1:	**Algorithm landmark_model_known_correspondence(**f_t^i, c_t^i, x_t, m**):**
2:	$j = c_t^i$
3:	$\hat{r} = \sqrt{(m_{j,x} - x)^2 + (m_{j,y} - y)^2}$
4:	$\hat{\phi} = \text{atan2}(m_{j,y} - y, m_{j,x} - x) - \theta$
5:	$q = \textbf{prob}(r_t^i - \hat{r}, \sigma_r) \cdot \textbf{prob}(\phi_t^i - \hat{\phi}, \sigma_\phi) \cdot \textbf{prob}(s_t^i - s_j, \sigma_s)$
6:	*return* q

Table 6.4 Algorithm for computing the likelihood of a landmark measurement. The algorithm requires as input an observed feature $f_t^i = (r_t^i \;\; \phi_t^i \;\; s_t^i)^T$, and the true identity of the feature c_t^i, the robot pose $x_t = (x \;\; y \;\; \theta)^T$, and the map m. Its output is the numerical probability $p(f_t^i \mid c_t^i, m, x_t)$.

6.6.4 Sampling Poses

Sometimes it is desirable to sample robot poses x_t that correspond to a measurement f_t^i with feature identity c_t^i. We already encountered such sampling algorithms in the previous chapter, where we discussed robot motion models. Such sampling models are also desirable for sensor models. For example, when localizing a robot globally, it shall become useful to generate sample poses that incorporate a sensor measurement to generate initial guesses for the robot pose.

While in the general case, sampling poses x_t that correspond to a sensor measurement z_t is difficult, for our landmark model we can actually provide an efficient sampling algorithm. However, such sampling is only possible under further assumptions. In particular, we have to know the prior $p(x_t \mid c_t^i, m)$. For simplicity, let us assume this prior is uniform (it generally is not!). Bayes rule then suggests that

$$\begin{aligned} p(x_t \mid f_t^i, c_t^i, m) &= \eta \, p(f_t^i \mid c_t^i, x_t, m) \, p(x_t \mid c_t^i, m) \\ &= \eta \, p(f_t^i \mid c_t^i, x_t, m) \end{aligned} \tag{6.41}$$

Sampling from $p(x_t \mid f_t^i, c_t^i, m)$ can now be achieved from the "inverse" of the sensor model $p(f_t^i \mid c_t^i, x_t, m)$. Table 6.5 depicts an algorithm that samples poses x_t. The algorithm is tricky: Even in the noise-free case, a landmark observation does not uniquely determine the location of the robot. Instead, the robot may be on a circle around the landmark, whose diameter is the range to the landmark. The indeterminacy of the robot pose also follows