1: **Algorithm inverse_range_sensor_model($\mathbf{m}_i, x_t, z_t$):**
2: *Let x_i, y_i be the center-of-mass of $\mathbf{m}_i$*
3: $r = \sqrt{(x_i - x)^2 + (y_i - y)^2}$
4: $\phi = \text{atan2}(y_i - y, x_i - x) - \theta$
5: $k = \text{argmin}_j \, |\phi - \theta_{j,\text{sens}}|$
6: *if* $r > \min(z_{\max}, z_t^k + \alpha/2)$ *or* $|\phi - \theta_{k,\text{sens}}| > \beta/2$ *then*
7: *return* l_0
8: *if* $z_t^k < z_{\max}$ *and* $|r - z_t^k| < \alpha/2$
9: *return* l_{occ}
10: *if* $r \leq z_t^k$
11: *return* l_{free}
12: *endif*

Table 9.2 A simple inverse measurement model for robots equipped with range finders. Here α is the thickness of obstacles, and β the width of a sensor beam. The values l_{occ} and l_{free} in lines 9 and 11 denote the amount of evidence a reading carries for the two different cases.

cell is shorter than the measured range by more than $\alpha/2$. The left and center panel of Figure 9.3 illustrates this calculation for the main cone of a sonar beam.

A typical application of an inverse sensor model for ultrasound sensors is shown in Figure 9.4. Starting with an initial map the robot successively extends the map by incorporating local maps generated using the inverse model. A larger occupancy grid map obtained with this model for the same environment is depicted in Figure 9.5.

Figures 9.6 shows an example map next to a blueprint of a large open exhibit hall, and relates it to the occupancy map acquired by a robot. The map was generated using laser range data gathered in a few minutes. The gray-level in the occupancy map indicates the posterior of occupancy over an evenly spaced grid: The darker a grid cell, the more likely it is to be occupied. While occupancy maps are inherently probabilistic, they tend to quickly converge to estimates that are close to the two extreme posteriors, 1 and 0. In comparison between the learned map and the blueprint, the occupancy grid map shows all major structural elements, and obstacles as they were visi-