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# Supplementary Materials: Visual-Inertial-Aided Online MAV System Identification

Chuchu Chen - ccchu@udel.edu  
Yulin Yang - yuyang@udel.edu  
Patrick Geneva - pgeneva@udel.edu  
Woosik Lee - woosik@udel.edu  
Guoquan Huang - ghuang@udel.edu

Department of Mechanical Engineering  
University of Delaware, Delaware, USA



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ROBOT PERCEPTION & NAVIGATION GROUP

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# 1 MAV Dynamics and Its Integration

The frame of references for the MAV system is illustrated in Fig. 1. The MAV states  $\mathbf{x}_M$  and system parameters  $\mathbf{x}_\theta$  are defined as:

$$\mathbf{x}_M = [{}^M_G \bar{q}^\top \quad {}^G \mathbf{p}_M^\top \quad {}^M \boldsymbol{\omega}^\top \quad {}^G \mathbf{v}_M^\top]^\top \quad (1)$$

$$\mathbf{x}_\theta = [\mathbf{x}_D^\top \quad \mathbf{x}_G^\top \quad \mathbf{x}_{MI}^\top]^\top \quad (2)$$

where:

$$\mathbf{x}_D = [c_t \quad c_m]^\top \quad (3)$$

$$\mathbf{x}_G = [m \quad {}^M \mathbf{j}^\top \quad {}^M \mathbf{p}_B^\top]^\top \quad (4)$$

$$\mathbf{x}_{MI} = [{}^I_M \bar{q}^\top \quad {}^I \mathbf{p}_M^\top]^\top \quad (5)$$

where  ${}^M_G \bar{q}$  is the unit quaternion representing the rotation  ${}^M_G \mathbf{R}$  from the global frame  $\{G\}$  to the MAV center of mass frame  $\{M\}$  [1],  ${}^M \boldsymbol{\omega}$  is the angular velocity of in  $\{M\}$ , and  ${}^G \mathbf{p}_M$  and  ${}^G \mathbf{v}_M$  are the MAV position and velocity in  $\{G\}$ , respectively. The aerodynamic parameters,  $\mathbf{x}_D$ , consist of the rotor thrust coefficient  $c_t$  and moment coefficient  $c_m$ . The geometrical parameters,  $\mathbf{x}_G$ , include the mass of the platform  $m$ , moment of inertial  ${}^M \mathbf{J}$ , which is a diagonal matrix defined in frame  $\{M\}$  with  ${}^M \mathbf{j}$  being its diagonal terms.  ${}^M \mathbf{p}_B$  represents the translation between the geometric body frame  $\{B\}$  and  $\{M\}$ .

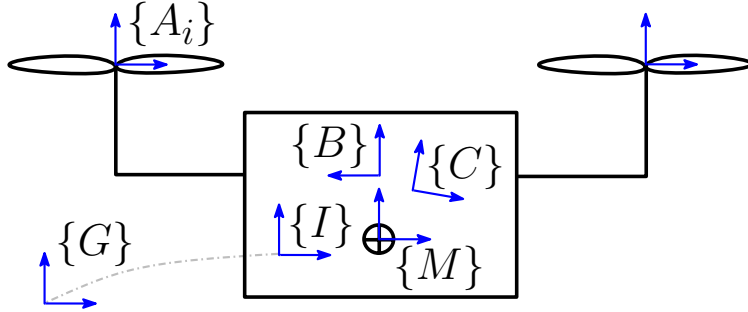


Figure 1: Frame of references of a typical MAV system:  $i$ -th rotor frame  $\{A_i\}$ , geometric body frame  $\{B\}$ , IMU frame  $\{I\}$ , camera frame  $\{C\}$ , MAV center of mass frame  $\{M\}$ , and global frame  $\{G\}$ .

## 1.1 MAV Force and Moment

The total force  ${}^M \mathbf{F}$  and moment  ${}^M \mathbf{M}$  of a MAV with  $N_r$  rotors are defined as [2]:

$${}^M \mathbf{F} = \sum_{i=1}^{N_r} {}^M_{A_i} \mathbf{R}^{A_i} \mathbf{F}_i \quad (6)$$

$${}^M \mathbf{M} = \sum_{i=1}^{N_r} ({}^M_{A_i} \mathbf{R}^{A_i} \mathbf{M} + [{}^M \mathbf{p}_{A_i}] {}^M \mathbf{F}_i) \quad (7)$$

where  ${}^M \mathbf{p}_{A_i} = {}^M_B \mathbf{R}^B \mathbf{p}_{A_i} + {}^M \mathbf{p}_B$  denotes the translation between rotor  $\{A_i\}$  and center of mass frame  $\{M\}$ , which is typically known from the CAD model. Assuming the rotor encoder measurements

$r_{m,i}$  from the  $i$ -th rotor is defined as  $r_{m,i} = r_i + n_{r,i}$  with  $n_{r,i}$  represents the white Gaussian noise, the individual force  $^{A_i}\mathbf{F}_i$  and moment  $^{A_i}\mathbf{M}_i$  from rotor  $\{A_i\}$  are approximated as [3]:

$$^{A_i}\mathbf{F}_i = c_t(r_{m,i} - n_{r,i})^2 \mathbf{e}_z + \mathbf{n}_{f,i} \quad (8)$$

$$^{A_i}\mathbf{M}_i = c_m(r_{m,i} - n_{r,i})^2 \lambda_i \mathbf{e}_z + \mathbf{n}_{m,i} \quad (9)$$

where  $\lambda_i \in \{-1, 1\}$  corresponds to the rotation direction of the  $i$ -th rotor and  $\mathbf{e}_z = [0, 0, 1]^\top$  is a unit vector along local  $z$  direction. As discussed in detail in the paper Sec. IV.A [4], rotor speed can only measure along the local  $z$ -axis, thus, the additional noises,  $\mathbf{n}_{f,i}$  and  $\mathbf{n}_{m,i}$ , are introduced to compensate for the inadequacy of the MAV measurements.

## 1.2 MAV Dynamic Model

The MAV dynamics are defined with the force and moment models as:

$$^M_G \dot{\bar{q}} = \frac{1}{2} \boldsymbol{\Omega} (^M \boldsymbol{\omega}) ^M_G \bar{q} \quad (10)$$

$$^G \dot{\mathbf{p}}_M = ^G \mathbf{v}_M \quad (11)$$

$$^M \dot{\boldsymbol{\omega}} = ^M \mathbf{J}^{-1} ( ^M \mathbf{M} - [^M \boldsymbol{\omega}] ^M \mathbf{J} ^M \boldsymbol{\omega} ) \quad (12)$$

$$^G \dot{\mathbf{v}}_M = \frac{1}{m} ^G_M \mathbf{R} ^M \mathbf{F} - ^G \mathbf{g} \quad (13)$$

where  $\boldsymbol{\Omega}(\boldsymbol{\omega}) = \begin{bmatrix} -[\boldsymbol{\omega}] & \boldsymbol{\omega} \\ -\boldsymbol{\omega}^\top & 0 \end{bmatrix}$  and  $[\cdot]$  is the skew-symmetric matrix;  $^G \mathbf{g} = [0 \ 0 \ 9.81]^\top$  denotes the gravity. Note that through the report we define the error quaternion as:

$$^M_G \bar{q} = \delta \bar{q} \otimes ^M_G \hat{\bar{q}} \quad (14)$$

which is equivalent as [1]:

$$^M_G \mathbf{R} = \exp(-\delta \boldsymbol{\theta}) \cdot ^M_G \hat{\mathbf{R}} \Rightarrow ^M_G \mathbf{R} \simeq (\mathbf{I} - [\delta \boldsymbol{\theta}]) \cdot ^M_G \hat{\mathbf{R}} \quad (15)$$

$$^G_M \mathbf{R} = ^G_M \hat{\mathbf{R}} \cdot \exp(\delta \boldsymbol{\theta}) \Rightarrow ^G_M \mathbf{R} \simeq ^G_M \hat{\mathbf{R}} \cdot (\mathbf{I} + [\delta \boldsymbol{\theta}]) \quad (16)$$

The MAV dynamics can be summarized as:

$$\dot{\mathbf{x}}_M = \mathbf{f}_M(\mathbf{x}_M, \mathbf{x}_\theta, \mathbf{n}_M) \quad (17)$$

where  $\mathbf{n}_M = [n_{r,1} \cdots n_{r,N_r} \ \mathbf{n}_{f,1}^\top \cdots \mathbf{n}_{f,N_r}^\top \ \mathbf{n}_{m,1}^\top \cdots \mathbf{n}_{m,N_r}^\top]^\top$  contains all noises [see Eq. (8) and (9)] with covariance  $\mathbf{Q}_M$ . We can integrate this model from time  $t_k$  to  $t_{k+1}$  based on first-order approximation:

$$^{k+1}_G \mathbf{R} = \Delta \mathbf{R}^\top {}^k_G \mathbf{R} \quad (18)$$

$$= \exp\left(-{}^k \boldsymbol{\theta}_{k+1}\right) {}^k_G \mathbf{R} \quad (19)$$

$$^G \mathbf{p}_{k+1} = ^G \mathbf{p}_k + \Delta \mathbf{p} \quad (20)$$

$$= ^G \mathbf{p}_k + ^G \mathbf{v}_k \Delta t + \frac{1}{2} \left( \frac{1}{m} {}^k_G \mathbf{R} {}^k \mathbf{F} - ^G \mathbf{g} \right) \Delta t^2 \quad (21)$$

$$^{k+1} \boldsymbol{\omega} = \Delta \mathbf{R}^\top ({}^k \boldsymbol{\omega} + \Delta \boldsymbol{\omega}) \quad (22)$$

$$= \exp\left(-{}^k \boldsymbol{\theta}_{k+1}\right) \left[ {}^k \boldsymbol{\omega} + {}^k \mathbf{J}^{-1} \left( {}^k \mathbf{M} - [{}^k \boldsymbol{\omega}] {}^k \mathbf{J} {}^k \boldsymbol{\omega} \right) \Delta t \right] \quad (23)$$

$$^G \mathbf{v}_{k+1} = ^G \mathbf{v}_k + \Delta \mathbf{v} \quad (24)$$

$$= ^G \mathbf{v}_k + \left[ \frac{1}{m} \left( {}^k_G \mathbf{R} {}^k \mathbf{F} \right) - ^G \mathbf{g} \right] \Delta t \quad (25)$$

where:

$${}^k\boldsymbol{\theta}_{k+1} = {}^k\boldsymbol{\omega}\Delta t + \frac{1}{2}{}^k\mathbf{J}^{-1} \left( {}^k\mathbf{M} - [{}^k\boldsymbol{\omega}]^k\mathbf{J}^k\boldsymbol{\omega} \right) \Delta t^2 \quad (26)$$

Note that we use  $k$  and  $k+1$  instead of  $M_k$  and  $M_{k+1}$  to simplify the notation and  $\Delta t = t_{k+1} - t_k$  express the time offset between two timestamps. With the above preintegration, we can have the following integrated discrete-time MAV dynamic model and its linearization:

$$\mathbf{x}_{M_{k+1}} = \mathbf{g}_M(\mathbf{x}_{M_k}, \mathbf{x}_\theta, \mathbf{n}_M) \quad (27)$$

$$\tilde{\mathbf{x}}_{M_{k+1}} \simeq \boldsymbol{\Phi}_M \tilde{\mathbf{x}}_{M_k} + \boldsymbol{\Phi}_\theta \tilde{\mathbf{x}}_\theta + \mathbf{G}_n \mathbf{n}_M \quad (28)$$

where  $\boldsymbol{\Phi}_M$  is the linearized state transition matrix.  $\boldsymbol{\Phi}_\theta$  and  $\mathbf{G}_n$  represent the Jacobians for  $\mathbf{x}_\theta$  and  $\mathbf{n}_M$ , respectively. In the next section, we will introduce in detail the derivations of the Jacobians.

### 1.3 Linearization for MAV Dynamic Model

To simplify the following derivations, we first define:

$$\mathbf{A} = {}^k\mathbf{J}^{-1} \left( {}^k\mathbf{M} - [{}^k\boldsymbol{\omega}]^k\mathbf{J}^k\boldsymbol{\omega} \right) \quad (29)$$

$$\mathbf{F} = \frac{1}{m} {}^k\mathbf{F} \quad (30)$$

The derivatives of  $\mathbf{F}$  and  $\mathbf{A}$  respect to the involved states following chain rule as:

$$\mathbf{H}_{\mathbf{x}_\theta}^{\mathbf{A}} = \begin{bmatrix} \frac{\partial \mathbf{A}}{\partial \mathbf{x}_D} & \frac{\partial \mathbf{A}}{\partial \mathbf{x}_G} & \frac{\partial \mathbf{A}}{\partial \mathbf{x}_{MI}} \end{bmatrix} \quad (31)$$

$$= \begin{bmatrix} \mathbf{H}_{\mathbf{x}_D}^{\mathbf{A}} & \mathbf{H}_{\mathbf{x}_G}^{\mathbf{A}} & \mathbf{0} \end{bmatrix} \quad (32)$$

$$\mathbf{H}_{\mathbf{x}_\theta}^{\mathbf{F}} = \begin{bmatrix} \frac{\partial \mathbf{F}}{\partial \mathbf{x}_D} & \frac{\partial \mathbf{F}}{\partial \mathbf{x}_G} & \frac{\partial \mathbf{F}}{\partial \mathbf{x}_{MI}} \end{bmatrix} \quad (33)$$

$$= \begin{bmatrix} \mathbf{H}_{\mathbf{x}_D}^{\mathbf{F}} & \mathbf{H}_{\mathbf{x}_G}^{\mathbf{F}} & \mathbf{0} \end{bmatrix} \quad (34)$$

where:

$$\mathbf{H}_{\mathbf{x}_D}^{\mathbf{A}} = \begin{bmatrix} \frac{\partial \mathbf{A}}{\partial c_t} & \frac{\partial \mathbf{A}}{\partial c_m} \end{bmatrix} \quad (35)$$

$$= \begin{bmatrix} {}^k\mathbf{J}^{-1} \sum_{i=1}^{N_r} [{}^M\mathbf{p}_{A_i}]_{A_i}^M \mathbf{R} r_i^2 \mathbf{e}_z & {}^k\mathbf{J}^{-1} \sum_{i=1}^{N_r} [{}^M\mathbf{p}_{A_i}]_{A_i}^M \mathbf{R} \lambda_i r_i^2 \mathbf{e}_z \end{bmatrix} \quad (36)$$

$$\mathbf{H}_{\mathbf{x}_G}^{\mathbf{A}} = \begin{bmatrix} \frac{\partial \mathbf{A}}{\partial m} & \frac{\partial \mathbf{A}}{\partial {}^M\mathbf{j}} & \frac{\partial \mathbf{A}}{\partial {}^M\mathbf{p}_B} \end{bmatrix} \quad (37)$$

$$= \begin{bmatrix} \mathbf{0}_{3 \times 1} & \frac{\partial \mathbf{A}}{\partial {}^M\mathbf{j}} & -{}^k\mathbf{J}^{-1} \sum_{i=1}^{N_r} [{}^M\mathbf{F}_i] \end{bmatrix} \quad (38)$$

$$\mathbf{H}_{\mathbf{x}_D}^{\mathbf{F}} = \begin{bmatrix} \frac{\partial \mathbf{F}}{\partial c_t} & \frac{\partial \mathbf{F}}{\partial c_m} \end{bmatrix} \quad (39)$$

$$= \begin{bmatrix} \frac{1}{m} \sum_{i=1}^{N_r} [{}^M\mathbf{p}_{A_i}]_{A_i}^M \mathbf{R} r_i^2 \mathbf{e}_z & \mathbf{0}_{3 \times 1} \end{bmatrix} \quad (40)$$

$$\mathbf{H}_{\mathbf{x}_G}^{\mathbf{F}} = \begin{bmatrix} \frac{\partial \mathbf{F}}{\partial m} & \frac{\partial \mathbf{F}}{\partial {}^M\mathbf{J}} & \frac{\partial \mathbf{F}}{\partial {}^M\mathbf{p}_B} \end{bmatrix} \quad (41)$$

$$= \begin{bmatrix} -\frac{1}{m^2} {}^k\mathbf{F} & \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix} \quad (42)$$

$$\frac{\partial \mathbf{A}}{\partial {}^M\mathbf{j}} = \begin{bmatrix} \frac{\partial \mathbf{A}}{\partial j_1} & \frac{\partial \mathbf{A}}{\partial j_2} & \frac{\partial \mathbf{A}}{\partial j_3} \end{bmatrix} \quad (43)$$

$$\frac{\partial \mathbf{A}}{\partial j_1} = \begin{bmatrix} -\frac{1}{j_1^2} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \left( {}^k\mathbf{M} - [{}^k\boldsymbol{\omega}] {}^k\mathbf{J} {}^k\boldsymbol{\omega} \right) - {}^k\mathbf{J}^{-1} [{}^k\boldsymbol{\omega}] \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} {}^k\boldsymbol{\omega} \quad (44)$$

$$\frac{\partial \mathbf{A}}{\partial j_2} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -\frac{1}{j_2^2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \left( {}^k\mathbf{M} - [{}^k\boldsymbol{\omega}] {}^k\mathbf{J} {}^k\boldsymbol{\omega} \right) - {}^k\mathbf{J}^{-1} [{}^k\boldsymbol{\omega}] \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} {}^k\boldsymbol{\omega} \quad (45)$$

$$\frac{\partial \mathbf{A}}{\partial j_3} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & -\frac{1}{j_3^2} \end{bmatrix} \left( {}^k\mathbf{M} - [{}^k\boldsymbol{\omega}] {}^k\mathbf{J} {}^k\boldsymbol{\omega} \right) - {}^k\mathbf{J}^{-1} [{}^k\boldsymbol{\omega}] \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} {}^k\boldsymbol{\omega} \quad (46)$$

Since  $\mathbf{A}$  consists of  ${}^k\boldsymbol{\omega}$ , we also have:

$$\mathbf{H}_{\boldsymbol{\omega}}^{\mathbf{A}} = \frac{\partial \mathbf{A}}{\partial {}^k\boldsymbol{\omega}} \quad (47)$$

$$= {}^k\mathbf{J}^{-1} \left( -[{}^k\boldsymbol{\omega}] {}^k\mathbf{J} + [{}^k\mathbf{J} {}^k\boldsymbol{\omega}] \right) \quad (48)$$

Finally, we can derive the related noise Jacobians:

$$\mathbf{H}_{\mathbf{n}_M}^{\mathbf{A}} = \begin{bmatrix} \mathbf{H}_{n_{r,i}}^{\mathbf{A}} & \mathbf{H}_{n_{f,i}}^{\mathbf{A}} & \mathbf{H}_{n_{m,i}}^{\mathbf{A}} \end{bmatrix} \quad (49)$$

$$= \begin{bmatrix} -2 {}^k\mathbf{J}^{-1} ({}^M\mathbf{R} c_m \lambda_i c_m \mathbf{e}_z + [{}^M\mathbf{p}_{A_i}]_{A_i}^M \mathbf{R} c_t r_i \mathbf{e}_z) & {}^k\mathbf{J}^{-1} [{}^M\mathbf{p}_{A_i}]_{A_i}^M & {}^k\mathbf{J}^{-1} {}^M\mathbf{R} \end{bmatrix} \quad (50)$$

$$\mathbf{H}_{\mathbf{n}_M}^{\mathbf{F}} = \begin{bmatrix} \mathbf{H}_{n_{r,i}}^{\mathbf{F}} & \mathbf{H}_{n_{f,i}}^{\mathbf{F}} & \mathbf{0}_3 \end{bmatrix} \quad (51)$$

$$= \begin{bmatrix} -\frac{2}{m} {}^M\mathbf{R} c_t r_i \mathbf{e}_z & \frac{1}{m} \mathbf{I}_3 & \mathbf{0}_3 \end{bmatrix} \quad (52)$$

Start with the orientation integration Eq. (18), we have:

$${}_{k+1}^G \hat{\mathbf{R}} (\mathbf{I} + [\delta \boldsymbol{\theta}_{k+1}]) \simeq {}_k^G \hat{\mathbf{R}} (\mathbf{I} + [\delta \boldsymbol{\theta}_k]) \exp({}^k\boldsymbol{\theta}_{k+1}) \quad (53)$$

$$\mathbf{I} + [\delta \boldsymbol{\theta}_{k+1}] = {}_k^{k+1} \mathbf{R} (\mathbf{I} + [\delta \boldsymbol{\theta}_k]) \exp({}^k\hat{\boldsymbol{\theta}}_{k+1}) \exp\left({}^k\mathbf{J}_r ({}^k\hat{\boldsymbol{\theta}}_{k+1}) {}^k\tilde{\boldsymbol{\theta}}_{k+1}\right) \quad (54)$$

$$= \mathbf{I} + [{}_k^{k+1} \hat{\mathbf{R}} \delta \boldsymbol{\theta}_k] + [\mathbf{J}_r ({}^k\hat{\boldsymbol{\theta}}_{k+1}) {}^k\tilde{\boldsymbol{\theta}}_{k+1}] \quad (55)$$

$$\Rightarrow \delta \boldsymbol{\theta}_{k+1} = {}_k^{k+1} \hat{\mathbf{R}} \delta \boldsymbol{\theta}_k + \mathbf{J}_r ({}^k\hat{\boldsymbol{\theta}}_{k+1}) {}^k\tilde{\boldsymbol{\theta}}_{k+1} \quad (56)$$

where from Eq. (26):

$${}^k\boldsymbol{\theta}_{k+1} = {}^k\boldsymbol{\omega}\Delta t + \frac{1}{2}\mathbf{A}\Delta t^2 \quad (57)$$

$$\Rightarrow {}^k\tilde{\boldsymbol{\theta}}_{k+1} \simeq \left( \frac{1}{2}\mathbf{H}_{\boldsymbol{\omega}}^{\mathbf{A}}\Delta t^2 + \mathbf{I}\Delta t \right) {}^k\tilde{\boldsymbol{\omega}} + \frac{1}{2}\mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{A}}\Delta t^2 \tilde{\mathbf{x}}_{\theta} \quad (58)$$

Therefore,

$$\delta\boldsymbol{\theta}_{k+1} \simeq {}_k^{k+1}\hat{\mathbf{R}}\delta\boldsymbol{\theta}_k + \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \left( \frac{1}{2}\mathbf{H}_{\boldsymbol{\omega}}^{\mathbf{A}}\Delta t^2 + \mathbf{I}\Delta t \right) {}^k\tilde{\boldsymbol{\omega}} + \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \left( \frac{1}{2}\mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{A}}\Delta t^2 \right) \tilde{\mathbf{x}}_{\theta} \quad (59)$$

The Jacobians w.r.t states can thus be derived as:

$$\mathbf{H}_{\mathbf{x}_k}^{\boldsymbol{\theta}} = \begin{bmatrix} \frac{\partial\delta\boldsymbol{\theta}_{k+1}}{\partial\delta\boldsymbol{\theta}_k} & \frac{\partial\delta\boldsymbol{\theta}_{k+1}}{\partial^G\tilde{\mathbf{p}}_k} & \frac{\partial\delta\boldsymbol{\theta}_{k+1}}{\partial^k\tilde{\boldsymbol{\omega}}} & \frac{\partial\delta\boldsymbol{\theta}_{k+1}}{\partial^G\tilde{\mathbf{v}}_k} \end{bmatrix} \quad (60)$$

$$= [\mathbf{H}_{\boldsymbol{\theta}}^{\boldsymbol{\theta}} \quad \mathbf{0}_3 \quad \mathbf{H}_{\boldsymbol{\omega}}^{\boldsymbol{\theta}} \quad \mathbf{0}_3] \quad (61)$$

$$= [{}_k^{k+1}\hat{\mathbf{R}} \quad \mathbf{0}_3 \quad \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \left( \frac{1}{2}\mathbf{H}_{\boldsymbol{\omega}}^{\mathbf{A}}\Delta t^2 + \mathbf{I}_3\Delta t \right) \quad \mathbf{0}_3] \quad (62)$$

$$\mathbf{H}_{\mathbf{x}_{\theta}}^{\boldsymbol{\theta}} = \begin{bmatrix} \frac{\partial\delta\boldsymbol{\theta}_{k+1}}{\partial\tilde{\mathbf{x}}_D} & \frac{\partial\delta\boldsymbol{\theta}_{k+1}}{\partial\tilde{\mathbf{x}}_G} & \frac{\partial\delta\boldsymbol{\theta}_{k+1}}{\partial\tilde{\mathbf{x}}_{MI}} \end{bmatrix} \quad (63)$$

$$= [\mathbf{H}_{\mathbf{x}_D}^{\boldsymbol{\theta}} \quad \mathbf{H}_{\mathbf{x}_G}^{\boldsymbol{\theta}} \quad \mathbf{0}_{3 \times 6}] \quad (64)$$

$$= \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \left( \frac{1}{2}\mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{A}}\Delta t^2 \right) \quad (65)$$

$$= \frac{1}{2}\mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1})\Delta t^2 [\mathbf{H}_{\mathbf{x}_D}^{\mathbf{A}} \quad \mathbf{H}_{\mathbf{x}_G}^{\mathbf{A}} \quad \mathbf{0}_{3 \times 6}] \quad (66)$$

$$\mathbf{H}_{\mathbf{n}_M}^{\boldsymbol{\theta}} = \frac{1}{2}\mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1})\Delta t^2\mathbf{H}_{\mathbf{n}_M}^{\mathbf{A}} \quad (67)$$

From angular velocity integration Eq. (22) we can get:

$${}^{k+1}\boldsymbol{\omega} = {}^{k+1}\hat{\boldsymbol{\omega}} + {}^{k+1}\tilde{\boldsymbol{\omega}} \quad (68)$$

$$= \exp\left(-{}^k\boldsymbol{\theta}_{k+1}\right) \left({}^k\boldsymbol{\omega} + \mathbf{A}\Delta t\right) \quad (69)$$

$$\simeq \left(\mathbf{I}_3 - \lfloor \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) {}^k\tilde{\boldsymbol{\theta}}_{k+1} \rfloor\right) {}_k^{k+1}\hat{\mathbf{R}} \left({}^k\boldsymbol{\omega} + \mathbf{A}\Delta t\right) \quad (70)$$

$$\Rightarrow {}^{k+1}\tilde{\boldsymbol{\omega}} = \left[ {}_k^{k+1}\hat{\mathbf{R}} + {}_k^{k+1}\hat{\mathbf{R}}\mathbf{H}_{\boldsymbol{\omega}}^{\mathbf{A}}\Delta t + \lfloor {}^{k+1}\hat{\boldsymbol{\omega}} \rfloor \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \left( \frac{1}{2}\mathbf{H}_{\boldsymbol{\omega}}^{\mathbf{A}}\Delta t^2 + \mathbf{I}_3\Delta t \right) \right] {}^k\tilde{\boldsymbol{\omega}} \quad (71)$$

$$+ \left[ \lfloor {}^{k+1}\hat{\boldsymbol{\omega}} \rfloor \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \left( \frac{1}{2}\mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{A}}\Delta t^2 \right) + {}_k^{k+1}\hat{\mathbf{R}}\mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{A}}\Delta t \right] \tilde{\mathbf{x}}_{\theta} \quad (72)$$

Jacobians are derived as:

$$\mathbf{H}_{\mathbf{x}_k}^\omega = \begin{bmatrix} \frac{\partial^{k+1}\tilde{\omega}}{\partial \delta \boldsymbol{\theta}_k} & \frac{\partial^{k+1}\tilde{\omega}}{\partial^G \tilde{\mathbf{p}}_k} & \frac{\partial^{k+1}\tilde{\omega}}{\partial^k \tilde{\omega}} & \frac{\partial^{k+1}\tilde{\omega}}{\partial^G \tilde{\mathbf{v}}_k} \end{bmatrix} \quad (73)$$

$$= [\mathbf{0}_3 \quad \mathbf{0}_3 \quad \mathbf{H}_\omega^\omega \quad \mathbf{0}_3] \quad (74)$$

$$\mathbf{H}_\omega^\omega = {}^k_{k+1}\hat{\mathbf{R}} + {}^k_{k+1}\hat{\mathbf{R}}\mathbf{H}_\omega^\mathbf{A}\Delta t + [{}^{k+1}\hat{\omega}] \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \left( \frac{1}{2}\mathbf{H}_\omega^\mathbf{A}\Delta t^2 + \mathbf{I}_3\Delta t \right) \quad (75)$$

$$\mathbf{H}_{\mathbf{x}_\theta}^\omega = \begin{bmatrix} \frac{\partial^{k+1}\tilde{\omega}}{\partial \tilde{\mathbf{x}}_D} & \frac{\partial^{k+1}\tilde{\omega}}{\partial \tilde{\mathbf{x}}_G} & \frac{\partial^{k+1}\tilde{\omega}}{\partial \tilde{\mathbf{x}}_{MI}} \end{bmatrix} \quad (76)$$

$$= [\mathbf{H}_{\mathbf{x}_D}^\omega \quad \mathbf{H}_{\mathbf{x}_G}^\omega \quad \mathbf{0}_{3 \times 6}] \quad (77)$$

$$= \frac{1}{2} [{}^{k+1}\hat{\omega}] \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \mathbf{H}_{\mathbf{x}_\theta}^\mathbf{A} \Delta t^2 + {}^k_{k+1}\hat{\mathbf{R}} \mathbf{H}_{\mathbf{x}_\theta}^\mathbf{A} \Delta t \quad (78)$$

$$= \left( \frac{1}{2} [{}^{k+1}\hat{\omega}] \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \Delta t^2 + {}^k_{k+1}\hat{\mathbf{R}} \Delta t \right) [\mathbf{H}_{\mathbf{x}_D}^\mathbf{A} \quad \mathbf{H}_{\mathbf{x}_G}^\mathbf{A} \quad \mathbf{0}_{3 \times 6}] \quad (79)$$

$$\mathbf{H}_{\mathbf{n}_M}^\omega = \frac{1}{2} [{}^{k+1}\hat{\omega}] \mathbf{J}_r({}^k\hat{\boldsymbol{\theta}}_{k+1}) \mathbf{H}_{\mathbf{n}_M}^\mathbf{A} \Delta t^2 + {}^k_{k+1}\hat{\mathbf{R}} \mathbf{H}_{\mathbf{n}_M}^\mathbf{A} \Delta t \quad (80)$$

From the linear velocity integration Eq. (24):

$${}^G\mathbf{v}_{k+1} = {}^G\hat{\mathbf{v}}_{k+1} + {}^G\tilde{\mathbf{v}}_{k+1} \quad (81)$$

$$= {}^G\hat{\mathbf{v}}_k + {}^G\tilde{\mathbf{v}}_k + {}^G_k\hat{\mathbf{R}} (\mathbf{I}_3 + [\delta \boldsymbol{\theta}_k]) \left( \hat{\mathbf{F}} + \mathbf{H}_{\mathbf{x}_\theta}^\mathbf{F} \tilde{\mathbf{x}}_\theta \right) \Delta t - {}^G\mathbf{g} \Delta t \quad (82)$$

$$\Rightarrow {}^G\tilde{\mathbf{v}}_{k+1} = -{}^G_k\hat{\mathbf{R}} [\hat{\mathbf{F}}] \Delta t \delta \boldsymbol{\theta}_k + {}^G\tilde{\mathbf{v}}_k + {}^G_k\hat{\mathbf{R}} \mathbf{H}_{\mathbf{x}_\theta}^\mathbf{F} \Delta t \tilde{\mathbf{x}}_\theta \quad (83)$$

Therefore, Jacobians w.r.t states are as follows:

$$\mathbf{H}_{\mathbf{x}_k}^\mathbf{v} = \begin{bmatrix} \frac{\partial^G \tilde{\mathbf{v}}_{k+1}}{\partial \delta \boldsymbol{\theta}_k} & \frac{\partial^G \tilde{\mathbf{v}}_{k+1}}{\partial^G \tilde{\mathbf{p}}_k} & \frac{\partial^G \tilde{\mathbf{v}}_{k+1}}{\partial^k \tilde{\omega}} & \frac{\partial^G \tilde{\mathbf{v}}_{k+1}}{\partial^G \tilde{\mathbf{v}}_k} \end{bmatrix} \quad (84)$$

$$= [\mathbf{H}_\theta^\mathbf{v} \quad \mathbf{0}_3 \quad \mathbf{0}_3 \quad \mathbf{I}_3] \quad (85)$$

$$= [-{}^G_k\hat{\mathbf{R}} [\hat{\mathbf{F}}] \Delta t \quad \mathbf{0}_3 \quad \mathbf{0}_3 \quad \mathbf{I}_3] \quad (86)$$

$$\mathbf{H}_{\mathbf{x}_\theta}^\mathbf{v} = \begin{bmatrix} \frac{\partial^G \tilde{\mathbf{v}}_k}{\partial \tilde{\mathbf{x}}_D} & \frac{\partial^G \tilde{\mathbf{v}}_k}{\partial \tilde{\mathbf{x}}_G} & \frac{\partial^G \tilde{\mathbf{v}}_k}{\partial \tilde{\mathbf{x}}_{MI}} \end{bmatrix} \quad (87)$$

$$= [\mathbf{H}_{\mathbf{x}_D}^\mathbf{v} \quad \mathbf{H}_{\mathbf{x}_G}^\mathbf{v} \quad \mathbf{0}_{3 \times 6}] \quad (88)$$

$$= {}^G_k\hat{\mathbf{R}} \mathbf{H}_{\mathbf{x}_\theta}^\mathbf{F} \Delta t \quad (89)$$

$$= {}^G_k\hat{\mathbf{R}} \Delta t [\mathbf{H}_{\mathbf{x}_D}^\mathbf{F} \quad \mathbf{H}_{\mathbf{x}_G}^\mathbf{F} \quad \mathbf{0}_{3 \times 6}] \quad (90)$$

$$\mathbf{H}_{\mathbf{n}_M}^\mathbf{v} = {}^G_k\hat{\mathbf{R}} \mathbf{H}_{\mathbf{n}_M}^\mathbf{F} \Delta t \quad (91)$$

From position integration Eq. (20) we can get:

$${}^G\mathbf{p}_{k+1} = {}^G\hat{\mathbf{p}}_{k+1} + {}^G\tilde{\mathbf{p}}_{k+1} \quad (92)$$

$$= {}^G\hat{\mathbf{p}}_k + {}^G\tilde{\mathbf{p}}_k + ({}^G\hat{\mathbf{v}}_k + {}^G\tilde{\mathbf{v}}_k) \Delta t + \frac{1}{2} [{}^G_k\hat{\mathbf{R}} (\mathbf{I}_3 + [\delta \boldsymbol{\theta}_k]) \left( \hat{\mathbf{F}} + \tilde{\mathbf{F}} \right) - {}^G\mathbf{g}] \Delta t^2 \quad (93)$$

$$\Rightarrow {}^G\tilde{\mathbf{p}}_{k+1} = {}^G\tilde{\mathbf{p}}_k - \frac{1}{2} {}^G_k\hat{\mathbf{R}} [\hat{\mathbf{F}}] \Delta t^2 \delta \boldsymbol{\theta}_k + \frac{1}{2} {}^G_k\hat{\mathbf{R}} \mathbf{H}_{\mathbf{x}_\theta}^\mathbf{F} \Delta t^2 \tilde{\mathbf{x}}_\theta + {}^G\tilde{\mathbf{v}}_k \Delta t \quad (94)$$



Therefore, we get the Jacobians as:

$$\mathbf{H}_{\mathbf{x}_k}^{\mathbf{p}} = \begin{bmatrix} \frac{\partial^G \tilde{\mathbf{p}}_k}{\partial \delta \tilde{\boldsymbol{\theta}}_k} & \frac{\partial^G \tilde{\mathbf{p}}_k}{\partial^G \tilde{\mathbf{p}}_k} & \frac{\partial^G \tilde{\mathbf{p}}_k}{\partial^k \tilde{\boldsymbol{\omega}}} & \frac{\partial^G \tilde{\mathbf{p}}_k}{\partial^G \tilde{\mathbf{v}}_k} \end{bmatrix} \quad (95)$$

$$= [\mathbf{H}_{\boldsymbol{\theta}}^{\mathbf{p}} \quad \mathbf{I}_3 \quad \mathbf{0}_3 \quad \mathbf{I}_3 \Delta t] \quad (96)$$

$$= [-\frac{1}{2} \frac{G}{k} \hat{\mathbf{R}} [\hat{\mathbf{F}}] \Delta t^2 \quad \mathbf{I}_3 \quad \mathbf{0}_3 \quad \mathbf{I}_3 \Delta t] \quad (97)$$

$$\mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{p}} = \begin{bmatrix} \frac{\partial^G \tilde{\mathbf{p}}_k}{\partial \tilde{\mathbf{x}}_D} & \frac{\partial^G \tilde{\mathbf{p}}_k}{\partial \tilde{\mathbf{x}}_G} & \frac{\partial^G \tilde{\mathbf{p}}_k}{\partial \tilde{\mathbf{x}}_{MI}} \end{bmatrix} \quad (98)$$

$$= [\mathbf{H}_{\mathbf{x}_D}^{\mathbf{p}} \quad \mathbf{H}_{\mathbf{x}_G}^{\mathbf{p}} \quad \mathbf{0}_{3 \times 6}] \quad (99)$$

$$= \frac{1}{2} \frac{G}{k} \hat{\mathbf{R}} \mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{F}} \Delta t^2 \quad (100)$$

$$= \frac{1}{2} \frac{G}{k} \hat{\mathbf{R}} \Delta t^2 [\mathbf{H}_{\mathbf{x}_D}^{\mathbf{F}} \quad \mathbf{H}_{\mathbf{x}_G}^{\mathbf{F}} \quad \mathbf{0}_{3 \times 6}] \quad (101)$$

$$\mathbf{H}_{\mathbf{n}_M}^{\mathbf{p}} = \frac{1}{2} \frac{G}{k} \hat{\mathbf{R}} \mathbf{H}_{\mathbf{n}_M}^{\mathbf{F}} \Delta t^2 \quad (102)$$

With the above integration, we can have the following integrated discrete-time MAV dynamic model and its linearization:

$$\mathbf{x}_{M_{k+1}} = \mathbf{g}_M(\mathbf{x}_{M_k}, \mathbf{x}_{\theta}, \mathbf{n}_M) \quad (103)$$

$$\tilde{\mathbf{x}}_{M_{k+1}} \simeq \Phi_M(k+1, k) \tilde{\mathbf{x}}_{M_k} + \Phi_{\theta} \tilde{\mathbf{x}}_{\theta} + \mathbf{G}_n \mathbf{n}_M \quad (104)$$

$$\begin{bmatrix} \delta \boldsymbol{\theta}_{k+1} \\ \frac{G}{k+1} \tilde{\mathbf{p}}_{k+1} \\ \tilde{\boldsymbol{\omega}} \\ \frac{G}{k+1} \tilde{\mathbf{v}}_{k+1} \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{\boldsymbol{\theta}}^{\theta} & \mathbf{0}_3 & \mathbf{H}_{\boldsymbol{\omega}}^{\theta} & \mathbf{0}_3 \\ \mathbf{H}_{\boldsymbol{\theta}}^{\mathbf{p}} & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{I}_3 \Delta t \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{H}_{\boldsymbol{\omega}}^{\omega} & \mathbf{0}_3 \\ \mathbf{H}_{\boldsymbol{\theta}}^{\mathbf{v}} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix} \begin{bmatrix} \delta \boldsymbol{\theta}_k \\ \frac{G}{k} \tilde{\mathbf{p}}_k \\ \tilde{\boldsymbol{\omega}} \\ \frac{G}{k} \tilde{\mathbf{v}}_k \end{bmatrix} + \begin{bmatrix} \mathbf{H}_{\mathbf{x}_{\theta}}^{\theta} \\ \mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{p}} \\ \mathbf{H}_{\mathbf{x}_{\theta}}^{\omega} \\ \mathbf{H}_{\mathbf{x}_{\theta}}^{\mathbf{v}} \end{bmatrix} \tilde{\mathbf{x}}_{\theta} + \begin{bmatrix} \mathbf{H}_{\mathbf{n}_M}^{\theta} \\ \mathbf{H}_{\mathbf{n}_M}^{\mathbf{p}} \\ \mathbf{H}_{\mathbf{n}_M}^{\omega} \\ \mathbf{H}_{\mathbf{n}_M}^{\mathbf{v}} \end{bmatrix} \mathbf{n}_M \quad (105)$$

## 2 MSCKF-based Parameter Identification

We first extend the standard MSCKF-based VIO estimator [5] to additionally estimate MAV system parameters, which later will be shown to be not robust due to the MAV modelling inaccuracy that is almost inevitable in practice. Specifically, we estimate:

$$\mathbf{x}_k = [\mathbf{x}_A^{\top} \quad \mathbf{x}_{\theta}^{\top}]^{\top} \quad (106)$$

$$\mathbf{x}_A = [\mathbf{x}_{I_k}^{\top} \quad \mathbf{x}_f^{\top} \quad \mathbf{x}_C^{\top}]^{\top} \quad (107)$$

where:

$$\mathbf{x}_{I_k} = \begin{bmatrix} I_k \bar{q}^{\top} & \frac{G}{k} \mathbf{p}_{I_k}^{\top} & \frac{G}{k} \mathbf{v}_{I_k}^{\top} & \mathbf{b}_{g_k}^{\top} & \mathbf{b}_{a_k}^{\top} \end{bmatrix}^{\top} \quad (108)$$

$$\mathbf{x}_f = \begin{bmatrix} \frac{G}{k} \mathbf{p}_{f1}^{\top} & \cdots & \frac{G}{k} \mathbf{p}_{fn}^{\top} \end{bmatrix}^{\top} \quad (109)$$

$$\mathbf{x}_C = \begin{bmatrix} \mathbf{x}_{T_{k-1}}^{\top} & \cdots & \mathbf{x}_{T_{k-c}}^{\top} \end{bmatrix}^{\top} \quad (110)$$

$$\mathbf{x}_{T_i} = \begin{bmatrix} I_i \bar{q}^{\top} & \frac{G}{k} \mathbf{p}_{I_i}^{\top} & I_i \boldsymbol{\omega}^{\top} & \frac{G}{k} \mathbf{v}_{I_i}^{\top} \end{bmatrix}^{\top} \quad (111)$$

We define the “active” state  $\mathbf{x}_A$  and parameter state  $\mathbf{x}_{\theta}$  [see Eq. (2)]. The active state contains the current IMU state  $\mathbf{x}_{I_k}$  and  $c$  historical clone states  $\mathbf{x}_C$ . Each historical clone contains the IMU pose, linear and angular velocities  $\{I_i \boldsymbol{\omega}, \frac{G}{k} \mathbf{v}_{I_i}\}$  [6].  $\mathbf{b}_g$  and  $\mathbf{b}_a$  are the gyroscope and accelerometer biases, respectively. Note that we follow similar steps in [6] to clone  $\{I_i \boldsymbol{\omega}, \frac{G}{k} \mathbf{v}_{I_i}\}$  and propagate the state.

## 2.1 IMU Kinematic Model

The IMU kinematics are used to evolve the state from time  $t_k$  to  $t_{k+1}$  [1]:

$${}^I_G \dot{\bar{q}}(t) = \frac{1}{2} \boldsymbol{\Omega}(\boldsymbol{\omega}(t)) {}^I_G \bar{q}(t) \quad (112)$$

$${}^G \dot{\mathbf{p}}_I(t) = {}^G \mathbf{v}_I(t) \quad (113)$$

$${}^G \dot{\mathbf{v}}_I(t) = {}^I_G \mathbf{R}^\top \mathbf{a}(t) - {}^G \mathbf{g} \quad (114)$$

$$\dot{\mathbf{b}}_g(t) = \mathbf{n}_{wg}(t) \quad (115)$$

$$\dot{\mathbf{b}}_a(t) = \mathbf{n}_{wa}(t) \quad (116)$$

where  $\boldsymbol{\omega}(t) = [\omega_1 \ \omega_2 \ \omega_3]^\top$  and  $\mathbf{a}(t)$  are the angular velocity and acceleration in the IMU local frame  $\{I\}$ ;  $\boldsymbol{\Omega}(\boldsymbol{\omega}(t)) = \begin{bmatrix} -[\boldsymbol{\omega}] & \boldsymbol{\omega} \\ -\boldsymbol{\omega}^\top & 0 \end{bmatrix}$  where  $[\cdot]$  is the skew-symmetric matrix.  $\mathbf{n}_{wg}$  and  $\mathbf{n}_{wa}$  are white Gaussian noise that drive the IMU biases. A canonical three-axis IMU provides linear acceleration and angular velocity measurements,  ${}^I \mathbf{a}_m$  and  ${}^I \boldsymbol{\omega}_m$ , expressed in the local IMU frame  $\{I\}$  modeled as:

$$\mathbf{a}_m(t) = \mathbf{a}(t) + \mathbf{b}_a(t) + \mathbf{n}_a(t) \quad (117)$$

$$\boldsymbol{\omega}_m(t) = \boldsymbol{\omega}(t) + \mathbf{b}_g(t) + \mathbf{n}_g(t) \quad (118)$$

where  $\mathbf{n}_g$  and  $\mathbf{n}_a$  are zero-mean white Gaussian noise.  ${}^I_G \mathbf{R}$  denotes the rotation matrix from global frame to local IMU frame. The IMU nonlinear kinematics can be formulated as follows:

$$\mathbf{x}_{I_{k+1}} = \mathbf{g}_I(\mathbf{x}_{I_k}, {}^I \mathbf{a}_k, {}^I \boldsymbol{\omega}_k, \mathbf{n}_I) \quad (119)$$

where  $\mathbf{n}_I = [\mathbf{n}_g^\top \ \mathbf{n}_a^\top \ \mathbf{n}_{wg}^\top \ \mathbf{n}_{wa}^\top]^\top$ . After linearization, the state translation matrix can be derived as [7]:

$$\Phi_I(k+1, k) = \begin{bmatrix} \Phi_{1,1} & \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{1,4} & \mathbf{0}_3 \\ \Phi_{2,1} & \mathbf{I}_3 & \mathbf{I}_3 \Delta t & \Phi_{2,4} & \Phi_{2,5} \\ \Phi_{3,1} & \mathbf{0}_3 & \mathbf{I}_3 & \Phi_{3,4} & \Phi_{3,5} \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix} \quad (120)$$

with:

$$\Phi_{1,1} = {}^{I_k}_{I_{k+1}} \hat{\mathbf{R}}^\top \quad \Phi_{1,4} = -\mathbf{J}_r \left( {}^{I_k} \hat{\boldsymbol{\theta}}_{I_{k+1}} \right) \Delta t \quad \Phi_{2,1} = -{}^{I_k}_G \hat{\mathbf{R}}^\top [\Xi_2 \hat{\mathbf{a}}_k] \quad \Phi_{2,4} = {}^{I_k}_G \hat{\mathbf{R}}^\top \Xi_4 \quad (121)$$

$$\Phi_{2,5} = -{}^{I_k}_G \hat{\mathbf{R}}^\top \Xi_2 \quad \Phi_{3,1} = -{}^{I_k}_G \hat{\mathbf{R}}^\top [\Xi_1 \hat{\mathbf{a}}_k] \quad \Phi_{3,4} = {}^{I_k}_G \hat{\mathbf{R}}^\top \Xi_3 \quad \Phi_{3,5} = -{}^{I_k}_G \hat{\mathbf{R}}^\top \Xi_1 \quad (122)$$

and:

$$\Xi_1 \triangleq \int_{t_k}^{t_{k+1}} \exp({}^{I_k} \hat{\boldsymbol{\omega}} \delta \tau) d\tau \quad \Xi_2 \triangleq \int_{t_k}^{t_{k+1}} \int_{t_k}^s \exp({}^{I_k} \hat{\boldsymbol{\omega}} \delta \tau) d\tau ds \quad (123)$$

$$\Xi_3 \triangleq \int_{t_k}^{t_{k+1}} {}^{I_k}_{I_\tau} \mathbf{R} [{}^{I_\tau} \hat{\mathbf{a}}] \mathbf{J}_r ({}^{I_k} \hat{\boldsymbol{\omega}} \delta \tau) \delta \tau d\tau \quad \Xi_4 \triangleq \int_{t_k}^{t_{k+1}} \int_{t_k}^s {}^{I_k}_{I_\tau} \mathbf{R} [{}^{I_\tau} \hat{\mathbf{a}}] \mathbf{J}_r ({}^{I_k} \hat{\boldsymbol{\omega}} \delta \tau) \delta \tau d\tau ds \quad (124)$$

The noise Jacobian is derived as [8, 9]:

$$\mathbf{G}_I(t) = \begin{bmatrix} -\mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & -\frac{I_k}{G} \hat{\mathbf{R}}^\top & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix} \quad (125)$$

The standard EKF propagates the error covariance as:

$$\mathbf{P}_{k+1|k} = \Phi_I(k+1, k) \mathbf{P}_{k|k} \Phi_I(k+1, k)^\top + \mathbf{Q}_k \quad (126)$$

We use  $\hat{\mathbf{x}}_{j|i}$  and  $\mathbf{P}_{j|i}$  to represent the state estimate and covariance at time-step  $j$  computed using measurements up to time-step  $i$ . The discrete-time system noise covariance  $\mathbf{Q}_k$  can be computed as:

$$\mathbf{Q}_k = \int_{t_k}^{t_{k+1}} \Phi_I(k+1, \tau) \mathbf{G}(\tau) \mathbf{Q} \mathbf{G}(\tau)^\top \Phi_I(k+1, \tau)^\top d\tau \quad (127)$$

**Remarks:** We have made the conscious decision to propagate the state forward with IMU measurements as compared to use the MAV dynamics since IMU readings can fully measure the platform's trajectory evolution. Additionally, we can leverage robust outlier gating tests to reject invalid integrated MAV measurements caused by un-modeled forces.

## 2.2 Visual Feature Measurements

When exploring the environment, bearing observations of static landmarks are tracked on the image plane. A bearing measurement seen at timestep  $k$  can be related to the state by the following (simplified for presentation, model in [10] is used):

$$\mathbf{z}_{C,k} = \mathbf{h}(\mathbf{x}_{T_k}, {}^G \mathbf{p}_f) + \mathbf{n}_{C,k} \quad (128)$$

$$=: \Lambda({}^{C_k} \mathbf{p}_f) + \mathbf{n}_{C,k} \quad (129)$$

$${}^{C_k} \mathbf{p}_f = {}^C_I \mathbf{R} {}^{I_k}_G \mathbf{R} ({}^G \mathbf{p}_f - {}^G \mathbf{p}_{I_k}) + {}^C_I \mathbf{p}_I \quad (130)$$

$$\Lambda([x \ y \ z]^\top) = [x/z \ y/z]^\top \quad (131)$$

where  $\mathbf{n}_{C,k}$  is the white Gaussian measurement noise. We can obtain the visual residual based Eq. (128):

$$\mathbf{r}_{C,k} = \mathbf{z}_{C,k} - \mathbf{h}(\hat{\mathbf{x}}_{T_k}, {}^G \hat{\mathbf{p}}_f) - \mathbf{n}_{C,k} \quad (132)$$

$$\simeq \mathbf{H}_{T_k} \tilde{\mathbf{x}}_{T_k} + \mathbf{H}_{f_k} {}^G \tilde{\mathbf{p}}_f - \mathbf{n}_{C,k} \quad (133)$$

where  $\mathbf{H}_{T_k}$  and  $\mathbf{H}_{f_k}$  are the measurement Jacobians,  $\tilde{\mathbf{x}}_{T_k}$  and  ${}^G\tilde{\mathbf{p}}_f$  are the error states for the pose and feature, respectively.

$$\mathbf{H}_{T_k} = \begin{bmatrix} \frac{\partial \mathbf{r}_{C,k}}{\partial \delta \theta_{I_k}} & \frac{\partial \mathbf{r}_{C,k}}{\partial {}^G\tilde{\mathbf{p}}_I} \end{bmatrix} \quad (134)$$

$$= \mathbf{H}_p \begin{bmatrix} {}^C\hat{\mathbf{R}}_I^{I_k} \hat{\mathbf{R}}_G ({}^G\hat{\mathbf{p}}_f - {}^G\hat{\mathbf{p}}_{I_k}) & -{}^C\hat{\mathbf{R}}_G^{I_k} \hat{\mathbf{R}}_I \end{bmatrix} \quad (135)$$

$$\mathbf{H}_{f_k} = \frac{\partial \mathbf{r}_{C,k}}{\partial {}^G\tilde{\mathbf{p}}_f} = \mathbf{H}_{pI} {}^C\hat{\mathbf{R}}_G^{I_k} \hat{\mathbf{R}}_I \quad (136)$$

$$\mathbf{H}_p = \begin{bmatrix} \frac{1}{C_k \hat{z}_f} & 0 & -\frac{C_k \hat{x}_f}{C_k \hat{z}_f^2} \\ 0 & \frac{1}{C_k \hat{z}_f} & -\frac{C_k \hat{y}_f}{C_k \hat{z}_f^2} \end{bmatrix} \quad (137)$$

After collecting enough measurements and “stacking” the above linearized model, the feature can be used to update the state. Features are either inserted into the state vector and updated until lost, or used to directly update the state by marginalizing the feature position through the MSCKF nullspace projection [5, 11]. Consistency is ensured through first-estimate Jacobian techniques [12, 13, 8, 9].

### 2.3 MAV Dynamic-Induced Measurements

We now present how to relate the integrated MAV dynamic model, Eq. (27), to our estimation state, Eq. (106). Through rigid body constraints we have:

$$\mathbf{x}_{M_k} = \mathbf{h}_{t,k}(\mathbf{x}_{T_k}, \mathbf{x}_\theta) \quad (138)$$

where:

$${}^M_k \mathbf{R} = {}^I_M \mathbf{R}^\top {}^{I_k}_G \mathbf{R} \quad (139)$$

$${}^G \mathbf{p}_{M_k} = {}^G \mathbf{p}_{I_k} + {}^G \mathbf{R}_{I_k}^I \mathbf{p}_M \quad (140)$$

$${}^M_k \boldsymbol{\omega} = {}^I_M \mathbf{R}^{I_k} \boldsymbol{\omega} \quad (141)$$

$${}^G \mathbf{v}_{M_k} = {}^G \mathbf{v}_{I_k} + {}^G \mathbf{R}_{I_k}^I [{}^{I_k} \boldsymbol{\omega}]^I \mathbf{p}_M \quad (142)$$

The MAV measurement residual and error-state Jacobians are defined accordingly:

$$\mathbf{r}_{M,k} = \hat{\mathbf{x}}_{M_{k+1}} - \mathbf{g}_M(\hat{\mathbf{x}}_{M_k}, \hat{\mathbf{x}}_\theta, \mathbf{0}) \quad (143)$$

$$= \mathbf{h}_{t,k+1}(\hat{\mathbf{x}}_{T_{k+1}}, \hat{\mathbf{x}}_\theta) - \mathbf{g}_M(\mathbf{h}_{t,k}(\hat{\mathbf{x}}_{T_k}, \hat{\mathbf{x}}_\theta), \hat{\mathbf{x}}_\theta, \mathbf{0}) \quad (144)$$

$$\simeq [\mathbf{H}_{T_{k+1}} \quad \mathbf{H}_{T_k} \quad \mathbf{H}_\theta] \tilde{\mathbf{x}}_k - \mathbf{G}_n \mathbf{n}_M \quad (145)$$

$$\triangleq [\mathbf{H}_A \quad \mathbf{H}_\theta] \tilde{\mathbf{x}}_k - \mathbf{G}_n \mathbf{n}_M$$

where  $\tilde{\mathbf{x}}_k = [\tilde{\mathbf{x}}_{T_{k+1}}^\top \quad \tilde{\mathbf{x}}_{T_k}^\top \quad \tilde{\mathbf{x}}_\theta^\top]^\top \triangleq [\tilde{\mathbf{x}}_A^\top \quad \tilde{\mathbf{x}}_\theta^\top]^\top$  is the error state. Throughout this paper  $\hat{\mathbf{x}}$  is used to denote the estimate of a random variable  $\mathbf{x}$ , while  $\tilde{\mathbf{x}} = \mathbf{x} \boxminus \hat{\mathbf{x}}$  is the error of this estimate. We define the orientation error quaternion,  $\delta \boldsymbol{\theta}$ , as  $\delta \bar{q} = \bar{q} \otimes \hat{q}^{-1} \simeq [\frac{1}{2} \delta \boldsymbol{\theta}^\top \quad 1]^\top$  [1]. The updated estimate from a correction  $\delta \mathbf{x}$  is  $\hat{\mathbf{x}}^\oplus = \hat{\mathbf{x}} \boxplus \delta \mathbf{x}$ . The Jacobians can be calculated through the chainrule:

$$\mathbf{H}_{T_{k+1}} = \frac{\partial \mathbf{h}_{t,k+1}}{\partial \mathbf{x}_{T_{k+1}}} \quad (146)$$

$$\mathbf{H}_{T_k} = -\Phi_M \frac{\partial \mathbf{h}_{t,k}}{\partial \mathbf{x}_{T_k}} \quad (147)$$

$$\mathbf{H}_\theta = \frac{\partial \mathbf{h}_{t,k+1}}{\partial \mathbf{x}_\theta} - \Phi_M \frac{\partial \mathbf{h}_{t,k}}{\partial \mathbf{x}_\theta} - \Phi_\theta \quad (148)$$

In the follows, we drop the subscripts (e.g.,  $k$  and  $k+1$ ) for simplicity. From Eq. (139):

$${}^M_G\mathbf{R} = (\mathbf{I} - \lfloor \delta\boldsymbol{\theta}_M \rfloor) {}^M_G\hat{\mathbf{R}} \quad (149)$$

$$= {}^I_M\hat{\mathbf{R}}^\top (\mathbf{I} + \lfloor {}^I_M\delta\boldsymbol{\theta} \rfloor - \lfloor \delta\boldsymbol{\theta}_I \rfloor) {}^I_G\hat{\mathbf{R}} \quad (150)$$

$$\Rightarrow \delta\boldsymbol{\theta}_M = {}^I_M\hat{\mathbf{R}}^\top \delta\boldsymbol{\theta}_I - {}^I_M\hat{\mathbf{R}}^\top {}^I_M\delta\boldsymbol{\theta} \quad (151)$$

From Eq. (140):

$${}^G\mathbf{p}_M = {}^G\hat{\mathbf{p}}_M + {}^G\tilde{\mathbf{p}}_M \quad (152)$$

$$= {}^G\hat{\mathbf{p}}_I + {}^G\tilde{\mathbf{p}}_I + {}^G_I\hat{\mathbf{R}} (\mathbf{I} + \lfloor \delta\boldsymbol{\theta}_I \rfloor) ({}^I\hat{\mathbf{p}}_M + {}^I\tilde{\mathbf{p}}_M) \quad (153)$$

$$\Rightarrow {}^G\tilde{\mathbf{p}}_M = {}^G\tilde{\mathbf{p}}_I - {}^G_I\hat{\mathbf{R}} \lfloor {}^I\hat{\mathbf{p}}_M \rfloor \delta\boldsymbol{\theta}_I + {}^G_I\hat{\mathbf{R}} {}^I\tilde{\mathbf{p}}_M \quad (154)$$

From Eq. (141):

$${}^M\boldsymbol{\omega} = {}^M\hat{\boldsymbol{\omega}} + {}^M\tilde{\boldsymbol{\omega}} \quad (155)$$

$$= {}^I_M\hat{\mathbf{R}}^\top (\mathbf{I} + \lfloor {}^I_M\delta\boldsymbol{\theta} \rfloor) {}^I\boldsymbol{\omega} \quad (156)$$

$$\Rightarrow {}^M\tilde{\boldsymbol{\omega}} = -{}^I_M\hat{\mathbf{R}}^\top \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor {}^I_M\delta\boldsymbol{\theta} \quad (157)$$

From Eq. (142):

$${}^G\mathbf{v}_M = {}^G\hat{\mathbf{v}}_M + {}^G\tilde{\mathbf{v}}_M \quad (158)$$

$$= {}^G\hat{\mathbf{v}}_I + {}^G\tilde{\mathbf{v}}_I - {}^G_I\hat{\mathbf{R}} \lfloor \lfloor {}^I\boldsymbol{\omega} \rfloor {}^I\mathbf{p}_M \rfloor \delta\boldsymbol{\theta}_I \quad (159)$$

$$= {}^G\hat{\mathbf{v}}_I + {}^G_I\hat{\mathbf{R}} \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor {}^I\hat{\mathbf{p}}_M - {}^G_I\hat{\mathbf{R}} \lfloor \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor {}^I\hat{\mathbf{p}}_M \rfloor \delta\boldsymbol{\theta}_I + {}^G\tilde{\mathbf{v}}_I + {}^G_I\hat{\mathbf{R}} \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor {}^I\tilde{\mathbf{p}}_M \quad (160)$$

$$\Rightarrow {}^G\tilde{\mathbf{v}}_M = -{}^G_I\hat{\mathbf{R}} \lfloor \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor {}^I\hat{\mathbf{p}}_M \rfloor \delta\boldsymbol{\theta}_I + {}^G\tilde{\mathbf{v}}_I + {}^G_I\hat{\mathbf{R}} \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor {}^I\tilde{\mathbf{p}}_M \quad (161)$$

Finally, we can summarize as:

$$\mathbf{H}_T = \begin{bmatrix} \frac{\partial \delta\boldsymbol{\theta}_M}{\partial \delta\boldsymbol{\theta}_I} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \frac{\partial {}^G\tilde{\mathbf{p}}_M}{\partial \delta\boldsymbol{\theta}_I} & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \frac{\partial {}^G\tilde{\mathbf{v}}_M}{\partial \delta\boldsymbol{\theta}_I} & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{1,1} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{H}_{2,1} & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{H}_{4,1} & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix} \quad (162)$$

$$= \begin{bmatrix} {}^I_M\hat{\mathbf{R}}^\top & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ -{}^G_I\hat{\mathbf{R}} \lfloor {}^I\hat{\mathbf{p}}_M \rfloor & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ -{}^G_I\hat{\mathbf{R}} \lfloor \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor {}^I\hat{\mathbf{p}}_M \rfloor & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix} \quad (163)$$

$$\frac{\partial \mathbf{h}_t}{\partial \mathbf{x}_\theta} = \begin{bmatrix} \frac{\partial \mathbf{h}_t}{\partial \mathbf{x}_D} & \frac{\partial \mathbf{h}_t}{\partial \mathbf{x}_G} & \frac{\partial \mathbf{h}_t}{\partial \mathbf{x}_{MI}} \end{bmatrix} \quad (164)$$

$$= \begin{bmatrix} \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & \frac{\partial {}^G\delta\boldsymbol{\theta}_M}{\partial {}^I\hat{\mathbf{p}}_M} \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & \frac{\partial {}^G\tilde{\mathbf{p}}_M}{\partial {}^I\hat{\mathbf{p}}_M} \\ \mathbf{0}_{3 \times 9} & \frac{\partial {}^M\tilde{\boldsymbol{\omega}}}{\partial {}^I_M\delta\boldsymbol{\theta}} & \mathbf{0}_3 \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & \frac{\partial {}^G\tilde{\mathbf{v}}_M}{\partial {}^I\hat{\mathbf{p}}_M} \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & -{}^I_M\hat{\mathbf{R}}^\top \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & {}^G_I\hat{\mathbf{R}} \\ \mathbf{0}_{3 \times 9} & -{}^I_M\hat{\mathbf{R}}^\top \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor & \mathbf{0}_3 \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & {}^G_I\hat{\mathbf{R}} \lfloor {}^I\hat{\boldsymbol{\omega}} \rfloor \end{bmatrix} \quad (165)$$

### 3 Observability Analysis

Follow [14, 15], we can perform the observability analysis. In the analysis, we redefine the state as:

$$\mathbf{x} = [\mathbf{x}_I^\top \quad \mathbf{x}_M^\top \quad \mathbf{x}_\theta^\top \quad \mathbf{x}_f^\top]^\top \quad (166)$$

where we have simplified to a single environmental feature in  $\mathbf{x}_f$  without lost of generality.

#### 3.1 State Transition Matrix

The full system state translation matrix can be defined as:

$$\Phi = \begin{bmatrix} \Phi_I(k+1, k) & \mathbf{0}_{15 \times 12} & \mathbf{0}_{15 \times 23} & \mathbf{0}_{15 \times 3} \\ \mathbf{0}_{12 \times 15} & \Phi_M(k+1, k) & \Phi_\theta & \mathbf{0}_{12 \times 3} \\ \mathbf{0}_{15 \times 15} & \mathbf{0}_{15 \times 12} & \mathbf{I}_{15} & \mathbf{0}_{15 \times 3} \\ \mathbf{0}_{3 \times 15} & \mathbf{0}_{3 \times 12} & \mathbf{0}_{3 \times 15} & \mathbf{I}_3 \end{bmatrix} \quad (167)$$

where

$$\Phi_I(k+1, k) = \begin{bmatrix} \Phi_{1,1} & \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{1,4} & \mathbf{0}_3 \\ \Phi_{2,1} & \mathbf{I}_3 & \mathbf{I}_3 \Delta t & \Phi_{2,4} & \Phi_{2,5} \\ \Phi_{3,1} & \mathbf{0}_3 & \mathbf{I}_3 & \Phi_{3,4} & \Phi_{3,5} \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix} \quad (168)$$

$$\Phi_M(k+1, k) = \begin{bmatrix} \Phi_{6,6} & \mathbf{0}_3 & \Phi_{6,8} & \mathbf{0}_3 \\ \Phi_{7,6} & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{I}_3 \Delta t \\ \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{8,8} & \mathbf{0}_3 \\ \Phi_{9,6} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix} = \begin{bmatrix} \mathbf{H}_\theta^\theta & \mathbf{0}_3 & \mathbf{H}_\omega^\theta & \mathbf{0}_3 \\ \mathbf{H}_\theta^p & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{I}_3 \Delta t \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{H}_\omega^\omega & \mathbf{0}_3 \\ \mathbf{H}_\theta^v & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 \end{bmatrix} \quad (169)$$

$$\Phi_\theta = \begin{bmatrix} \Phi_{6,10 \sim 16} \\ \Phi_{7,10 \sim 16} \\ \Phi_{8,10 \sim 16} \\ \Phi_{9,10 \sim 16} \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{\mathbf{x}_\theta}^\theta \\ \mathbf{H}_{\mathbf{x}_\theta}^p \\ \mathbf{H}_{\mathbf{x}_\theta}^\omega \\ \mathbf{H}_{\mathbf{x}_\theta}^v \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{\mathbf{x}_D}^\theta & \mathbf{H}_{\mathbf{x}_G}^\theta & \mathbf{0}_{3 \times 6} \\ \mathbf{H}_{\mathbf{x}_D}^p & \mathbf{H}_{\mathbf{x}_G}^p & \mathbf{0}_{3 \times 6} \\ \mathbf{H}_{\mathbf{x}_D}^\omega & \mathbf{H}_{\mathbf{x}_G}^\omega & \mathbf{0}_{3 \times 6} \\ \mathbf{H}_{\mathbf{x}_D}^v & \mathbf{H}_{\mathbf{x}_G}^v & \mathbf{0}_{3 \times 6} \end{bmatrix} \quad (170)$$

The overall state translation matrix can be found as:

$$\Phi = \begin{bmatrix} \Phi_{1,1} & \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{1,4} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{3 \times 15} & \mathbf{0}_3 \\ \Phi_{2,1} & \mathbf{I}_3 & \mathbf{I}_3 \Delta t & \Phi_{2,4} & \Phi_{2,5} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{3 \times 15} & \mathbf{0}_3 \\ \Phi_{3,1} & \mathbf{0}_3 & \mathbf{I}_3 & \Phi_{3,4} & \Phi_{3,5} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{3 \times 15} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{3 \times 15} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{3 \times 15} & \mathbf{0}_3 \\ \hline \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{6,6} & \mathbf{0}_3 & \Phi_{6,8} & \mathbf{0}_3 & \Phi_{6,10 \sim 16} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{7,6} & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{I}_3 \Delta t & \Phi_{7,10 \sim 16} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{8,8} & \mathbf{0}_3 & \Phi_{8,10 \sim 16} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \Phi_{9,6} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{I}_3 & \Phi_{9,10 \sim 16} & \mathbf{0}_3 \\ \hline \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{0}_{15 \times 3} & \mathbf{I}_{15} & \mathbf{0}_{15 \times 3} \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{3 \times 15} & \mathbf{I}_3 \end{bmatrix} \quad (171)$$

### 3.2 Visual-Observation Jacobian

The visual measurement Jacobian can be summarized as [see Eq. (132)]:

$$\mathbf{H}_C = \begin{bmatrix} \frac{\partial \mathbf{r}_C}{\partial \mathbf{x}_I} & \frac{\partial \mathbf{r}_C}{\partial \mathbf{x}_M} & \frac{\partial \mathbf{r}_C}{\partial \mathbf{x}_\theta} & \frac{\partial \mathbf{r}_C}{\partial \mathbf{x}_f} \end{bmatrix} \quad (172)$$

$$= \begin{bmatrix} \mathbf{H}_{C,1} & \mathbf{H}_{C,2} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{C,10\sim 16} & \mathbf{H}_{C,f} \end{bmatrix} \quad (173)$$

where we have summarized the multiplied camera observation chainrule as  $\mathbf{H}_{C,*}$  for each.

### 3.3 MAV Dynamics Jacobian

As compared to performing an update by predicting the relative change from one state clone to another, we have simplified the state for observability analysis to contain both the inertial state  $\mathbf{x}_I$  and MAV state  $\mathbf{x}_M$  both of which evolve with time. Then following a propagation step, we perform an update which enforces that both are related to each other through the extrinsic calibration. The rigid body constraint is:

$$\mathbf{r}_M = \mathbf{x}_{M_k} - \mathbf{h}_{t,k}(\mathbf{x}_{I_k}, \mathbf{x}_\theta) \quad (174)$$

$${}^M_k \mathbf{R} = {}^I_M \mathbf{R}^\top {}^{I_k}_G \mathbf{R} \quad (175)$$

$${}^G \mathbf{p}_{M_k} = {}^G \mathbf{p}_{I_k} + {}^{I_k}_G \mathbf{R} {}^I \mathbf{p}_M \quad (176)$$

$${}^M_k \boldsymbol{\omega} = {}^I_M \mathbf{R} {}^{I_k}_I \boldsymbol{\omega} \quad (177)$$

$${}^G \mathbf{v}_{M_k} = {}^G \mathbf{v}_{I_k} + {}^{I_k}_G \mathbf{R} [{}^{I_k}_I \boldsymbol{\omega}] {}^I \mathbf{p}_M \quad (178)$$

We linearize this to get the overall measurement Jacobian as follows:

$$\mathbf{H}_M = \begin{bmatrix} \frac{\partial \mathbf{r}_M}{\partial \mathbf{x}_I} & \frac{\partial \mathbf{r}_M}{\partial \mathbf{x}_M} & \frac{\partial \mathbf{r}_M}{\partial \mathbf{x}_\theta} & \frac{\partial \mathbf{r}_M}{\partial \mathbf{x}_f} \end{bmatrix} \quad (179)$$

$$= \begin{bmatrix} \mathbf{H}_{1,1} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & -\mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{H}_{1,10\sim 16} & \mathbf{0}_3 \\ \mathbf{H}_{2,1} & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & -\mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{H}_{2,10\sim 16} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & -\mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{H}_{3,10\sim 16} & \mathbf{0}_3 \\ \mathbf{H}_{4,1} & \mathbf{0}_3 & \mathbf{I}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & -\mathbf{I}_3 & \mathbf{H}_{4,10\sim 16} & \mathbf{0}_3 \end{bmatrix} \quad (180)$$

$$\begin{bmatrix} \mathbf{H}_{1,10\sim 16} \\ \mathbf{H}_{2,10\sim 16} \\ \mathbf{H}_{3,10\sim 16} \\ \mathbf{H}_{4,10\sim 16} \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & \mathbf{H}_{1,16} \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & \mathbf{H}_{2,16} \\ \mathbf{0}_{3 \times 9} & \mathbf{H}_{3,15} & \mathbf{0}_3 \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & \mathbf{H}_{4,16} \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & -{}^I_M \hat{\mathbf{R}}^\top \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & {}^G \hat{\mathbf{R}} \\ \mathbf{0}_{3 \times 9} & -{}^I_M \hat{\mathbf{R}}^\top [{}^I \hat{\boldsymbol{\omega}}] & \mathbf{0}_3 \\ \mathbf{0}_{3 \times 9} & \mathbf{0}_3 & {}^G \hat{\mathbf{R}} [{}^I \hat{\boldsymbol{\omega}}] \end{bmatrix} \quad (181)$$

### 3.4 Observability Matrix

The observability matrix can be found as:

$$\mathcal{M} \triangleq \begin{bmatrix} \mathbf{H}_0 \boldsymbol{\Phi}(0, 0) \\ \mathbf{H}_1 \boldsymbol{\Phi}(1, 0) \\ \vdots \\ \mathbf{H}_{k+1} \boldsymbol{\Phi}(k+1, 0) \end{bmatrix} \quad (182)$$

For a given block row of this matrix, we have:

$$\mathcal{M}_k = \mathbf{H}_k \Phi(k, 0) \quad (183)$$

$$= \begin{bmatrix} \Gamma_{C,1} & \Gamma_{C,2} & \Gamma_{C,3} & \Gamma_{C,4} & \Gamma_{C,5} & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_{2 \times 15} & \Gamma_{C,f} \\ \Gamma_{1,1} & \mathbf{0}_3 & \mathbf{0}_3 & \Gamma_{1,4} & \mathbf{0}_3 & \Gamma_{1,6} & \mathbf{0}_3 & \Gamma_{1,8} & \mathbf{0}_3 & \Gamma_{1,10 \sim 16} & \mathbf{0}_3 \\ \Gamma_{2,1} & \mathbf{I}_3 & \mathbf{I}_3 \Delta t & \Gamma_{2,4} & \Gamma_{2,5} & \Gamma_{2,6} & -\mathbf{I}_3 & \mathbf{0}_3 & -\mathbf{I}_3 \Delta t & \Gamma_{2,10 \sim 16} & \mathbf{0}_3 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 & \Gamma_{3,8} & \mathbf{0}_3 & \Gamma_{3,10 \sim 16} & \mathbf{0}_3 \\ \Gamma_{4,1} & \mathbf{0}_3 & \mathbf{I}_3 & \Gamma_{4,4} & \Gamma_{4,5} & \Gamma_{4,6} & \mathbf{0}_3 & \mathbf{0}_3 & -\mathbf{I}_3 & \Gamma_{4,10 \sim 16} & \mathbf{0}_3 \end{bmatrix} \quad (184)$$

where

$$\Gamma_{1,1} = \mathbf{H}_{1,1} \Phi_{1,1} = {}^I_M \hat{\mathbf{R}}^\top {}^{I_0} \hat{\mathbf{R}} \quad (185)$$

$$\Gamma_{1,4} = \mathbf{H}_{1,1} \Phi_{1,4} = {}^I_M \hat{\mathbf{R}}^\top \Phi_{1,4} = -{}^I_M \hat{\mathbf{R}}^\top \mathbf{J}_r \left( {}^k \hat{\boldsymbol{\theta}}_{k+1} \right) \Delta t \quad (186)$$

$$\Gamma_{1,6} = -\Phi_{6,6} = -{}^{M_0} \hat{\mathbf{R}} \quad (187)$$

$$\Gamma_{1,8} = -\Phi_{6,8} = -\mathbf{J}_r({}^{M_0} \hat{\boldsymbol{\theta}}_{M_k}) \left( \frac{1}{2} \mathbf{H}_\omega^\mathbf{A} \Delta t^2 + \mathbf{I}_3 \Delta t \right) \quad (188)$$

$$\Gamma_{2,1} = \mathbf{H}_{2,1} \Phi_{1,1} + \Phi_{2,1} = -{}^G_{I_k} \hat{\mathbf{R}} [{}^I \hat{\mathbf{p}}_M]_{I_0}^{I_k} \hat{\mathbf{R}} - {}^G_{I_k} \hat{\mathbf{R}}^\top [\Xi_2 {}^{I_k} \hat{\mathbf{a}}] \quad (189)$$

$$\Gamma_{2,4} = \mathbf{H}_{2,1} \Phi_{1,4} + \Phi_{2,4} = {}^G_{I_k} \hat{\mathbf{R}} [{}^I \hat{\mathbf{p}}_M] \mathbf{J}_r({}^{I_0} \hat{\boldsymbol{\theta}}_{I_k}) \Delta t + {}^G_{I_k} \hat{\mathbf{R}}^\top \Xi_4 \quad (190)$$

$$\Gamma_{2,5} = \Phi_{2,5} = -{}^G_{I_k} \hat{\mathbf{R}}^\top \Xi_2 \quad (191)$$

$$\Gamma_{2,6} = -\Phi_{7,6} = \frac{1}{2} {}^G_{M_0} \hat{\mathbf{R}} [\hat{\mathbf{F}}] \Delta t^2 = [{}^G \hat{\mathbf{p}}_{M_k} - {}^G \hat{\mathbf{p}}_{M_0} - {}^G \hat{\mathbf{v}}_{M_0} \Delta t + \frac{1}{2} {}^G \mathbf{g} \Delta t^2] \quad (192)$$

$$\Gamma_{3,8} = -\Phi_{8,8} = -\mathbf{H}_\omega^\mathbf{A} = -{}^{M_k} \hat{\mathbf{R}} - {}^{M_k} \hat{\mathbf{R}} \mathbf{H}_\omega^\mathbf{A} \Delta t - [{}^{M_k} \hat{\boldsymbol{\omega}}] \mathbf{J}_r({}^{M_0} \hat{\boldsymbol{\theta}}_{M_k}) \frac{1}{2} (\mathbf{H}_\omega^\mathbf{A} \Delta t^2 + \mathbf{I}_3 \Delta t) \quad (193)$$

$$\Gamma_{4,1} = \mathbf{H}_{4,1} \Phi_{1,1} + \Phi_{3,1} = -{}^G_{I_k} \hat{\mathbf{R}} [{}^{I_k} \hat{\boldsymbol{\omega}}] {}^I \hat{\mathbf{p}}_M]_{I_0}^{I_k} \hat{\mathbf{R}} - {}^G_{I_k} \hat{\mathbf{R}}^\top [\Xi_1 {}^{I_k} \hat{\mathbf{a}}] \quad (194)$$

$$\Gamma_{4,4} = \mathbf{H}_{4,1} \Phi_{1,4} + \Phi_{3,4} = {}^G_{I_k} \hat{\mathbf{R}} [{}^{I_k} \hat{\boldsymbol{\omega}}] {}^I \hat{\mathbf{p}}_M] \mathbf{J}_r({}^{I_0} \hat{\boldsymbol{\theta}}_{I_k}) \Delta t + {}^G_{I_k} \hat{\mathbf{R}}^\top \Xi_3 \quad (195)$$

$$\Gamma_{4,5} = \Phi_{3,5} = -{}^G_{I_k} \hat{\mathbf{R}}^\top \Xi_1 \quad (196)$$

$$\Gamma_{4,6} = \Phi_{9,6} = {}^G_{M_0} \hat{\mathbf{R}} [\hat{\mathbf{F}}] \Delta t = [{}^G \hat{\mathbf{v}}_{M_k} - {}^G \hat{\mathbf{v}}_{M_0} + {}^G \mathbf{g} \Delta t] {}^G_{M_0} \hat{\mathbf{R}} \quad (197)$$

We now focus on the subset of the system related to the MAV dynamics and its parameters. For the system parameters we conclude:

$$\mathcal{M}_\theta = \begin{bmatrix} \Gamma_{1,10 \sim 16} \\ \Gamma_{2,10 \sim 16} \\ \Gamma_{3,10 \sim 16} \\ \Gamma_{4,10 \sim 16} \end{bmatrix} = \begin{bmatrix} -\mathbf{H}_{\mathbf{x}_D}^\theta & -\mathbf{H}_{\mathbf{x}_G}^\theta & \mathbf{0}_3 & -{}^I_M \hat{\mathbf{R}}^\top \\ -\mathbf{H}_{\mathbf{x}_D}^p & -\mathbf{H}_{\mathbf{x}_G}^p & \mathbf{0}_3 & {}^G_{I_k} \hat{\mathbf{R}} \\ -\mathbf{H}_{\mathbf{x}_D}^\omega & -\mathbf{H}_{\mathbf{x}_G}^\omega & -{}^I_M \hat{\mathbf{R}}^\top [{}^{I_k} \hat{\boldsymbol{\omega}}] & \mathbf{0}_3 \\ -\mathbf{H}_{\mathbf{x}_D}^v & -\mathbf{H}_{\mathbf{x}_G}^v & \mathbf{0}_3 & {}^G_{I_k} \hat{\mathbf{R}} [{}^{I_k} \hat{\boldsymbol{\omega}}] \end{bmatrix} \quad (198)$$

where:

$$\begin{bmatrix} -\mathbf{H}_{\mathbf{x}_D}^\theta & -\mathbf{H}_{\mathbf{x}_G}^\theta \\ -\mathbf{H}_{\mathbf{x}_D}^p & -\mathbf{H}_{\mathbf{x}_G}^p \\ -\mathbf{H}_{\mathbf{x}_D}^\omega & -\mathbf{H}_{\mathbf{x}_G}^\omega \\ -\mathbf{H}_{\mathbf{x}_D}^v & -\mathbf{H}_{\mathbf{x}_G}^v \end{bmatrix} = \begin{bmatrix} -\frac{1}{2} \mathbf{J}_r({}^{M_0} \hat{\boldsymbol{\theta}}_{M_k}) \Delta t^2 & \mathbf{0}_3 & -\frac{1}{2} {}^G_{M_0} \mathbf{R} \Delta t^2 \\ \mathbf{0}_3 & \mathbf{0}_3 & \mathbf{0}_3 \\ -\frac{1}{2} [{}^{M_k} \hat{\boldsymbol{\omega}}] \mathbf{J}_r({}^{M_0} \hat{\boldsymbol{\theta}}_{M_k}) \Delta t^2 - {}^{M_k} \hat{\mathbf{R}} \Delta t & \mathbf{0}_3 & -{}^G_{M_0} \mathbf{R} \Delta t \\ \mathbf{0}_3 & \mathbf{0}_3 & -{}^G_{M_0} \mathbf{R} \Delta t \end{bmatrix} \begin{bmatrix} \mathbf{H}_{\mathbf{x}_D}^\mathbf{A} & \mathbf{H}_{\mathbf{x}_G}^\mathbf{A} \\ \mathbf{H}_{\mathbf{x}_D}^\mathbf{F} & \mathbf{H}_{\mathbf{x}_G}^\mathbf{F} \end{bmatrix} \quad (199)$$



and

$$\begin{aligned}
& \begin{bmatrix} \mathbf{H}_{\mathbf{x}_D}^{\mathbf{A}} & \mathbf{H}_{\mathbf{x}_G}^{\mathbf{A}} \\ \mathbf{H}_{\mathbf{x}_D}^{\mathbf{F}} & \mathbf{H}_{\mathbf{x}_G}^{\mathbf{F}} \end{bmatrix} \\
& = \begin{bmatrix} {}^k\mathbf{J}^{-1} \sum_{i=1}^{N_r} [{}^M\mathbf{p}_{A_i}]_{A_i} {}^M\mathbf{R} r_i^2 \mathbf{e}_z & {}^k\mathbf{J}^{-1} \sum_{i=1}^{N_r} {}^M\mathbf{R} \lambda_i r_i^2 \mathbf{e}_z & \mathbf{0}_{3 \times 1} & \frac{\partial \mathbf{A}}{\partial {}^M\mathbf{j}} & -{}^k\mathbf{J}^{-1} \sum_{i=1}^{N_r} [{}^M\mathbf{F}_i] \\ \frac{1}{m} \sum_{i=1}^{N_r} {}^M\mathbf{R} r_i^2 \mathbf{e}_z & \mathbf{0}_{3 \times 1} & -\frac{1}{m^2} {}^M\mathbf{F}_k & \mathbf{0}_3 & \mathbf{0}_3 \end{bmatrix} \quad (200)
\end{aligned}$$

We can find that  $c_t$ ,  $c_m$ ,  $m$  and  ${}^M\mathbf{j}$  are jointly unobservable, with null space  $\mathbf{N}$  as  $\mathcal{M}\mathbf{N} = \mathbf{0}$ , where  $\mathcal{M}$  is the “stacked” observability matrix (i.e. holds over all timesteps):

$$\mathbf{N} = \begin{bmatrix} \mathbf{0}_{15 \times 1} \\ \mathbf{0}_{12 \times 1} \\ c_t \\ c_m \\ m \\ j_1 \\ j_2 \\ j_3 \\ \mathbf{0}_{3 \times 1} \\ \mathbf{0}_{6 \times 1} \\ \mathbf{0}_{3 \times 1} \end{bmatrix} \quad (201)$$

This null space holds for the original visual-inertial system, and is independent from the standard VIO null space.

**Remarks:** Thus we can conclude that we should not perform joint estimation of  ${}^M\mathbf{j}$ ,  $m$ ,  $c_t$ , and  $c_m$  as it introduces another observable direction (increasing from the 4DoF to 5DoF). In practice, we can avoid this additional unobservable direction by either only estimating  ${}^M\mathbf{j}$ ,  $m$ , or the  $c_t$  and  $c_m$  pair. This can be seen by the unobservable sets J2 and J3 in Table I of [15].

## 4 Simulation

### 4.1 Rotor Speed Generation

With the B-spline formulation of the simulated trajectory, we can generate IMU angular velocity  ${}^I\boldsymbol{\omega}$ , angular acceleration  ${}^I\boldsymbol{\alpha}$ , and linear acceleration  ${}^G\mathbf{a}_I$  at any desired time. The MAV motion status is computed with the rigid body constraints accordingly:

$${}^M\boldsymbol{\omega} = {}^M_I \mathbf{R} {}^I\boldsymbol{\omega} \quad (202)$$

$${}^G\mathbf{a}_M = {}^G\mathbf{a}_I + {}^I_G \mathbf{R}^\top ([{}^I\boldsymbol{\omega}][{}^I\boldsymbol{\omega}] + [{}^I\boldsymbol{\alpha}]) {}^I\mathbf{p}_M \quad (203)$$

The desired total force and moment at a specific time are:

$$\begin{bmatrix} {}^M\mathbf{F} \\ {}^M\mathbf{M} \end{bmatrix} = \begin{bmatrix} m \cdot {}^M_G \mathbf{R} ({}^G\mathbf{a}_M + {}^G\mathbf{g}) \\ {}^M\mathbf{J} {}^M\boldsymbol{\alpha} + [{}^M\boldsymbol{\omega}] {}^M\mathbf{J} {}^M\boldsymbol{\omega} \end{bmatrix} \quad (204)$$

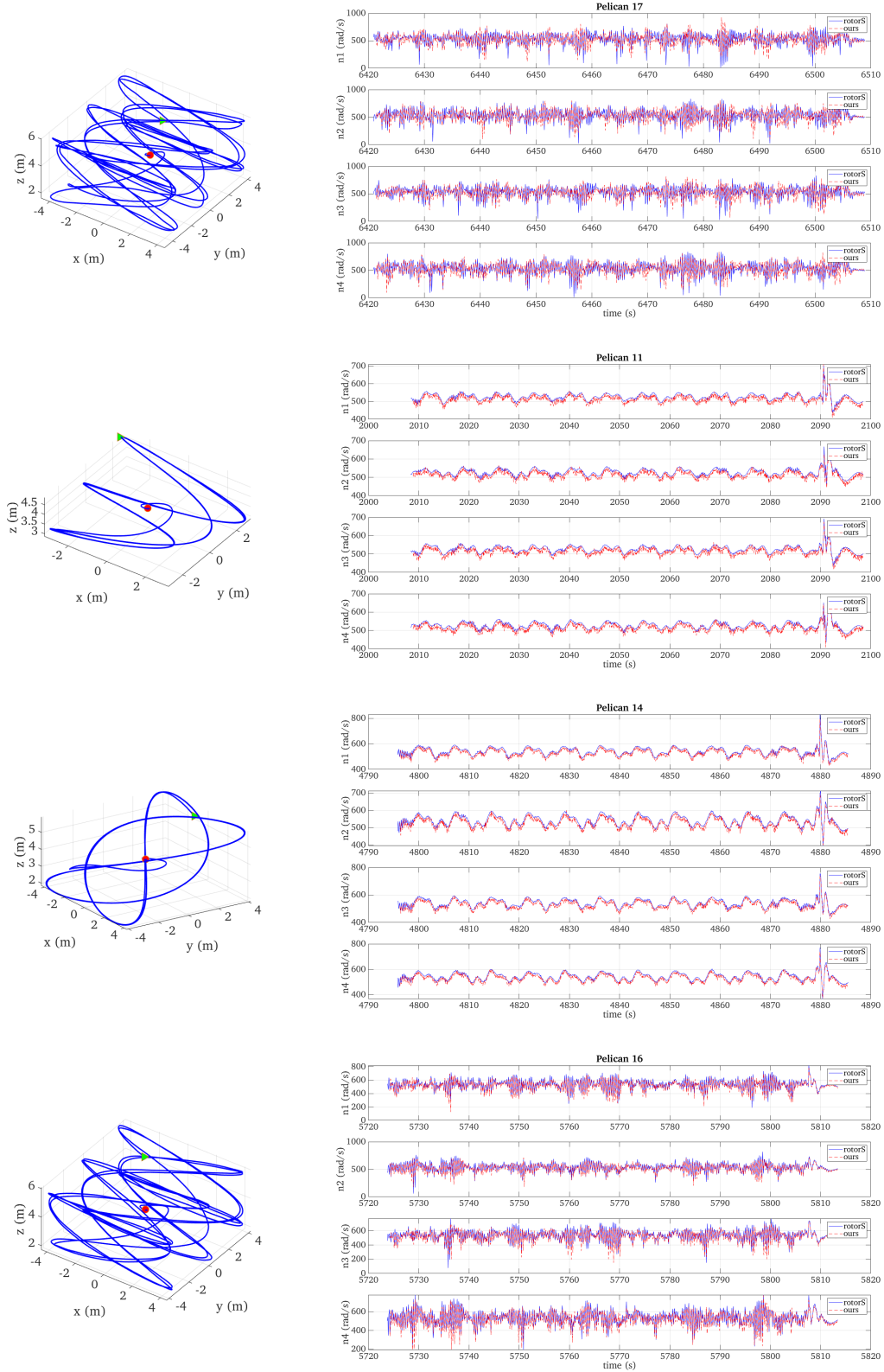


Figure 2: Left: Simulated trajectories. Right: Comparisons of rotor speeds generated by rotorS and our simulator.

Then, with Eq. (6) and (7), we formulate the following linear system to solve for the rotor speeds:

$$[\mathbf{B}_1 \quad \mathbf{B}_2 \quad \mathbf{B}_3 \quad \mathbf{B}_4] \cdot \mathbf{r} = \begin{bmatrix} {}^M\mathbf{F} \\ {}^M\mathbf{M} \end{bmatrix} \quad (205)$$

where  $\mathbf{r} = [r_1^2 \quad \dots \quad r_4^2]^\top$  and  $\mathbf{B}_i$  are defined as:

$$\mathbf{B}_i = \begin{bmatrix} c_{tA_i}^M \mathbf{R} \mathbf{e}_z \\ c_m \lambda_{iA_i}^M \mathbf{R} \mathbf{e}_z + c_t [{}^M \mathbf{p}_{A_i} \mathbf{e}_z] \end{bmatrix} \quad (206)$$

Finally, white Gaussian noise  $n_{r,i}$  is added to  $r_i$  for realistic simulation of rotor encoder measurement  $r_{m,i}$  (e.g.,  $r_{m,i} = n_{r,i} + r_i$ ). In the following Fig. 2, we show the simulated trajectories and the comparisons of rotor speed generated by rotorS and our simulator. From the figures we notice that the rotor speeds are very similar for most of the time. The detailed descriptions of the MAV configurations are referred to our paper.

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