

Here $B(b, z, u)$ is computed using the Bayes filter. In robotics, we only have a choice over the control action u , we cannot pick z . Consequently, we consider the conditional entropy of the control u , with the measurement integrated out:

$$(17.3) \quad H_b(x' | u) \approx E_z[H_b(x' | z, u)] \\ = \int \int H_b(x' | z, u) p(z | x') p(x' | u, x) b(x) dz dx'$$

INFORMATION GAIN Notice that this is only an approximation, as the final expression inverts the order of a summation and a logarithm. The *information gain* associated with action u in belief b is thus given by the difference

$$(17.4) \quad I_b(u) = H_p(x) - E_z[H_b(x' | z, u)]$$

17.2.2 Greedy Techniques

The expected information gain lets us phrase the exploration problem as a decision-theoretic problem of the type addressed in previous chapters. In particular, let $r(x, u)$ be the cost of applying control action u in state x ; here we assume $r(x, u) < 0$ to keep our notation consistent. Then the optimal greedy exploration for the belief b maximizes the difference between the information gain and the costs, weighted by a factor α .

$$(17.5) \quad \pi(b) = \operatorname{argmax}_u \alpha \underbrace{(H_p(x) - E_z[H_b(x' | z, u)])}_{\text{expected information gain}} + \underbrace{\int r(x, u) b(x) dx}_{\text{expected costs}}$$

The factor α relates information to the cost of executing u . It specifies the value a robot assigns to information, which measures the price it is willing to pay in terms of costs for obtaining information.

Equation (17.5) resolves to

$$(17.6) \quad \pi(b) = \operatorname{argmax}_u -\alpha E_z[H_b(x' | z, u)] + \int r(x, u) b(x) dx \\ = \operatorname{argmax}_u \int [r(x, u) - \alpha \int \int H_b(x' | z, u) p(z | x') \\ p(x' | u, x) dz dx'] b(x) dx$$

In short, to understand the utility of the control u , we need to compute the expected entropy after executing u and observing. This expected entropy is obtained by integrating over all possible measurements z that we might be