

# A solution to dynamic errors-in-variables within system equations

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**Abstract** We noticed that if INS data is used as system equations of a Kalman filter algorithm for integrated direct geo-referencing, one encounters with a dynamic errors-in-variables (DEIV) model. Although DEIV model has been already considered for observation equations of the Kalman filter algorithm and a solution namely total Kalman filter (TKF) has been given to it, this model has not been considered for system equations (dynamic model) of the Kalman filter algorithm. Thus, in this contribution, for the first time we consider DEIV model for both observation equations and system equations of the Kalman filter algorithm and propose a least square prediction namely integrated total Kalman filter in contrast to the TKF solution of the previous approach. The variance matrix of the unknown parameters are obtained. Moreover, the residuals for all variables are predicted. In a numerical example, integrated direct geo-referencing problem is solved for a GPS–INS system.

**Keywords** Dynamic errors-in-variables · System equations · Integrated total Kalman filter · Direct geo-referencing

## 1 Introduction

Recently, there has been an explosion in the number, type and diversity of system designs and application areas of mobile sensors. The geo-referencing of these systems is one of the main problems. In this problem, one aims to determine the position and attitude of a mobile sensor in a geo-referenced frame. When this information is attained directly by means of

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measurements from sensors on-board the vehicle the term *direct geo-referencing* is used (Skaloud 1999). The integration of these data is done during a Kalman filter algorithm (Kalman 1960). For more details on Kalman filter one may refer to Sorenson (1966) and Maybeck (1979). The Kalman filter is essentially a set of mathematical equations that implement a predictor–corrector type estimator that is *optimal* in the sense that it minimizes the estimated *error* covariance, when some presumed conditions are met (Welch and Bishop 2001). In the literature, the Kalman filter is derived as either a best predictor (BP) or a best linear predictor (BLP), see e.g. Kalman (1960), Gelb (1974), Sanso (1986). The minimum mean squared error (MMSE) is the criterion which selects the best predictor or estimator.

Observation equations and system equations are two main parts of a dynamic problem. The former is in fact a relation between the observations and time dependent unknown parameters while the latter relates the unknown parameters at an epoch  $i$  to an earlier epoch  $i - 1$ . Due to how these two parts are modeled, several linear and non-linear Kalman filters have been proposed. For more information see e.g. Yi (2007). Some filters are as follows: the Sigma Point Kalman Filters (SPKF) (van der Merwe and Wan 2003) or Linear Regression Kalman Filters (LRKF) (Lefebvre et al. 2002), Extended Kalman Filter (EKF) (Jazwinski 1970), the Particle Filters (PF) (Liu and Chen 1998), the Ensemble Kalman Filter (EnKF) (Evensen 1994), Unscented Kalman Filter (UKF) based on unscented transformation (UT) (Julier and Uhlmann 1997) and etc. However, in all of these algorithms, the coefficient matrix of the system equations does not contain random errors. As such an assumption cannot always be guaranteed, we allow random observational errors to enter the respective matrix. In practice, this situation can be seen when we are going to use INS data as the system equations since in such a case, the random observed angular increments and velocity increments measured by gyroscope and accelerometer of the INS system, make the coefficient matrix of the system equations noisy.

Note that although Schaffrin and Iz (2008), Schaffrin and Uzun (2011) and Mahboub et al. (2016) considered the case which only the design matrix of the observation equations is random, we solve the problem which both of the coefficient matrix of the observation equations and system equations are corrupted by random noise. Hence in contrast to Schaffrin and Iz (2008) that named their solution total Kalman filter (TKF), we propose an integrated total Kalman filter (ITKF) algorithm.

This paper is organized as follows: in Sect. 2, the DEIV model and the TKF solution proposed by Schaffrin and Iz (2008) are introduced. In Sect. 3, the ITKF algorithm is developed, then, in a later section, a numerical example gives insight into the efficiency of the algorithm proposed. Finally we conclude the paper.

## 2 Dynamic errors-in-variables (DEIV) model

In this section the concepts of dynamic errors-in-variables (DEIV) model are introduced and a TKF solution proposed by Schaffrin and Iz (2008) is given. It must be mentioned that EIV model in its time invariant case i.e. static case has been investigated by several valuable publications. Therefore, we only give some references e.g. Zeng et al. (2015), Zhang et al. (2013), Neitzel (2010), Neitzel and Schaffrin (2016), Snow and Schaffrin (2012), Shen et al. (2011), Schaffrin et al. (2014), Schaffrin and Felus (2008), Mahboub (2012, 2014, 2016), Mahboub et al. (2012, 2015), Mahboub and Sharifi (2013a, b), Paláncz and Awange (2012), Amiri-simkooei and Jazaeri (2012), Fang (2011, 2013, a, b c, 2015),

Fang et al. (2015, 2016), Lu et al. (2014), Zhou and Fang (2015) and Fang and Wu (2015) etc. In the rest of this paper we define these two parts for a DEIV model. Observation equations is given as follows:

$$y_i = (A_i - \underline{E}_{A_i})x_i + \underline{e}_i \tag{1}$$

In the above equations  $y_i$  is the  $m \times 1$  random observation vector,  $\underline{e}_i$  is the  $m \times 1$  vector of observational noise,  $A_i$  is the  $m \times n$  coefficient matrix of input variables (observed),  $\underline{E}_{A_i}$  is the corresponding the  $m \times n$  matrix of random noise,  $x_i$  is the  $n \times 1$  random parameter vector (time dependent unknowns). The following equation represents system equations which is also called dynamic model. It relates the unknown parameters at an epoch  $i$  to an earlier epoch  $i - 1$ .

$$x_i = (\Phi_i - \underline{E}_{\Phi_i})x_{i-1} + f_i + \underline{u}_i \tag{2}$$

$\Phi_i$  is the transition matrix  $\underline{E}_{\Phi_i}$  is the corresponding the  $n \times n$  matrix of random noise and  $\underline{u}_i$  is the random system noise,  $f_i$  is an independent time variable function and underlining ( ) indicates random variables. The random noise of the transition matrix is our main problem in this paper. We also assume that the state vector is observed at an initial (previous) epoch:

$$x_{i-1} = x_{i-1} + \underline{e}_{i-1}^0 \tag{3}$$

Here,  $\underline{e}_{i-1}^0$  is the random noise at the first epoch. Equations (1)–(3) represent the functional model of the DEIV model in this paper. We also define the corresponding stochastic model as follows:

$$\begin{bmatrix} \underline{e}_i \\ \underline{e}_{A_i} = \text{vec}(\underline{E}_{A_i}) \\ \underline{u}_i \\ \underline{e}_{\Phi_i} = \text{vec}(\underline{E}_{\Phi_i}) \\ \underline{e}_{i-1}^0 \end{bmatrix} \sim \left( \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} Q_{y_i} & 0 & 0 & 0 & 0 \\ 0 & Q_{A_i} & 0 & 0 & 0 \\ 0 & 0 & \theta_i & 0 & 0 \\ 0 & 0 & 0 & Q_{\Phi_i} & 0 \\ 0 & 0 & 0 & 0 & \sum_{i-1}^0 \end{bmatrix} \right) \tag{4}$$

where  $Q_{y_i}$ ,  $\theta_i$ ,  $\sum_{i-1}^0$ ,  $Q_{A_i}$  and  $Q_{\Phi_i}$  are the corresponding dispersion matrixes of the observation vector, system equations, the observed unknown parameters at an initial epoch, the random coefficient matrix  $\underline{E}_{A_i}$  and the random coefficient matrix  $\underline{E}_{\Phi_i}$ . Schaffrin and Iz (2008) supposed that  $\underline{E}_{\Phi_i} = 0, f_i = 0, Q_{A_i} = I_n \otimes Q_{y_i}$  and set the following target function:

$$\begin{aligned} \Phi(\underline{e}_i, \underline{e}_{A_i}, \lambda_i, \mu_i) &:= \left( \underline{e}_i^T Q_{y_i}^{-1} \underline{e}_i + \underline{e}_{A_i}^T (I_n \otimes Q_{y_i})^{-1} \underline{e}_{A_i} \right. \\ &+ (\underline{u}_i - \Phi_i \underline{e}_{i-1}^0)^T \left( \theta_i + \Phi_i \sum_{i-1}^0 \Phi_i^T \right)^{-1} (\underline{u}_i - \Phi_i \underline{e}_{i-1}^0) \\ &\left. + 2\lambda_i^T (y_i - A_i(\underline{u}_i - \Phi_i \underline{e}_{i-1}^0 + \check{x}_i) + (\underline{u}_i - \Phi_i \underline{e}_{i-1}^0 + \check{x}_i)^T \otimes I_m) \underline{e}_{A_i} - \underline{e}_i \right) \end{aligned} \tag{5}$$

where  $\lambda_i$  is a  $m \times 1$  vector of Lagrange multipliers. They obtained the following least-squares prediction and named it total Kalman filter (TKF):

$$\tilde{x}_i = \check{x}_i + \left( \theta_i + \Phi_i \sum_{i-1}^0 \Phi_i^T \right) \left[ A_i^T \hat{\lambda}_i + \tilde{x}_i \left( \hat{\lambda}_i^T Q_{y_i} \hat{\lambda}_i \right) \right] \tag{6}$$

where  $\check{x}_i$  and  $\hat{\lambda}_i$  are given as follows:

$$\hat{\lambda}_i = (Q_{y_i})^{-1}(y_i - A_i \tilde{x}_i)(1 + \tilde{x}_i^T \tilde{x}_i)^{-1} \tag{7}$$

$$\tilde{x}_i = \Phi_i \tilde{x}_{i-1}. \tag{8}$$

As the assumption  $\underline{E}_{\Phi_i} = 0$  may not be always correct in particular when the system Eqs. (2) are produced by INS data, in the next section we obtain a new solution to this problem.

### 3 Integrated total Kalman filter (ITKF)

In this section we solve the DEIV model given by Eqs. (1)–(4). Since we suppose that both of the coefficient matrixes in the observation equations and system equations are noisy i.e.  $\underline{E}_{\Phi_i} \neq 0$  and  $\underline{E}_{A_i} \neq 0$ , we call our least-squares prediction “*integrated total Kalman filter (ITKF)*”. If we want to use condition equations for our optimization, we require combining Eqs. (1)–(3). For this aim, first we insert Eq. (3) into Eq. (1) as follows:

$$\underline{x}_i = (\Phi_i - \underline{E}_{\Phi_i})(\underline{x}_{i-1} - \underline{e}_{i-1}^0) + f_i + \underline{u}_i \tag{9}$$

Then we put Eq. (9) into Eq. (1):

$$\underline{y}_i = (A_i - \underline{E}_{A_i})((\Phi_i - \underline{E}_{\Phi_i})(\underline{x}_{i-1} - \underline{e}_{i-1}^0) + f_i + \underline{u}_i) + \underline{e}_i \tag{10}$$

Eventually we can set the following least-squares target function:

$$\begin{aligned} \Phi(\underline{e}_i, \underline{e}_{A_i}, \hat{\lambda}_i, \underline{e}_{\Phi_i}, \underline{u}_i, \underline{e}_{i-1}^0) &:= \underline{e}_i^T Q_{y_i}^{-1} \underline{e}_i + \underline{e}_{A_i}^T Q_{A_i}^{-1} \underline{e}_{A_i} + \underline{u}_i^T \theta_i^{-1} \underline{u}_i + \underline{e}_{\Phi_i}^T Q_{\Phi_i}^{-1} \underline{e}_{\Phi_i} + \underline{e}_{i-1}^0 \left( \sum_{i-1}^0 \right)^{-1} \underline{e}_{i-1}^0 \\ &+ 2\hat{\lambda}_i^T (y_i - \underline{e}_i - (A_i - \underline{E}_{A_i})((\Phi_i - \underline{E}_{\Phi_i})(\underline{x}_{i-1} - \underline{e}_{i-1}^0) + f_i + \underline{u}_i)) \end{aligned} \tag{11}$$

Note that in contrast to target function of Eq. (5) proposed by Schaffrin and Iz (2008), the target function given by Eq. (11) can produce the predicted residuals of all random observed variables. In Schaffrin and Iz (2008) the quantities  $\tilde{u}_i$  an  $\tilde{e}_{i-1}^0$  were not predicted. For optimization, if tildas ( $\tilde{\phantom{x}}$ ) indicate predicted vectors and hats ( $\hat{\phantom{x}}$ ) denote estimated ones the following necessary conditions must hold:

$$\left. \frac{\partial \Phi}{\partial \tilde{e}_i} \right|_{\tilde{e}_i, \tilde{e}_{A_i}, \hat{\lambda}_i, \tilde{e}_{\Phi_i}, \tilde{u}_i, \tilde{e}_{i-1}^0} = 2(Q_{y_i}^{-1} \tilde{e}_i - \hat{\lambda}_i) = 0 \tag{12}$$

$$\begin{aligned} \left. \frac{\partial \Phi}{\partial \tilde{e}_{A_i}} \right|_{\tilde{e}_i, \tilde{e}_{A_i}, \hat{\lambda}_i, \tilde{e}_{\Phi_i}, \tilde{u}_i, \tilde{e}_{i-1}^0} &= 2(((\Phi_i - \tilde{E}_{\Phi_i})(\underline{x}_{i-1} - \tilde{e}_{i-1}^0) + f_i + \tilde{u}_i) \otimes I_m) \hat{\lambda}_i + 2Q_{A_i}^{-1} \tilde{e}_{A_i} = 0 \\ &= 0 \end{aligned} \tag{13}$$

$$\left. \frac{\partial \Phi}{\partial \tilde{e}_{\Phi_i}} \right|_{\tilde{e}_i, \tilde{e}_{A_i}, \hat{\lambda}_i, \tilde{e}_{\Phi_i}, \tilde{u}_i, \tilde{e}_{i-1}^0} = 2((\underline{x}_{i-1} - \tilde{e}_{i-1}^0) \otimes (A_i - \tilde{E}_{A_i})^T) \hat{\lambda}_i + 2Q_{\Phi_i}^{-1} \tilde{e}_{\Phi_i} = 0 \tag{14}$$

$$\left. \frac{\partial \Phi}{\partial \tilde{u}_i} \right|_{\tilde{e}_i, \tilde{e}_{A_i}, \hat{\lambda}_i, \tilde{e}_{\Phi_i}, \tilde{u}_i, \tilde{e}_{i-1}^0} = -2(A_i - \tilde{E}_{A_i})^T \hat{\lambda}_i + 2\theta_i^{-1} \tilde{u}_i = 0 \tag{15}$$

$$\frac{\partial \Phi}{\partial \tilde{e}_{i-1}^0} \Big|_{\tilde{e}_i, \tilde{e}_{A_i}, \hat{\lambda}_i, \tilde{e}_{\Phi_i}, \tilde{u}_i, \tilde{e}_{i-1}^0} = 2(\Phi_i - \tilde{E}_{\Phi_i})^T (A_i - \tilde{E}_{A_i})^T \hat{\lambda}_i + 2(\Sigma_{i-1}^0)^{-1} \tilde{e}_{i-1}^0 = 0 \tag{16}$$

$$\frac{\partial \Phi}{\partial \hat{\lambda}_i} \Big|_{\tilde{e}_i, \tilde{e}_{A_i}, \hat{\lambda}_i, \tilde{e}_{\Phi_i}, \tilde{u}_i, \tilde{e}_{i-1}^0} = 2(y_i - \tilde{e}_i - (A_i - \tilde{E}_{A_i})((\Phi_i - \tilde{E}_{\Phi_i})(\underline{x}_{i-1} - \underline{e}_{i-1}^0) + f_i + \tilde{u}_i)) = 0. \tag{17}$$

$\tilde{e}_i$  and  $\tilde{e}_{A_i}$  can be obtained from Eqs. (12) and (13) as follows

$$\tilde{e}_i = Q_{y_i} \hat{\lambda}_i \tag{18}$$

$$\tilde{e}_{A_i} = -Q_{A_i}(((\Phi_i - \tilde{E}_{\Phi_i})(\underline{x}_{i-1} - \underline{e}_{i-1}^0) + f_i + \tilde{u}_i) \otimes I_m) \hat{\lambda}_i = -Q_{A_i} R_i \hat{\lambda}_i \tag{19}$$

Equations (14) and (15) immediately lead to

$$\tilde{e}_{\Phi_i} = -Q_{\Phi_i}((\underline{x}_{i-1} - \underline{e}_{i-1}^0) \otimes (A_i - \tilde{E}_{A_i})^T) \hat{\lambda}_i = -Q_{\Phi_i} S_i \hat{\lambda}_i. \tag{20}$$

$$\tilde{u}_i = \theta_i (A_i - \tilde{E}_{A_i})^T \hat{\lambda}_i \tag{21}$$

Equation (16) gives  $\tilde{e}_{i-1}^0$  as follows:

$$\tilde{e}_{i-1}^0 = -\Sigma_{i-1}^0 ((A_i - \tilde{E}_{A_i})(\Phi_i - \tilde{E}_{\Phi_i}))^T \hat{\lambda}_i \tag{22}$$

Eventually by inserting Eqs. (18)–(22) into Eq. (17), the vector of *Lagrange* multipliers  $\hat{\lambda}_i$  can be estimated as follows:

$$\begin{aligned} & y_i - Q_{y_i} \hat{\lambda}_i - (A_i - \tilde{E}_{A_i}) \theta_i (A_i - \tilde{E}_{A_i})^T \hat{\lambda}_i - S_i^T Q_{\Phi_i} S_i \hat{\lambda}_i \\ & - (A_i - \tilde{E}_{A_i}) \Sigma_{i-1}^0 ((A_i - \tilde{E}_{A_i})(\Phi_i - \tilde{E}_{\Phi_i}))^T \hat{\lambda}_i - A_i \Phi_i \underline{x}_{i-1} \\ & - ((\Phi_i \underline{x}_{i-1} + f_i) \otimes I_m) Q_{A_i} R_i \hat{\lambda}_i - A_i f_i = 0 \rightarrow \\ & \hat{\lambda}_i = \left( Q_{y_i} + (A_i - \tilde{E}_{A_i}) \theta_i (A_i - \tilde{E}_{A_i})^T + S_i^T Q_{\Phi_i} S_i \right. \\ & \left. + (A_i - \tilde{E}_{A_i}) \Sigma_{i-1}^0 ((A_i - \tilde{E}_{A_i})(\Phi_i - \tilde{E}_{\Phi_i}))^T + ((\Phi_i \underline{x}_{i-1} + f_i)^T \otimes I_m) Q_{A_i} R_i \right)^{-1} \\ & (y_i - A_i (\Phi_i \underline{x}_{i-1} + f_i)) \end{aligned} \tag{23}$$

In the above equation, the inverse exists since the matrix  $S_i$  is full column rank i.e. its quadratic form is invertible. After prediction of random observed variables  $\tilde{e}_i, \tilde{e}_{A_i}, \tilde{e}_{\Phi_i}, \tilde{u}_i$  and  $\tilde{e}_{i-1}^0$  iteratively using Eqs. (18)–(23), we must update the measured unknown parameters  $\underline{x}_{i-1}$  and the corresponding dispersion matrix for the next epoch  $i$ . By applying variance propagation rules to Eq. (9), the updated dispersion matrix for the next epoch is given by

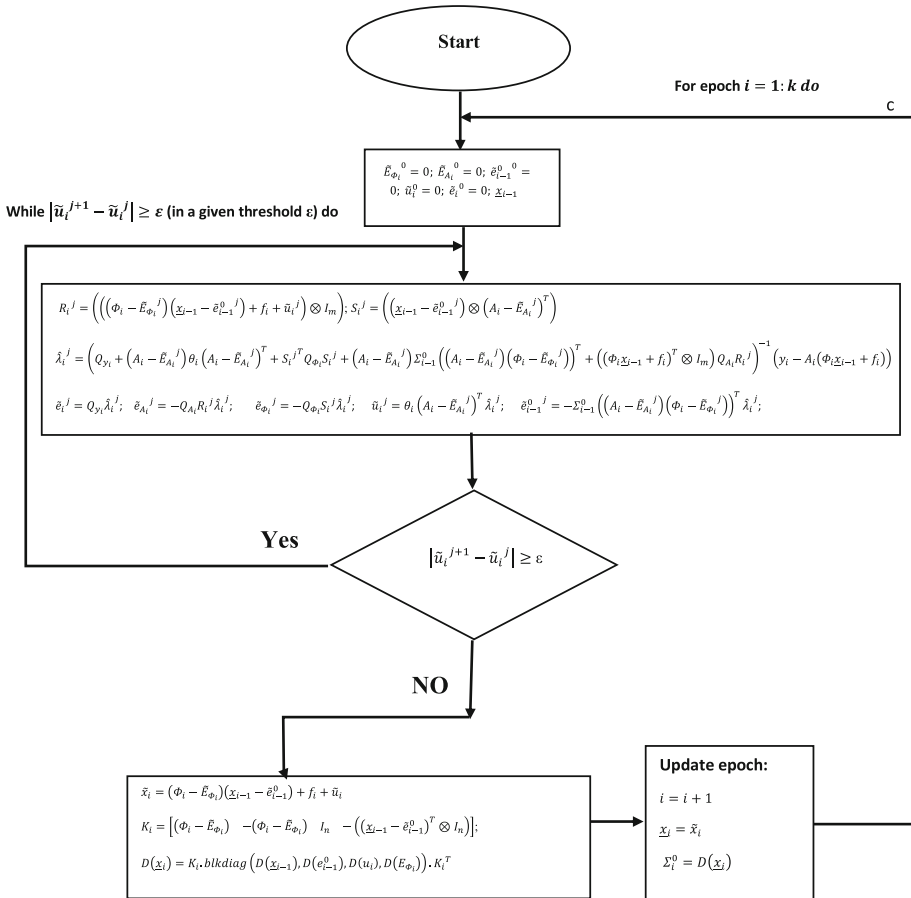
$$D(\underline{x}_i) = K_i \cdot \text{blkdiag}(D(\underline{x}_{i-1}), D(\underline{e}_{i-1}^0), D(u_i), D(E_{\Phi_i})). K_i^T \tag{24}$$

With 
$$K_i = \begin{bmatrix} \frac{\partial \underline{x}_i}{\partial \underline{x}_{i-1}} & \frac{\partial \underline{x}_i}{\partial \underline{e}_{i-1}^0} & \frac{\partial \underline{x}_i}{\partial u_i} & \frac{\partial \underline{x}_i}{\partial E_{\Phi_i}} \end{bmatrix} = [ (\Phi_i - \tilde{E}_{\Phi_i}) \quad -(\Phi_i - \tilde{E}_{\Phi_i}) \quad I_n \quad -((\underline{x}_{i-1} - \underline{e}_{i-1}^0)^T \otimes I_n) ]$$

From Eq. (9) the update of the unknown parameters  $\tilde{x}_i$  is obtained as follows:

$$\tilde{x}_i = (\Phi_i - \tilde{E}_{\Phi_i})(\underline{x}_{i-1} - \underline{e}_{i-1}^0) + f_i + \tilde{u}_i \tag{25}$$

Thus the update part for the next epoch is given by Eqs. (24) and (25). Summarizing, we propose the ITKF algorithm by the following flowchart:



#### 4 ITKF algorithm for integrated direct geo-referencing

If we want to produce the system equations by INS data for integrated direct geo-referencing, one has to consider Eq. (2) as the system equations where the coefficient matrix  $\Phi_i$  is noisy i.e.  $\underline{E}_{\Phi_i} \neq 0$ . In order to sense this condition, we must examine the mathematical model of an INS system. It is obtained after solving navigation equations. For a background one may refer to Sheta (2012) or Jekeli (2001). Navigation equations are a set of differential equations which describe the input gyroscopes and accelerometers measurements input to the local frame mechanization and the output curvilinear coordinates, three velocity components, and three attitude components. Input gyroscopes are angular increments which are measured by IMU. Solving these vector differential equations, through integration, will result in a time variable state vector with kinematic sub-vectors for position, velocity, and attitude. The input to computation process are the angular increments measured by gyroscope and the velocity increments measured by accelerometer. The rotation matrix is updated by following Eq. (26). The Quaternion approach is used in the update because it deals with the singularity problems of the Euler angles at the 90 degrees angle. The quaternion is a 4 elements vector represented in space and contains the amplitude in one element and the direction is described using the three remaining elements. In general, the system equations can be described by the following equation

$$\begin{bmatrix} P_{i+1} \\ q_{i+1} \end{bmatrix} = \begin{bmatrix} I_3 & 0 \\ 0 & I_4 + \underline{G}_i \end{bmatrix} \begin{bmatrix} P_i \\ q_i \end{bmatrix} + \begin{bmatrix} D_i \underline{V}_i \Delta t_i \\ 0 \end{bmatrix} \quad (26)$$

where  $\underline{G}_i = \frac{1}{2} \begin{bmatrix} \underline{c} & \underline{d} & -\underline{b} & \underline{a} \\ -\underline{d} & \underline{c} & \underline{a} & \underline{b} \\ \underline{b} & -\underline{a} & \underline{c} & \underline{d} \\ -\underline{a} & -\underline{b} & -\underline{d} & \underline{c} \end{bmatrix}$ ,  $D_i$  is a deterministic matrix depends on radius of

curvature,  $\Delta t_i$  is time increments between two epochs and  $P_i^T = [\varphi_i \quad \lambda_i \quad h_i]$  is position and  $q_i^T = [q_1 \quad q_2 \quad q_3 \quad q_4]_i$  denotes quaternion rotations. The noisy coefficients  $\underline{a}$ ,  $\underline{b}$ ,  $\underline{c}$  and  $\underline{d}$  are provided by the observed angular increments and the updated velocity  $\underline{V}_i$  is produced by the observed velocity increments.

Consequently, the noisy coefficient matrix  $\underline{\Phi}_i$ , the unknown parameters  $x_i$  and the vector  $f_i$  introduced in Eq. (2) are as follows:

$$\underline{\Phi}_i = \begin{bmatrix} I_3 & 0 \\ 0 & I_4 + \underline{G}_i \end{bmatrix} \quad (27)$$

$$f_i = \begin{bmatrix} D_i \underline{V}_i \Delta t_i \\ 0 \end{bmatrix} \quad (28)$$

$$x_i = \begin{bmatrix} P_i \\ q_i \end{bmatrix} \quad (29)$$

Now suppose that for an integrated geo-referencing of a mobile sensor, we are going to determine the position and attitude of a mobile sensor at five epochs. Due to Eqs. (27)–(29), the components of the DEIV model of the system equations at these epochs are as follows:

$$\Phi_1 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0413 & 0.3382 & -0.063321 & 0.10879 \\ 0 & 0 & 0 & -0.33916 & 1.0707 & 0.11561 & 0.061701 \\ 0 & 0 & 0 & 0.060071 & -0.085862 & 1.0615 & 0.33525 \\ 0 & 0 & 0 & 0.096412 & -0.060515 & -0.32074 & 1.0688 \end{pmatrix}$$

$$\Phi_2 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0479 & 0.31649 & -0.037621 & 0.11486 \\ 0 & 0 & 0 & -0.3207 & 1.0434 & 0.1252 & 0.0826 \\ 0 & 0 & 0 & 0.062775 & -0.10455 & 1.0768 & 0.32767 \\ 0 & 0 & 0 & 0.094081 & -0.067946 & -0.30125 & 1.0621 \end{pmatrix}$$

$$\Phi_3 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0654 & 0.3171 & -0.052309 & 0.093268 \\ 0 & 0 & 0 & -0.3152 & 1.0586 & 0.10666 & 0.071872 \\ 0 & 0 & 0 & 0.079853 & -0.10846 & 1.0636 & 0.3111 \\ 0 & 0 & 0 & 0.10865 & -0.07516 & -0.30661 & 1.047 \end{pmatrix}$$

$$\Phi_4 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0565 & 0.32588 & -0.095492 & 0.10737 \\ 0 & 0 & 0 & -0.30382 & 1.0477 & 0.090393 & 0.064299 \\ 0 & 0 & 0 & 0.065948 & -0.096585 & 1.0389 & 0.32894 \\ 0 & 0 & 0 & 0.093003 & -0.060761 & -0.33936 & 1.0655 \end{pmatrix}$$

$$\Phi_5 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0505 & 0.31213 & -0.09079 & 0.099056 \\ 0 & 0 & 0 & -0.31343 & 1.0605 & 0.090093 & 0.071849 \\ 0 & 0 & 0 & 0.061155 & -0.11065 & 1.0377 & 0.31949 \\ 0 & 0 & 0 & 0.091518 & -0.081141 & -0.33478 & 1.0527 \end{pmatrix}$$



$$f_1 = \begin{bmatrix} 1.9 \\ 3.6 \\ 2.2 \\ 0 \\ 0 \\ 0 \end{bmatrix}; f_2 = \begin{bmatrix} 5.13 \\ 8.9 \\ 5.5 \\ 0 \\ 0 \\ 0 \end{bmatrix}; f_3 = \begin{bmatrix} 2.79 \\ 4.9 \\ 3.12 \\ 0 \\ 0 \\ 0 \end{bmatrix}; f_4 = \begin{bmatrix} 3.9 \\ 7.1 \\ 4.5 \\ 0 \\ 0 \\ 0 \end{bmatrix}; f_5 = \begin{bmatrix} 3.3 \\ 5.7 \\ 3.4 \\ 0 \\ 0 \\ 0 \end{bmatrix};$$

For all of the DEIV models of these system equations, the stochastic model is given by

$$Q_{\Phi_i} = (I_7 \otimes q)(I_7 \otimes q)^T; q = 10^{-2} \begin{bmatrix} 0.6 & 0 & 0.4 & 0 & 0.1 & 0.2 & 0.1 \\ 0 & 0.3 & 1 & 0.9 & 0.5 & 0.7 & 0 \\ 0.6 & 0 & 1 & 1 & 0.2 & 1 & 0 \\ 0.6 & 0.1 & 1 & 1 & 0.6 & 0.1 & 1 \\ 0.2 & 0.3 & 0.4 & 1 & 0.6 & 0.1 & 0 \\ 0.64 & 0.7 & 0.1 & 0.4 & 0.6 & 0.1 & 1 \\ 0.1 & 0.3 & 0.5 & 0.4 & 0.3 & 0.02 & 1 \end{bmatrix};$$

$$\theta_i = 10^{-2} \begin{bmatrix} 2.96 & 3.4 & 1 & 0 & 0 & 0 & 0 \\ 3.4 & 6 & 3.2 & 0 & 0 & 0 & 0 \\ 1 & 3.2 & 2.44 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Note that for  $i = 0, 1, 2, \dots, 6$  the  $(7i + 1)$  to  $(7i + 3)$ th. rows and columns of the matrix  $(I_7 \otimes q)$  must be replaced by zero.

The observation equations which can be produced by GPS and remote sensed data are given by 5 DEIV models at 5 epochs  $i = 1, 2, 3, 4, 5$  as

$y_1=$	$y_2=$	$y_3=$	$y_4=$	$y_5=$
117.34	113.16	110.37	105.07	102.81
158.14	151.1	145.48	136.77	132.9
181.34	176.91	173.77	168.25	165.95
604.6	462.26	332.86	206.12	93.749
18.52	23.689	29.178	35.876	42.525
-26.431	-5.5668	18.249	40.574	68.688
88.136	84.662	82.124	79.716	78.546
681.14	520.54	373.63	229.62	101.29
2466.6	1914	1409	911.46	470.96

	1	0	0	0	0	0	0
	0	1	0	0	0	0	0
	0	0	1	0	0	0	0
$A_1 =$	1.0094	-0.08032	-0.27102	1.3907	0.59041	0.16948	0.18762
	-1.1564	-0.039561	0.9704	5.1452	2.3269	0.39127	0.0010988
	-2.334	1.4488	0.48338	-2.6668	0.25197	0.075307	0.099471
	1.4511	-0.66802	-0.011386	-0.22686	2.2459	1.2784	-0.2805
	0.63161	0.11008	-0.28957	2.4732	0.40092	0.18709	-0.52125
	3.7491	0.36467	-0.23158	-2.8492	2.2569	0.80019	-0.19393

	1	0	0	0	0	0	0
	0	1	0	0	0	0	0
	0	0	1	0	0	0	0
$A_2 =$	2.4707	-0.099481	-0.35429	1.5192	0.7432	0.11466	0.019044
	-1.0753	-0.075316	0.99939	5.1984	4.5722	0.38824	0.032692
	-4.1786	2.7395	0.50222	-4.6932	-0.021168	-0.02341	-0.027835
	1.636	-0.73114	0.016827	-0.0075877	2.0563	2.458	-0.34538
	2.6925	0.25707	-0.044085	2.7252	-0.005275	0.010675	0.02576
	8.3343	0.53808	0.044516	-2.284	1.7764	1.8865	0.12706

	1	0	0	0	0	0	0
	0	1	0	0	0	0	0
	0	0	1	0	0	0	0
$A_3 =$	3.6732	-0.10997	-0.39623	1.615	0.9301	0.027076	-0.025282
	-1.1203	-0.17519	1.0344	5.2334	6.9007	0.39659	0.040885
	-6.2941	3.9875	0.72843	-6.8312	0.022204	-0.012321	0.27109
	1.6144	-0.81103	0.21158	0.038123	2.1286	3.8728	-0.28363
	3.2513	-0.11541	0.098239	3.4351	0.083798	-0.066311	-0.045156
	12.181	0.015706	0.37409	-2.3089	2.1878	3.0923	0.33023

	1	0	0	0	0	0	0
	0	1	0	0	0	0	0
	0	0	1	0	0	0	0
$A_4 =$	4.7735	0.061363	-0.46255	1.5062	1.334	-0.11011	0.34735
	-1.1271	-0.19774	1.0138	5.1957	9.2138	0.36953	0.056945
	-8.5569	5.5994	0.64438	-9.2217	0.2091	0.14771	0.35888
	1.4718	-0.67564	0.0097173	-0.1208	2.1343	5.1686	-0.19908
	4.7702	-0.0086341	0.097021	2.6353	0.35812	-0.309	0.046051
	16.055	0.28166	0.13936	-2.2967	2.1511	3.7861	0.51141

	1	0	0	0	0	0	0
	0	1	0	0	0	0	0
	0	0	1	0	0	0	0
$A_5 =$	5.9639	0.03191	-0.60776	1.4211	1.5153	-0.04741	0.23179
	-1.1027	-0.24537	0.97207	5.165	11.511	0.41599	0.043181
	-10.4	7.0747	0.61147	-11.546	0.27357	0.15443	0.045528
	1.6455	-0.6405	0.033169	-0.023809	2.2963	6.5331	-0.31565
	5.7747	-0.059541	-0.44762	2.462	-0.14936	0.082947	0.14955
	20.582	0.32071	-0.12439	-2.6433	2.4281	5.2551	0.43379

For all of the DEIV models of the observation equations, the stochastic model is given by

$$Q_x = (I_7 \otimes q)(I_7 \otimes q)^T; q$$

$$= 10^{-1} \begin{bmatrix} 1 & 0 & 0 & 1 & 0.1 & 0 & 0.4 & 0.6 & 0.2 \\ 0.6 & 1 & 0 & 0 & 0.4 & 0 & 0.1 & 0.2 & 0.1 \\ 1 & 0.3 & 1 & 0.9 & 0.5 & 0.7 & 0.1 & 0.2 & 0 \\ 0.6 & 0 & 1 & 1 & 0.02 & 0.1 & 0 & 0.3 & 0 \\ 0.6 & 0.01 & 0.1 & 0.02 & 0.1 & 0.1 & 0.06 & 0.1 & 0.1 \\ 0.2 & 0.03 & 0.4 & 0.06 & 0.1 & 1 & 0.6 & 0.1 & 0 \\ 0.4 & 0.07 & 0.1 & 0.04 & 0.2 & 0.4 & 0.6 & 0.1 & 0.1 \\ 0.1 & 0.03 & 0.5 & 0.06 & 0.6 & 0.4 & 0.3 & 2 & 1 \\ 0.6 & 0.01 & 1 & 0.06 & 1 & 1 & 0.6 & 0.1 & 1 \end{bmatrix};$$

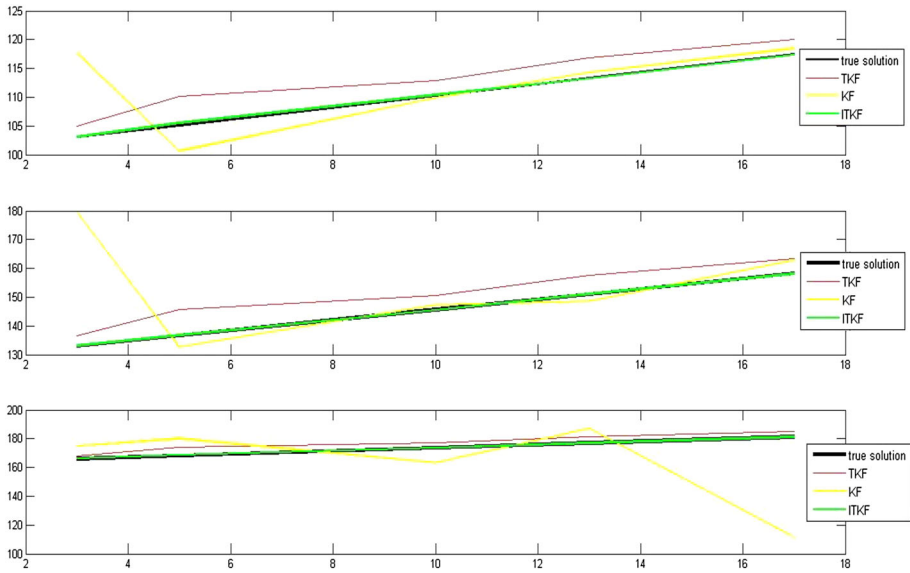
For  $i = 0, 1, 2, \dots, 6$  the  $(9i + 1)$  to  $(9i + 3)$ th rows and columns of the matrix  $(I_6 \otimes q)$  must be replaced by zero.

$$Q_y = 10^{-4} \begin{bmatrix} 69.06 & 9.78 & 33.69 & 16.73 & 9.15 & 5.58 & 29.6 & 5.53 & 9.11 \\ 9.78 & 80.44 & -9.24 & 5.57 & 8.97 & 5.08 & 24.29 & 2.14 & 0.48 \\ 33.69 & -9.24 & 57.78 & 2.28 & 23.12 & 5.43 & 33.16 & 18.54 & 12.08 \\ 16.73 & 5.57 & 2.28 & 49.13 & 1.45 & 1.58 & 1.03 & 1.42 & 0.97 \\ 9.15 & 8.97 & 23.12 & 1.45 & 37.34 & 1.172 & 2.07 & 4.68 & 5.32 \\ 5.58 & 5.08 & 5.43 & 1.58 & 1.172 & 2.31 & 7.34 & 2.82 & 1.76 \\ 29.6 & 24.29 & 33.162 & 1.03 & 2.07 & 7.34 & 117.3 & 43.52 & 6.88 \\ 5.53 & 2.14 & 18.54 & 1.42 & 4.68 & 2.82 & 43.52 & 26.11 & 4.64 \\ 9.11 & 0.48 & 12.08 & 0.97 & 5.32 & 1.76 & 6.88 & 4.64 & 3.91 \end{bmatrix};$$

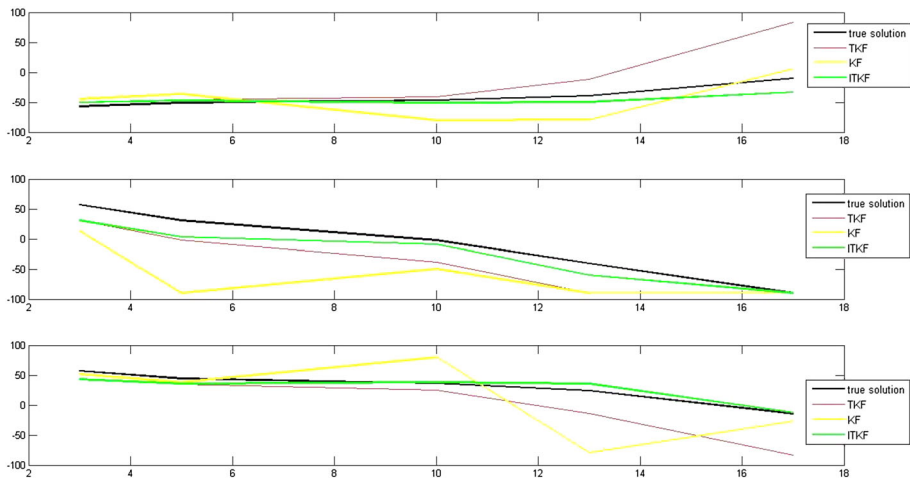
Also the observed state vector  $x_i$  at an initial epoch with its corresponding dispersion matrix is given by:

$$\sum_0^0 = 10^{-4} \begin{bmatrix} 4.01 & 0.4 & 0.1 & 0 & 0.0 & 0.0 & 0.0 \\ 0.4 & 5 & 3 & 0 & 0.0 & 0.0 & 0.0 \\ 0.1 & 3 & 2 & 0 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0.01 & 0.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0 & 0.01 & 0.0 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0 & 0.0 & 0.01 & 0.0 \\ 0.0 & 0.0 & 0.0 & 0 & 0.0 & 0.0 & 0.01 \end{bmatrix}, x_1 = \begin{bmatrix} 103.01 \\ 132.9 \\ 166 \\ -0.57 \\ -0.16 \\ -0/57 \\ 0.56 \end{bmatrix};$$

In this problem both of the observation equations and system equations are in fact DEIV models. Three algorithms KF, TKF and ITKF are applied to this problem. We compare the result with true solution which are illustrated by Figs. 1 and 2 for 3-D position and attitude of the mobile sensor in a local frame respectively. The results demonstrated that the proposed ITKF approach can significantly improve the solution of the predicted position and attitude in contrast to other algorithms. Note that after computing the attitudes in quaternion representation, we converted them into three rotations about three axis in degrees. The improvement of the predicted position is more considerable than the predicted attitude. However, the TKF solution has larger difference with respect to true solution than the ITKF solution since it does not consider the random property of the random design matrix  $\underline{\Phi}_i$ . This situation gets worse for the KF solution in which not only we neglect the random property of the noisy design matrix  $\underline{\Phi}_i$  but also the random design matrix  $\underline{A}_i$  is considered deterministic i.e. with no noise. Moreover, the general treatment of



**Fig. 1** solutions of different algorithms for 3-D position of the mobile sensor in a local frame



**Fig. 2** solutions of different algorithms for 3-D attitude of the mobile sensor in a local frame

the TKF and ITKF approach are similar, however, we can see a significant bias in the TKF solution respect to the ITKF solution which is because of inappropriate modeling of the system equations made by the TKF approach, particularly when the magnitude of the weights of the elements in the random design matrixes  $\underline{A}_i$  and  $\underline{\Phi}_i$  cannot be neglected.

## 5 Conclusions and outlook

In this paper, we developed a new Kalman filter algorithm. Its main assumption is that the system equations of a dynamic problem can itself be a DEIV model i.e. the design matrix  $\Phi_i$  of the system equations is also noisy. In practice one can see this situation when the system equations are provided by INS data. In such a case, the random noises are produced by observed angular increments and velocity increments. The predicted residuals for all variables besides the variance matrix of the unknown parameters were obtained by the proposed ITKF algorithm. In a numerical example, it was shown that the proposed ITKF approach can make the best improvement in solution in contrast to other algorithms, if both of the coefficient matrixes in the observation equations and the system equations are noisy. The prediction part is done by Eqs. (18)–(23) and the update part for the next epoch is given by Eqs. (24) and (25). In the forthcoming publication, we try to improve the prediction part due to several practical vulnerabilities of direct geo-referencing problem.

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