$$
\begin{aligned}
&\stackrel{\text{Bayes}}{=} \quad \eta \frac{p(z_t \mid x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t})\; p(x_{1:t-1}^{[k]} \mid u_{1:t}, z_{1:t-1}, c_{1:t})}{p(x_{1:t-1}^{[k]} \mid u_{1:t-1}, z_{1:t-1}, c_{1:t-1})} \\
&\stackrel{\text{Markov}}{=} \quad \eta \frac{p(z_t \mid x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t})\; p(x_{1:t-1}^{[k]} \mid u_{1:t-1}, z_{1:t-1}, c_{1:t-1})}{p(x_{1:t-1}^{[k]} \mid u_{1:t-1}, z_{1:t-1}, c_{1:t-1})} \\
&= \quad \eta\; p(z_t \mid x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t})
\end{aligned}
$$

The reader may notice that this expression is the inverse of our normalization constant $\eta^{[k]}$ in (13.27). Further transformations give us the following form:

$$
\begin{aligned}
w_t^{[k]} \quad &= \quad \eta \int p(z_t \mid x_t, x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t}) \\
&\qquad\qquad p(x_t \mid x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t})\; dx_t \\
&\stackrel{\text{Markov}}{=} \quad \eta \int p(z_t \mid x_t, x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t})\; p(x_t \mid x_{t-1}^{[k]}, u_t)\; dx_t \\
&= \quad \eta \int \int p(z_t \mid m_{c_t}, x_t, x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t}) \\
&\qquad p(m_{c_t} \mid x_t, x_{1:t-1}^{[k]}, u_{1:t}, z_{1:t-1}, c_{1:t})\; dm_{c_t}\; p(x_t \mid x_{t-1}^{[k]}, u_t)\; dx_t \\
&\stackrel{\text{Markov}}{=} \quad \eta \int \underbrace{p(x_t \mid x_{t-1}^{[k]}, u_t)}_{\sim \mathcal{N}(x_t; g(\hat{x}_{t-1}^{[k]}, u_t), R_t)} \int \underbrace{p(z_t \mid m_{c_t}, x_t, c_t)}_{\sim \mathcal{N}(z_t; h(m_{c_t}, x_t), Q_t)} \\
&\qquad \underbrace{p(m_{c_t} \mid x_{1:t-1}^{[k]}, u_{1:t-1}, z_{1:t-1}, c_{1:t-1})}_{\sim \mathcal{N}(m_{c_t}; \mu_{c_t,t-1}^{[k]}, \Sigma_{c_t,t-1}^{[k]})}\; dm_{c_t}\; dx_t
\end{aligned} \tag{13.52}
$$

We find that this expression can once again be approximated by a Gaussian over measurements z_t by linearizing h. As it is easily shown, the mean of the resulting Gaussian is $\hat{z}_t$, and its covariance is

$$
L_t^{[t]} \quad = \quad H_x\; R_t\; H_x^T + H_m \Sigma_{c_t,t-1}^{[k]} H_m^T + Q_t \tag{13.53}
$$

Put differently, the (non-normalized) importance factor of the k-th particle is given by the following expression:

$$
w_t^{[k]} \quad = \quad |2\pi L_t^{[t]}|^{-\frac{1}{2}} \exp\left\{ -\tfrac{1}{2}(z_t - \hat{z}_t)^T\; L_t^{[t]-1}\; (z_t - \hat{z}_t) \right\} \tag{13.54}
$$

As in FastSLAM 1.0, particles generated in Steps 1 and 2, along with their importance factor calculated in Step 3, are collected in a temporary particle set.

The final step of the FastSLAM 2.0 update is a resampling step. Just as in FastSLAM 1.0, FastSLAM 2.0 draws (with replacement) M particles from