mathbf{k+1}}\right)^{-1}\mathbf{A}'_{\mathbf{k+1}}\right)^{-1} \tag{14}$$

In short, the co-variance transportability can be described as:

$\mathbf{C}'_{\mathbf{y/k+1}} \equiv$ Given accuracies of the GCPs $\equiv \mathbf{C}''_{\hat{\mathbf{x}}\mathbf{/k}}$
$\mathbf{C}'_{\hat{\mathbf{x}}\mathbf{/k+1}} \equiv$ Computed accuracies of the EOP
$\mathbf{C}''_{\mathbf{y/k+1}} \equiv$ Given accuracies of the EOP $\equiv \mathbf{C}'_{\hat{\mathbf{x}}\mathbf{/k+1}}$
$\mathbf{C}''_{\hat{\mathbf{x}}\mathbf{/k+1}} \equiv$ Computed accuracies of epoch's (k+2) GCPs

The combination of Equations 1 to 14 into a one step approach is called "Bundle Adjustment". The one step approach is pursued when there is no other technique to determine the EOP, which is not the case here. In addition to the two cameras, an IMU will also provide the EOP. After incorporating the IMU data, the analysis above changes as follows. The output of the resection at the epoch k becomes external measurements for the INS Kalman Filter (KF) (Kalman, 1960). After obtaining the corrections of the navigation parameters from the KF, intersection is carried out at the same epoch k. As a consequence, instead of using the $\mathbf{C}''_{\hat{x}/k}$ to build up $\mathbf{C}'_{y/k}$, the variance-covariance matrix output of KF is used. This analysis will be looked at in the next section.

4. INTEGRATING PHOTOGRAMMETRY AND INS IN A KALMAN FILTER

The previously described initialisation remains the same. The items that differ are: the employment of the lever-arm and angles transformation, and the Kalman Filter.

Before talking about these items, we consider the flowchart of Figure 4. The algorithm can be depicted as follows:

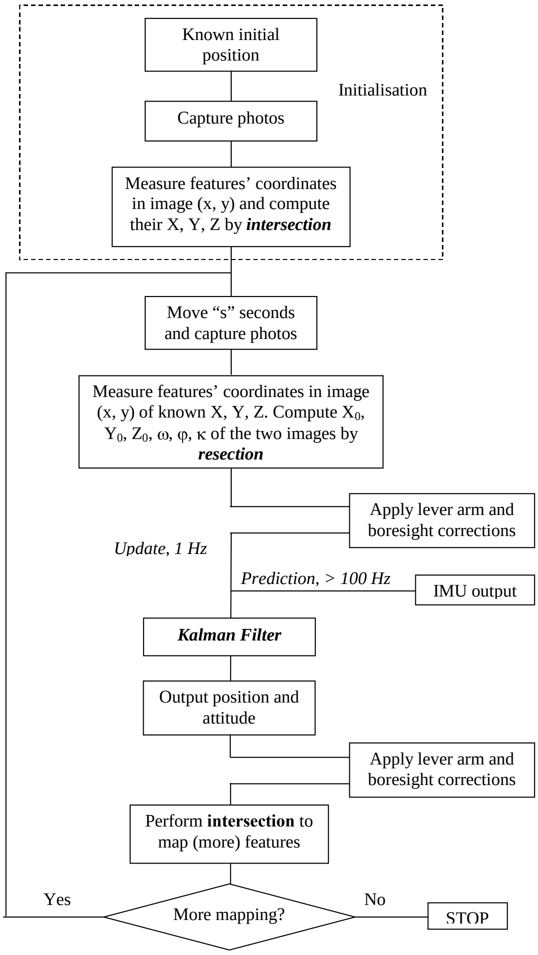

Figure 4: Flowchart of the Photogrammetric and INS integration

Initialisation:

1. Position and attitude of the two cameras considered as known
2. Intersection is employed to map objects

After mapping enough objects:

1. Vehicle moves
2. Resection computes the cameras' EOP using the features mapped from the previous location
3. Lever-arm and angles transformation (and boresight) are applied to the EOPs to determine the IMU's position and attitude
4. IMU and resection outputs are integrated in Kalman Filter to compute filtered position and attitude of the current location
5. Lever-arm and angles transformation (and boresight) are applied to the filtered position and attitude to determine the EOP of the cameras
6. Intersection is used to map more objects from the current location
7. Vehicle moves and algorithm repeats

The lever-arm and angles transformation are different in steps 3 and 5. In the following, only the angles transformation is discussed; the lever-arm is dealt with similarly.

4.1 Angles Transformation

The angles transformation applied in Step 5 is used to transform the output of the KF to the camera's reference frame to perform the mapping. This is well documented in the relevant literature (Skaloud and Schaer, 2003). The complete transformation is:

$$\mathbf{R}_{\mathbf{m}}^{\mathbf{c}} = \mathbf{R}_{\mathbf{b}}^{\mathbf{c}} \left(\mathbf{R}_{\mathbf{b}}^{\mathbf{e}}\right)^{\mathbf{T}} \mathbf{R}_{\mathbf{m}}^{\mathbf{e}} \qquad (15)$$

where $\mathbf{R}_{\mathrm{m}}^{\mathbf{c}}$ = transformation matrix between mapping and camera frames

$\mathbf{R}_{\mathbf{b}}^{\mathbf{c}}$ = transformation matrix between IMU and camera frames (depends on the definition of the axes)

$\mathbf{R}_{\mathbf{b}}^{\mathbf{e}}$ = transformation matrix between IMU and earth-fixed frames, i.e., KF output

$\mathbf{R}_{\mathbf{m}}^{\mathbf{e}}$ = transformation matrix between Earth-fixed and mapping frames

The boresight correction applied in Step 3, is exactly the inverse of Equation (15). In the step, the user is going from $\mathbf{R}_{\mathrm{m}}^{\mathbf{c}}$ to $\mathbf{R}_{\mathbf{b}}^{\mathbf{e}}$, and this takes place as follows:

$$\mathbf{R}_{\mathbf{b}}^{\mathbf{e}} = \mathbf{R}_{\mathbf{m}}^{\mathbf{e}} \left(\mathbf{R}_{\mathbf{m}}^{\mathbf{c}}\right)^{\mathbf{T}} \mathbf{R}_{\mathbf{b}}^{\mathbf{c}} \qquad (16)$$

In this stage, we showed the relations among the coordinate systems for the transfer of position and attitude. In the second section, the KF is described.

4.2 Data Integration Via Kalman Filter

The navigation KF can link either the INS measurements (orientation rates and accelerations) or the integrated values (coordinates, velocity, orientation) with external measurements.

In open spaces, GPS measurements play the role of external measurements. In areas with limited GPS signal, these are replaced by other autonomous sensors like odometer, compass, barometer, etc. Here, we consider as the KF external measurements the output of the photogrammetric resection; these are the Coordinates Update (CUPT) and Attitude Update (AUPT). In addition, Zero-Velocity Updates (ZUPT) are also used as measurements. This kind of updates allows adopting loosely coupled integration, which is easiest to implement.

Since there are two cameras, two datasets of external measurements are available; one is the EOP of the left camera and the other is the EOP of the right camera. There are three possibilities for this integration.

The first possibility is to take the average of the two EOPs. The second considers the two EOP as two independent correlated updates. The difference between the two possibilities is reflected in the size and shape of the measurements' vector, co-variance matrix, and design matrix.

In the first possibility, the measurements' vector can take the following form (with ZUPTs):

$$\mathbf{z_k} = \big[A - x^e \quad B - y^e \quad C - z^e \quad D - \omega_{IMU} \quad E - \varphi_{IMU} \quad F - \kappa_{IMU} \quad -v_x^e \quad -v_y^e \quad -v_z^e\big]^T \tag{16}$$

Where

$$A = \frac{X_{0L} + X_{0R}}{2} \qquad B = \frac{Y_{0L} + Y_{0R}}{2}$$

$$C = \frac{Z_{0L} + Z_{0R}}{2} \qquad D = \frac{\omega_L + \omega_R}{2}$$

$$E = \frac{\varphi_L + \varphi_R}{2} \qquad F = \frac{\kappa_L + \kappa_R}{2}$$

With $X_{0L/R}, Y_{0L/R}, Z_{0L/R}$ = coordinates of the left/right camera (lever-arm added)

$\omega_{L/R}, \varphi_{L/R}, \kappa_{L/R}$ = attitude of the left/right camera (Boresight added)

$x^e, y^e, z^e, \omega_{IMU}, {}_{IMU}, \kappa_{IMU}, v_x^e, v_y^e, v_z^e$ = Position, attitude, and velocity output of the mechanisation equations

In the second possibility, the measurements vector can take the following form (with ZUPTS):

$$\mathbf{z_k} = \big[X_{0L} - x^e \quad Y_{0L} - y^e \quad Z_{0L} - z^e \quad \omega_L - \omega_{IMU} \quad \varphi_L - \varphi_{IMU} \quad \kappa_L - \kappa_{IMU} \quad X_{0R} - x^e \quad Y_{0R} - y^e \quad Z_{0R} - z^e \quad \omega_R - \omega_{IMU} \quad \varphi_R - \varphi_{IMU} \quad \kappa_R - \kappa_{IMU} \quad -v_x^e \quad -v_y^e \quad -v_z^e\big]^T \tag{16}$$

5. CONCLUSIONS AND FUTURE WORK

In this paper, we formulated a combination strategy between photogrammetric and IMU outputs via a Kalman Filter. We borrowed the term SLAM-problem from Robotics and tried to solve it using Geomatics Engineering modus operandi.

It was shown that SLAM could be achieved using Photogrammetry and IMU outputs integrated in a loosely coupled Kalman Filter.

The merits of this integration can be divided into practical and scientific. Practical advantage lies in the long-term independence of GPS. The scientific gain poses itself in the necessity of taking photogrammetry to the stage of full automation.

Collaboration between and merging of different scientific disciplines –e.g. Geomatics and Robotics– must be highly considered in order to accomplish advancements.

Future work will concentrate on numerically testing the methodology and the possibility of automation.

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