

E-Companion

Can We Work More Safely and Healthily with Robot Partners? A Human-Friendly Robot-Human Coordinated Order Fulfillment Scheme

Online Appendix A. Proofs

A.1. Proof of Theorem 4.1

Using Eq. (8) (the text), we have

$$\begin{aligned} \gamma_k &= \frac{Y_k}{Q_{k-1} + \mu_k X_k}, \quad \forall k \\ \Rightarrow Y_k &= \gamma_k (Q_{k-1} + \mu_k X_k) \end{aligned} \tag{A1}$$

Input Eq. (A1) into Eq. (9) (the text), and then, we have

$$\begin{aligned} \delta_k &= \frac{X_k}{A_k + v_k Y_k} \\ \Rightarrow X_k &= \delta_k (A_k + v_k \gamma_k (Q_{k-1} + \mu_k X_k)) \\ \Rightarrow X_k (1 - \delta_k \mu_k v_k \gamma_k) &= \delta_k (A_k + v_k \gamma_k Q_{k-1}), \quad \forall k \\ \Rightarrow \hat{X}_k &= \frac{\delta_k (A_k + v_k \gamma_k Q_{k-1})}{1 - \Omega_k} = \frac{1}{1 - \Omega_k} \left(\delta_k A_k + \frac{\Omega_k Q_{k-1}}{\mu_k} \right) \end{aligned} \tag{A2}$$

Input Eq. (A2) into Eq. (A1), and then, we have

$$\begin{aligned} Y_k &= \gamma_k (Q_{k-1} + \mu_k X_k) \\ \Rightarrow \hat{Y}_k &= \gamma_k \left(Q_{k-1} + \frac{\delta_k \mu_k A_k + \Omega_k Q_{k-1}}{1 - \Omega_k} \right) = \frac{1}{1 - \Omega_k} \left(\frac{\Omega_k A_k}{v_k} + \gamma_k Q_{k-1} \right), \quad \forall k \end{aligned} \tag{A3}$$

Thus, Theorem 4.1 is proven.

A.2. Proof of Corollary 4.1

Given Theorem 4.1, we have the estimates \hat{X}_k (Eq. (A2)) and \hat{Y}_k (Eq. (A3)). Using Eqs. (A2)

and Eq. (1) (the text), we have \hat{Q}_k

$$\hat{Q}_k = Q_{k-1} + \hat{X}_k = Q_{k-1} + \frac{\mu_k}{1 - \Omega_k} \left(\delta_k A_k + \frac{\Omega_k Q_{k-1}}{\mu_k} \right) = \frac{1}{1 - \Omega_k} (\delta_k \mu_k A_k + Q_{k-1}) \quad , \quad \forall k \quad (\text{A4})$$

Using Eqs. (3) (text), (A3) and (A4), we can derive the estimate $\hat{\lambda}_k$ as

$$\begin{aligned} \hat{\lambda}_k &= \beta_0 + \beta_1 \hat{Y}_k + \beta_2 \hat{Q}_k \\ &= \beta_0 + \beta_1 \frac{\gamma_k}{1 - \Omega_k} (\delta_k \mu_k A_k + Q_{k-1}) + \beta_2 \frac{1}{1 - \Omega_k} (\delta_k \mu_k A_k + Q_{k-1}) \quad , \quad \forall k \quad (\text{A5}) \\ &= \beta_0 + (\beta_1 \gamma_k + \beta_2) \left(\frac{\delta_k \mu_k A_k + Q_{k-1}}{1 - \Omega_k} \right) \end{aligned}$$

Based on Eqs. (A5) and (2) (text), we have the estimate ($\Delta \hat{\rho}_k$) of the fatigue increment in each time interval k ($\forall k$) as

$$\Delta \hat{\rho}_k = 1 - e^{-\hat{\lambda}_k} = 1 - e^{-\left(\beta_0 + (\beta_1 \gamma_k + \beta_2) \left(\frac{\delta_k \mu_k A_k + Q_{k-1}}{1 - \Omega_k} \right) \right)} \quad , \quad \forall k \quad (\text{A6})$$

A.3. Proof of Corollary 5.1

Given Eq. (15) (the text) and the data regarding A_k and Y_k collected through time interval k , the optimal estimate ($\hat{\Phi}_{k+1}$) of Φ_{k+1} is

$$\hat{\Phi}_{k+1} = \hat{\mathbf{F}}_k + \hat{\mathbf{W}}_k \quad (\text{A7})$$

where $\hat{\mathbf{F}}_k$ is the linear minimum mean square (LMMS) estimate of \mathbf{F}_k . If $\hat{\mathbf{W}}_k$ is the LMMS estimate of \mathbf{W}_k using the data regarding A_k and Y_k collected through time interval k , we, then, have

$$\hat{\mathbf{W}}_k = E \left[(\mathbf{W}_k - \mathbf{m}_W)(\mathbf{Y}_k - \mathbf{m}_Y)^T \right] \left\{ E \left[(\mathbf{Y}_k - \mathbf{m}_Y)(\mathbf{Y}_k - \mathbf{m}_Y)^T \right] \right\}^{-1} (\mathbf{Y}_k - \mathbf{m}_Y) + \mathbf{m}_W \quad (\text{A8})$$

where \mathbf{m}_W is the mean of \mathbf{W}_k ; and \mathbf{m}_Y is the mean of \mathbf{Y}_k . Since $\mathbf{W}_k - \mathbf{m}_W$ and $\mathbf{Y}_k - \mathbf{m}_Y$ are orthogonal, we have $(\mathbf{W}_k - \mathbf{m}_W)(\mathbf{Y}_k - \mathbf{m}_Y)^T = \mathbf{0}$. Moreover, $\mathbf{m}_W = \mathbf{0}$ as \mathbf{W}_k is a white noise vector.

Thus, we can derive $\hat{\mathbf{W}}_k = \mathbf{0}$ from Eq. (A8) such that $\hat{\Phi}_{k+1} = \hat{\mathbf{F}}_k$ by Eq. (A7). Thus, Corollary 5.1 is proven.

A.4. Proof of Corollary 5.2

Given Eqs. (15) and (26) of Corollary 5.1 (the text), we have Φ_{k+1} and $\hat{\Phi}_{k+1|k}$ given, respectively, by

$$\Phi_{k+1} = \mathbf{F}_k + \mathbf{W}_k \quad (\text{A9})$$

$$\hat{\Phi}_{k+1|k} = \hat{\mathbf{F}}_k \quad (\text{A10})$$

Then, we have the state prediction error $\Delta\Phi_{k+1|k}$ given by

$$\begin{aligned} \Delta\Phi_{k+1|k} &\equiv \Phi_{k+1} - \hat{\Phi}_{k+1|k} \\ &= (\mathbf{F}_k - \hat{\mathbf{F}}_k) + \mathbf{W}_k \\ &= (\hat{\mathbf{F}}_k' \Delta\Phi_{k|k}) + \mathbf{W}_k, \quad \text{where } \Delta\Phi_{k|k} \equiv \Phi_k - \hat{\Phi}_k \end{aligned} \quad (\text{A11})$$

Using Eq. (A11), the prior prediction ($\hat{\mathbf{P}}_{k+1|k}$) for the covariance matrix of state estimation error \mathbf{P}_{k+1} is,

thus, given by

$$\begin{aligned} \hat{\mathbf{P}}_{k+1|k} &\equiv E[\Delta\Phi_{k+1|k} \Delta\Phi_{k+1|k}^T] \\ &= E\left[\left[(\hat{\mathbf{F}}_k' \Delta\Phi_{k|k}) + \mathbf{W}_k\right] \left[(\hat{\mathbf{F}}_k' \Delta\Phi_{k|k}) + \mathbf{W}_k\right]^T\right] \\ &= \hat{\mathbf{F}}_k' E[\Delta\Phi_{k|k} \Delta\Phi_{k|k}^T] \hat{\mathbf{F}}_k^T + \hat{\mathbf{F}}_k' E[\Delta\Phi_{k|k} \mathbf{W}_k^T] + E[\mathbf{W}_k \Delta\Phi_{k|k}^T] \hat{\mathbf{F}}_k^T + E[\mathbf{W}_k \mathbf{W}_k^T] \end{aligned} \quad (\text{A12})$$

Since $\Delta\Phi_{k|k}$ and \mathbf{W}_k are uncorrelated, $E[\Delta\Phi_{k|k} \mathbf{W}_k^T] = E[\mathbf{W}_k \Delta\Phi_{k|k}^T] = \mathbf{0}$. Thus, Eq. (A12) can be

rewritten as

$$\begin{aligned} \hat{\mathbf{P}}_{k+1|k} &= \hat{\mathbf{F}}_k' E[\Delta\Phi_{k|k} \Delta\Phi_{k|k}^T] \hat{\mathbf{F}}_k^T + E[\mathbf{W}_k \mathbf{W}_k^T] \\ &= \hat{\mathbf{F}}_k' \hat{\mathbf{P}}_{k|k} \hat{\mathbf{F}}_k^T + \mathbf{R}_k \end{aligned} \quad (\text{A13})$$

Thus, Corollary 5.2 is proven.

A.5. Proof of Corollary 5.3

It is noted that the measurement residual $\Delta \mathbf{y}_{k+1|k}$ in time interval $k+1$ and the measurement residual vector $\Delta \mathbf{Y}_k$ collected through time interval k are orthogonal. Moreover, $\hat{\Phi}_{k+1|k}$ can be treated as the LMMS estimate of the state vector (Φ_{k+1}) based on $\Delta \mathbf{Y}_k$ (by Corollary 5.1). Utilizing the properties of LMMS estimation in the aspect of incorporation of orthogonal data, the LMMS estimate ($\hat{\Phi}_{k+1}$) of Φ_{k+1} based on $\Delta \mathbf{Y}_k$ and $\Delta \mathbf{y}_{k+1|k}$ are the sum of the two individual estimates. That is

$$\hat{\Phi}_{k+1} = \hat{\Phi}_{k+1|k} + E[\Phi_{k+1} | \Delta \mathbf{y}_{k+1|k}] \quad , \forall k \quad (\text{A14})$$

where $E[\Phi_{k+1} | \Delta \mathbf{y}_{k+1|k}]$ is defined as the best estimate of Φ_{k+1} based on $\Delta \mathbf{y}_{k+1|k}$. Utilizing the LMMS estimation, $E[\Phi_{k+1} | \Delta \mathbf{y}_{k+1|k}]$ can be written as

$$\begin{aligned} E[\Phi_{k+1} | \Delta \mathbf{y}_{k+1|k}] &= E[(\Phi_{k+1} - \mathbf{m}_\Phi)(\Delta \mathbf{y}_{k+1|k} - \mathbf{m}_{\Delta \mathbf{y}})^T] \cdot \{E[(\Delta \mathbf{y}_{k+1|k} - \mathbf{m}_{\Delta \mathbf{y}})(\Delta \mathbf{y}_{k+1|k} - \mathbf{m}_{\Delta \mathbf{y}})^T]\}^{-1} \cdot (\Delta \mathbf{y}_{k+1|k} - \mathbf{m}_{\Delta \mathbf{y}}) + \mathbf{m}_\Phi \\ &= E[(\Phi_{k+1} - \mathbf{m}_\Phi) \Delta \mathbf{y}_{k+1|k}^T] \cdot \{E[\Delta \mathbf{y}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T]\}^{-1} \cdot \Delta \mathbf{y}_{k+1|k} + \mathbf{m}_\Phi \\ &= (E[\Phi_{k+1} \Delta \mathbf{y}_{k+1|k}^T] - \mathbf{m}_\Phi E[\Delta \mathbf{y}_{k+1|k}^T]) \cdot \{E[\Delta \mathbf{y}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T]\}^{-1} \cdot \Delta \mathbf{y}_{k+1|k} + \mathbf{m}_\Phi \quad , \forall k \\ &= E[\Phi_{k+1} \Delta \mathbf{y}_{k+1|k}^T] \cdot \{E[\Delta \mathbf{y}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T]\}^{-1} \cdot \Delta \mathbf{y}_{k+1|k} + \mathbf{m}_\Phi \end{aligned} \quad (\text{A15})$$

where \mathbf{m}_Φ and $\mathbf{m}_{\Delta \mathbf{y}}$ are the means of Φ_{k+1} and $\Delta \mathbf{y}_{k+1|k}$, respectively; and $\mathbf{m}_{\Delta \mathbf{y}} = \mathbf{0}$. Let the

Kalman gain \mathbf{G}_{k+1} be defined as

$$\mathbf{G}_{k+1} \equiv E[\Phi_{k+1} \Delta \mathbf{y}_{k+1|k}^T] \cdot \{E[\Delta \mathbf{y}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T]\}^{-1} \quad , \forall k \quad (\text{A16})$$

Using Eqs. (A15) and (A16), Eq. (A14) can, then, be rewritten as

$$\hat{\Phi}_{k+1} = \hat{\Phi}_{k+1|k} + \mathbf{G}_{k+1} \cdot \Delta \mathbf{y}_{k+1|k} + \mathbf{m}_\Phi \quad , \forall k \quad (\text{A17})$$

Thus, Corollary 5.3 is proven.

A.6. Proof of Corollary 5.4

Given Corollary 5.3 and Eq. (19), we have $\Delta \mathbf{y}_{k+1|k}$ given by

$$\begin{aligned}\Delta \mathbf{y}_{k+1|k} &= \mathbf{Y}_{k+1} - \hat{\mathbf{Y}}_{k+1|k} \\ &= \mathbf{H}_{k+1} + \boldsymbol{\varepsilon}_{k+1} - \hat{\mathbf{H}}_{k+1|k}, \quad \forall k \\ &= \hat{\mathbf{H}}'_{k+1} \Delta \boldsymbol{\Phi}_{k+1|k} + \boldsymbol{\varepsilon}_{k+1}\end{aligned}\tag{A18}$$

Using Eq. (A18), we can have $E[\Delta \mathbf{y}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T]$ (shown in Eq. (A16)) given by

$$\begin{aligned}E[\Delta \mathbf{y}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T] &= E\left[\left(\hat{\mathbf{H}}'_{k+1} \Delta \boldsymbol{\Phi}_{k+1|k} + \boldsymbol{\varepsilon}_{k+1}\right)\left(\hat{\mathbf{H}}'_{k+1} \Delta \boldsymbol{\Phi}_{k+1|k} + \boldsymbol{\varepsilon}_{k+1}\right)^T\right], \quad \forall k \\ &= \hat{\mathbf{H}}'_{k+1} E[\Delta \boldsymbol{\Phi}_{k+1|k} \Delta \boldsymbol{\Phi}_{k+1|k}^T] \hat{\mathbf{H}}_{k+1}^T + \hat{\mathbf{H}}'_{k+1} E[\Delta \boldsymbol{\Phi}_{k+1|k} \boldsymbol{\varepsilon}_{k+1}^T] + E[\boldsymbol{\varepsilon}_{k+1} \Delta \boldsymbol{\Phi}_{k+1|k}^T] \hat{\mathbf{H}}_{k+1}^T + E[\boldsymbol{\varepsilon}_{k+1} \boldsymbol{\varepsilon}_{k+1}^T]\end{aligned}\tag{A19}$$

Since $\Delta \boldsymbol{\Phi}_{k+1|k}$ and $\boldsymbol{\varepsilon}_{k+1}$ are uncorrelated, $E[\Delta \boldsymbol{\Phi}_{k+1|k} \boldsymbol{\varepsilon}_{k+1}^T] = E[\boldsymbol{\varepsilon}_{k+1} \Delta \boldsymbol{\Phi}_{k+1|k}^T] = \mathbf{0}$ in Eq. (A19). Using

the definition of the prior prediction ($\hat{\mathbf{P}}_{k+1|k}$) for the covariance matrix of state estimation error, we have

$\hat{\mathbf{P}}_{k+1|k}$ given by

$$\hat{\mathbf{P}}_{k+1|k} \equiv E[\Delta \boldsymbol{\Phi}_{k+1|k} \Delta \boldsymbol{\Phi}_{k+1|k}^T], \quad \forall k\tag{A20}$$

Then, Eq. (A19) can be rewritten as

$$E[\Delta \mathbf{y}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T] = \hat{\mathbf{H}}'_{k+1} \hat{\mathbf{P}}_{k+1|k} \hat{\mathbf{H}}_{k+1}^T + \boldsymbol{\Lambda}_{k+1}, \quad \forall k\tag{A21}$$

where $\boldsymbol{\Lambda}_{k+1} \equiv E[\boldsymbol{\varepsilon}_k \boldsymbol{\varepsilon}_k^T]$.

Similarly, utilizing the definition of the state prediction error, we have $E[\boldsymbol{\Phi}_{k+1} \Delta \mathbf{y}_{k+1|k}]$ (shown in Eq. (A16)) given by

$$\begin{aligned}E[\boldsymbol{\Phi}_{k+1} \Delta \mathbf{y}_{k+1|k}^T] &= E[(\hat{\boldsymbol{\Phi}}_{k+1|k} + \Delta \boldsymbol{\Phi}_{k+1|k}) \Delta \mathbf{y}_{k+1|k}^T] \\ &= E[\hat{\boldsymbol{\Phi}}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T] + E[\Delta \boldsymbol{\Phi}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T]\end{aligned}, \quad \forall k\tag{A22}$$

Since $\hat{\boldsymbol{\Phi}}_{k+1|k}$ and $\Delta \mathbf{y}_{k+1|k}^T$ are uncorrelated with each other; and moreover, $\hat{\boldsymbol{\Phi}}_{k+1|k}$ and $\Delta \boldsymbol{\Phi}_{k+1|k}$ are orthogonal, we have $E[\hat{\boldsymbol{\Phi}}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T] = \mathbf{0}$. Accordingly, Eq. (A22) can be rewritten as

$$E[\boldsymbol{\Phi}_{k+1} \Delta \mathbf{y}_{k+1|k}^T] = E[\Delta \boldsymbol{\Phi}_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T], \quad \forall k\tag{A23}$$

Input Eq. (A18) into (A23), we have

$$\begin{aligned}
E[\Phi_{k+1} \Delta \mathbf{y}_{k+1|k}^T] &= E[\Delta \Phi_{k+1|k} \Delta \mathbf{y}_{k+1|k}^T] \\
&= E[\Delta \Phi_{k+1|k} (\hat{\mathbf{H}}'_{k+1} \Delta \Phi_{k+1|k} + \boldsymbol{\varepsilon}_{k+1})^T] \quad , \quad \forall k \\
&= E[(\Delta \Phi_{k+1|k} \Delta \Phi_{k+1|k}^T \hat{\mathbf{H}}'^T_{k+1}) + \Delta \Phi_{k+1|k} \boldsymbol{\varepsilon}_{k+1}^T]
\end{aligned} \tag{A24}$$

But $\Delta \Phi_{k+1|k}$ and $\boldsymbol{\varepsilon}_{k+1}^T$ are uncorrelated, indicating $E[\Delta \Phi_{k+1|k} \boldsymbol{\varepsilon}_{k+1}^T] = \mathbf{0}$, and thus, Eq. (A24) can be rewritten as

$$E[\Phi_{k+1} \Delta \mathbf{y}_{k+1|k}^T] = E[(\Delta \Phi_{k+1|k} \Delta \Phi_{k+1|k}^T \mathbf{H}'^T_{k+1})] = \hat{\mathbf{P}}_{k+1|k} \hat{\mathbf{H}}'^T_{k+1} \quad , \quad \forall k \tag{A25}$$

By Eqs. (A16), (A21), and (A25), we, therefore, have the Kalman gain \mathbf{G}_{k+1} given by

$$\mathbf{G}_{k+1} = \hat{\mathbf{P}}_{k+1|k} \hat{\mathbf{H}}'^T_{k+1} (\hat{\mathbf{H}}'_{k+1} \hat{\mathbf{P}}_{k+1|k} \hat{\mathbf{H}}'^T_{k+1} + \boldsymbol{\Lambda}_{k+1})^{-1} \quad , \quad \forall k \tag{A25}$$

where $\boldsymbol{\Lambda}_{k+1} \equiv E[\boldsymbol{\varepsilon}_k \boldsymbol{\varepsilon}_k^T]$. Thus, Corollary 5.4 is proven.

A.7. Proof of Corollary 5.5

First, let the state estimation error vector $\Delta \Phi_{k+1|k+1}$ be defined as $\Delta \Phi_{k+1|k+1} \equiv \Phi_{k+1} - \hat{\Phi}_{k+1}$.

Using Eq. (A17), $\Delta \Phi_{k+1|k+1}$, then, becomes

$$\begin{aligned}
\Delta \Phi_{k+1|k+1} &\equiv \Phi_{k+1} - \hat{\Phi}_{k+1} \\
&= \Phi_{k+1} - (\hat{\Phi}_{k+1|k} + \mathbf{G}_{k+1} \cdot \Delta \mathbf{y}_{k+1|k} + \mathbf{m}_\Phi) \\
&= \Delta \Phi_{k+1|k} - \mathbf{G}_{k+1} \Delta \mathbf{y}_{k+1|k} - \mathbf{m}_\Phi \\
&= \Delta \Phi_{k+1|k} - \mathbf{G}_{k+1} (\hat{\mathbf{H}}'_{k+1} \Delta \Phi_{k+1|k} + \boldsymbol{\varepsilon}_{k+1}) - \mathbf{m}_\Phi \quad (\text{by Eq. (A18)}) \quad , \quad \forall k \\
&= \Delta \Phi_{k+1|k} - \mathbf{G}_{k+1} \hat{\mathbf{H}}'_{k+1} \Delta \Phi_{k+1|k} - \mathbf{G}_{k+1} \boldsymbol{\varepsilon}_{k+1} - \mathbf{m}_\Phi \\
&= (\mathbf{I} - \mathbf{G}_{k+1} \hat{\mathbf{H}}'_{k+1}) \Delta \Phi_{k+1|k} - \mathbf{G}_{k+1} \boldsymbol{\varepsilon}_{k+1} - \mathbf{m}_\Phi
\end{aligned} \tag{A26}$$

Therefore, using Eq. (A26) we have $\hat{\mathbf{P}}_{k+1|k+1}$ given by

$$\begin{aligned}
\hat{\mathbf{P}}_{k+1|k+1} &\equiv E[\Delta\Phi_{k+1|k+1}\Delta\Phi_{k+1|k+1}^T] \\
&= E\left[\left(\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1}\right)\Delta\Phi_{k+1|k}-\mathbf{G}_{k+1}\boldsymbol{\varepsilon}_{k+1}-\mathbf{m}_\Phi\right]\left[\left(\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1}\right)\Delta\Phi_{k+1|k}-\mathbf{G}_{k+1}\boldsymbol{\varepsilon}_{k+1}-\mathbf{m}_\Phi\right]^T \\
&= (\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})E[\Delta\Phi_{k+1|k}\Delta\Phi_{k+1|k}^T](\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})^T - (\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})E[\Delta\Phi_{k+1|k}\boldsymbol{\varepsilon}_{k+1}^T]\mathbf{G}_{k+1}^T \\
&\quad - (\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})E[\Delta\Phi_{k+1|k}]\mathbf{m}_\Phi^T \\
&\quad - \mathbf{G}_{k+1}E[\boldsymbol{\varepsilon}_{k+1}\Delta\Phi_{k+1|k}^T](\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})^T + \mathbf{G}_{k+1}E[\boldsymbol{\varepsilon}_{k+1}\boldsymbol{\varepsilon}_{k+1}^T]\mathbf{G}_{k+1}^T + \mathbf{G}_{k+1}E[\boldsymbol{\varepsilon}_{k+1}]\mathbf{m}_\Phi^T \\
&\quad - \mathbf{m}_\Phi E[\Delta\Phi_{k+1|k}^T](\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})^T + \mathbf{m}_\Phi E[\boldsymbol{\varepsilon}_{k+1}]\mathbf{G}_{k+1}^T + \mathbf{m}_\Phi\mathbf{m}_\Phi^T, \quad \forall k
\end{aligned} \tag{A27}$$

Since $\Delta\Phi_{k+1|k}$ and $\boldsymbol{\varepsilon}_{k+1}$ are uncorrelated; and moreover, $E[\Delta\Phi_{k+1|k}] = E[\boldsymbol{\varepsilon}_{k+1}] = \mathbf{0}$, Eq. (A27) can be

rewritten as

$$\begin{aligned}
\hat{\mathbf{P}}_{k+1|k+1} &= (\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})E[\Delta\Phi_{k+1|k}\Delta\Phi_{k+1|k}^T](\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})^T + \mathbf{G}_{k+1}E[\boldsymbol{\varepsilon}_{k+1}\boldsymbol{\varepsilon}_{k+1}^T]\mathbf{G}_{k+1}^T + \mathbf{m}_\Phi\mathbf{m}_\Phi^T \\
&= (\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})\hat{\mathbf{P}}_{k+1|k}(\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})^T + \mathbf{G}_{k+1}\boldsymbol{\Lambda}_{k+1}\mathbf{G}_{k+1}^T + \mathbf{m}_\Phi\mathbf{m}_\Phi^T, \quad \forall k \\
&= (\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})\hat{\mathbf{P}}_{k+1|k} - \hat{\mathbf{P}}_{k+1|k}\hat{\mathbf{H}}'^T_{k+1}\mathbf{G}_{k+1}^T + \mathbf{G}_{k+1}(\hat{\mathbf{H}}'_{k+1}\hat{\mathbf{P}}_{k+1|k}\hat{\mathbf{H}}'^T_{k+1} + \boldsymbol{\Lambda}_{k+1})\mathbf{G}_{k+1}^T + \mathbf{m}_\Phi\mathbf{m}_\Phi^T
\end{aligned} \tag{A28}$$

But from Eq. (A25), we have $\mathbf{G}_{k+1} = \hat{\mathbf{P}}_{k+1|k}\hat{\mathbf{H}}'^T_{k+1}(\hat{\mathbf{H}}'_{k+1}\hat{\mathbf{P}}_{k+1|k}\hat{\mathbf{H}}'^T_{k+1} + \boldsymbol{\Lambda}_{k+1})^{-1}$. Let Eq. (A25) be inputted into

Eq. (A28), and then, we have

$$\hat{\mathbf{P}}_{k+1|k+1} = (\mathbf{I}-\mathbf{G}_{k+1}\hat{\mathbf{H}}'_{k+1})\hat{\mathbf{P}}_{k+1|k} + \mathbf{m}_\Phi\mathbf{m}_\Phi^T, \quad \forall k \tag{A29}$$

Thus, Corollary 5.5 is proven.