POSITIVE INFORMATION

The EKF SLAM algorithm, just like the EKF localizer discussed in Chapter 7.4, can only process *positive* sightings of landmarks. It cannot process negative information that arises from the absence of landmarks in sensor measurements. This is a direct consequence of the Gaussian belief representation and was already discussed in Chapter 7.4.

10.2.2 SLAM with Known Correspondence

The SLAM algorithm for the case with known correspondence addresses the continuous portion of the SLAM problem only. Its development is in many ways parallel to the derivation of the EKF localization algorithm in Chapter 7.4, but with one key difference: In addition to estimating the robot pose x_t, the EKF SLAM algorithm also estimates the coordinates of all landmarks encountered along the way. This makes it necessary to include the landmark coordinates into the state vector.

COMBINED STATE VECTOR

For convenience, let us call the state vector comprising robot pose and the map the *combined state vector*, and denote this vector y_t. The combined vector is given by

$$
\begin{aligned}
y_t &= \begin{pmatrix} x_t \\ m \end{pmatrix} \\
&= \begin{pmatrix} x & y & \theta & m_{1,x} & m_{1,y} & s_1 & m_{2,x} & m_{2,y} & s_2 & \ldots & m_{N,x} & m_{N,y} & s_N \end{pmatrix}^T
\end{aligned}
\tag{10.7}
$$

Here x, y, and θ denote the robot's coordinates at time t (not to be confused with the state variables x_t and y_t), $m_{i,x}, m_{i,y}$ are the coordinates of the i-th landmark, for $i = 1, \ldots, N$, and s_i is its signature. The dimension of this state vector is $3N + 3$, where N denotes the number of landmarks in the map. Clearly, for any reasonable number of N, this vector is significantly larger than the pose vector that is being estimated in Chapter 7.4, which introduced the EKF localization algorithm. EKF SLAM calculates the online posterior $p(y_t \mid z_{1:t}, u_{1:t})$.

The *EKF SLAM algorithm* is depicted in Table 10.1—notice the similarity to the EKF localization algorithm in Table 7.2. Lines 2 through 5 apply the motion update, whereas lines 6 through 20 incorporate the measurement vector.

Lines 3 and 5 manipulate the mean and covariance of the belief in accordance to the motion model. This manipulation only affects those elements of the belief distribution concerned with the robot pose. It updates the pose-map covariances but leaves all mean and covariance variables for the map unchanged. Lines 7 through 20 iterate through all measurements. The test in line 9 returns true only for landmarks for which we have