

1:	<b>Algorithm EKF_localization</b> ( $\mu_{t-1}, \Sigma_{t-1}, u_t, z_t, m$ ):
2:	$\theta = \mu_{t-1, \theta}$
3:	$G_t = \begin{pmatrix} 1 & 0 & -\frac{v_t}{\omega_t} \cos \theta + \frac{v_t}{\omega_t} \cos(\theta + \omega_t \Delta t) \\ 0 & 1 & -\frac{v_t}{\omega_t} \sin \theta + \frac{v_t}{\omega_t} \sin(\theta + \omega_t \Delta t) \\ 0 & 0 & 1 \end{pmatrix}$
4:	$V_t = \begin{pmatrix} \frac{\sin \theta + \sin(\theta + \omega_t \Delta t)}{\omega_t} & \frac{v_t(\sin \theta - \sin(\theta + \omega_t \Delta t))}{\omega_t^2} + \frac{v_t \cos(\theta + \omega_t \Delta t) \Delta t}{\omega_t} \\ \frac{\cos \theta - \cos(\theta + \omega_t \Delta t)}{\omega_t} & -\frac{v_t(\cos \theta - \cos(\theta + \omega_t \Delta t))}{\omega_t^2} + \frac{v_t \sin(\theta + \omega_t \Delta t) \Delta t}{\omega_t} \\ 0 & 0 & \Delta t \end{pmatrix}$
5:	$M_t = \begin{pmatrix} \alpha_1 v_t^2 + \alpha_2 \omega_t^2 & 0 \\ 0 & \alpha_3 v_t^2 + \alpha_4 \omega_t^2 \end{pmatrix}$
6:	$\bar{\mu}_t = \mu_{t-1} + \begin{pmatrix} -\frac{v_t}{\omega_t} \sin \theta + \frac{v_t}{\omega_t} \sin(\theta + \omega_t \Delta t) \\ \frac{v_t}{\omega_t} \cos \theta - \frac{v_t}{\omega_t} \cos(\theta + \omega_t \Delta t) \\ \omega_t \Delta t \end{pmatrix}$
7:	$\bar{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + V_t M_t V_t^T$
8:	$Q_t = \begin{pmatrix} \sigma_r^2 & 0 & 0 \\ 0 & \sigma_\phi^2 & 0 \\ 0 & 0 & \sigma_s^2 \end{pmatrix}$
9:	for all observed features $z_t^i = (r_t^i \phi_t^i s_t^i)^T$ do
10:	for all landmarks $k$ in the map $m$ do
11:	$q = (m_{k,x} - \bar{\mu}_{t,x})^2 + (m_{k,y} - \bar{\mu}_{t,y})^2$
12:	$\hat{z}_t^k = \begin{pmatrix} \sqrt{q} \\ \text{atan2}(m_{k,y} - \bar{\mu}_{t,y}, m_{k,x} - \bar{\mu}_{t,x}) - \bar{\mu}_{t,\theta} \\ m_{k,s} \end{pmatrix}$
13:	$H_t^k = \begin{pmatrix} \frac{m_{k,x} - \bar{\mu}_{t,x}}{\sqrt{q}} & \frac{m_{k,s}}{\sqrt{q}} & 0 \\ \frac{m_{k,y} - \bar{\mu}_{t,y}}{q} & \frac{m_{k,x} - \bar{\mu}_{t,x}}{q} & -1 \\ 0 & 0 & 0 \end{pmatrix}$
14:	$S_t^k = H_t^k \bar{\Sigma}_t [H_t^k]^T + Q_t$
15:	endfor
16:	$j(i) = \underset{k}{\operatorname{argmax}} \det(2\pi S_t^k)^{-\frac{1}{2}} \exp\left\{-\frac{1}{2} (z_t^i - \hat{z}_t^k)^T [S_t^k]^{-1} (z_t^i - \hat{z}_t^k)\right\}$
17:	$K_t^i = \bar{\Sigma}_t [H_t^{j(i)}]^T [S_t^{j(i)}]^{-1}$
18:	$\bar{\mu}_t = \bar{\mu}_t + K_t^i (z_t^i - \hat{z}_t^{j(i)})$
19:	$\bar{\Sigma}_t = (I - K_t^i H_t^{j(i)}) \bar{\Sigma}_t$
20:	endfor
21:	$\mu_t = \bar{\mu}_t$
22:	$\Sigma_t = \bar{\Sigma}_t$
23:	return $\mu_t, \Sigma_t$

**Table 7.3** The extended Kalman filter (EKF) localization algorithm with unknown correspondences. The correspondences  $j(i)$  are estimated via a maximum likelihood estimator.