**Algorithm SEIF_SLAM_known_correspondences**($\xi_{t-1}, \Omega_{t-1}, \mu_{t-1}, u_t, z_t, c_t$):

$\bar{\xi}_t, \bar{\Omega}_t, \bar{\mu}_t = \textbf{SEIF\_motion\_update}(\xi_{t-1}, \Omega_{t-1}, \mu_{t-1}, u_t)$

$\xi_t, \Omega_t = \textbf{SEIF\_measurement\_update}(\bar{\xi}_t, \bar{\Omega}_t, \bar{\mu}_t, z_t, c_t)$

$\mu_t = \textbf{SEIF\_update\_state\_estimate}(\xi_t, \Omega_t, \bar{\mu}_t)$

$\tilde{\xi}_t, \tilde{\Omega}_t = \textbf{SEIF\_sparsification}(\xi_t, \Omega_t, \mu_t)$

*return* $\tilde{\xi}_t, \tilde{\Omega}_t, \mu_t$

**Table 12.1** The Sparse Extended Information Filter algorithm for the SLAM Problem, here with known data association.

**Algorithm SEIF_motion_update**($\xi_{t-1}, \Omega_{t-1}, \mu_{t-1}, u_t$):

$$F_x = \begin{pmatrix} 1 & 0 & 0 & 0 \cdots 0 \\ 0 & 1 & 0 & 0 \cdots 0 \\ 0 & 0 & 1 & \underbrace{0 \cdots 0}_{3N} \end{pmatrix}$$

$$\delta = \begin{pmatrix} -\frac{v_t}{\omega_t} \sin \mu_{t-1,\theta} + \frac{v_t}{\omega_t} \sin(\mu_{t-1,\theta} + \omega_t \Delta t) \\ \frac{v_t}{\omega_t} \cos \mu_{t-1,\theta} - \frac{v_t}{\omega_t} \cos(\mu_{t-1,\theta} + \omega_t \Delta t) \\ \omega_t \Delta t \end{pmatrix}$$

$$\Delta = \begin{pmatrix} 0 & 0 & \frac{v_t}{\omega_t} \cos \mu_{t-1,\theta} - \frac{v_t}{\omega_t} \cos(\mu_{t-1,\theta} + \omega_t \Delta t) \\ 0 & 0 & \frac{v_t}{\omega_t} \sin \mu_{t-1,\theta} - \frac{v_t}{\omega_t} \sin(\mu_{t-1,\theta} + \omega_t \Delta t) \\ 0 & 0 & 0 \end{pmatrix}$$

$\Psi_t = F_x^T \, [(I + \Delta)^{-1} - I] \, F_x$

$\lambda_t = \Psi_t^T \, \Omega_{t-1} + \Omega_{t-1} \, \Psi_t + \Psi_t^T \, \Omega_{t-1} \, \Psi_t$

$\Phi_t = \Omega_{t-1} + \lambda_t$

$\kappa_t = \Phi_t \, F_x^T (R_t^{-1} + F_x \, \Phi_t \, F_x^T)^{-1} \, F_x \, \Phi_t$

$\bar{\Omega}_t = \Phi_t - \kappa_t$

$\bar{\xi}_t = \xi_{t-1} + (\lambda_t - \kappa_t) \, \mu_{t-1} + \bar{\Omega}_t \, F_x^T \, \delta_t$

$\bar{\mu}_t = \mu_{t-1} + F_x^T \, \delta$

*return* $\bar{\xi}_t, \bar{\Omega}_t, \bar{\mu}_t$

**Table 12.2** The motion update in SEIFs.