Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Probabilistic Control of Mobile Robot

HwangRyol Ryu * **KiSung You** ** **ChinTae Choi** ***

* *Research Institute of Science and Technology, Pohang, Korea (Tel: 82-054-279-6653; e-mail: ldsryu@rist.re.kr).*
** *Research Institute of Science and Technology, Pohang, Korea (e-mail: yks@rist.re.kr)*
*** *Research Institute of Science and Technology, Pohang, Korea, (e-mail: chintae@rist.re.kr)*

Abstract: We propose the use of Bayesian approach to a reactive robot control in conjunction with a nonlinear filtering scheme known as particle filters. The approach integrates the optimal control from Bayesian framework with one of the path planning methods known as Vector Field Histogram. Doing this ensures the particle filtering method to track an optimal steering direction. In addition, collision avoidance method is inherently embedded into that scheme due to the fast computing power and a simple implementation of these integrated approach.

1. FROM BAYESIAN TO PARTICLE FILTERS

The Bayesian approach provides a formal framework such that measurements, parameter estimation errors, and state/control trajectory costs are to be evaluated. The particle filtering methods allow us to carry out Bayesian parameter and state estimation for a quite general class of nonlinear stochastic systems. In order to obtain the estimate of the system, two models are introduced as follows: a dynamic model and a observation model.The dynamic model here describes the evolution of the state of the system with time. On the other hand, the observation model encapsulates the noisy uncertainty present on measuring the current state.

To explicitly deal with the uncertainty present in the observations and the dynamics, the Bayesian approach represents its estimate of the system state as a posterior probability density function (*pdf*) computed based on all available information. First, a mathematically tractable representation of the system is needed, often called a *state-space model*. In the case of detecting the obstacles, state could for example be the position and angle of the obstacles. The state of the system at time t is represented by a random variable x_t. Assuming that there are T frames of data to be processed, and at time t only data from times $1 \dots t-1$ are available, the measurements at time t are labeled z_t and will contain a list of feature measurements. The measurements up to t are denoted Z^t, $Z^t = \{z_1, \cdots, z_t\}$.

The objective of a Bayesian filter is now to find the posterior density $p(x_t|Z^t)$ conditioned over all observations until time t, using Bayes' formula:

$$\begin{aligned} p(x_t|Z^t) &= p(x_t|z_t, Z^{t-1}) \\ &= \frac{p(z_t|x_t, Z^{t-1})p(x_t|Z^{t-1})}{p(z_t|Z^{t-1})} \\ &= \frac{p(z_t|x_t)p(x_t|Z^{t-1})}{p(z_t|Z^{t-1})} \end{aligned} \tag{1}$$

A full description of this standard particle filter is beyond the scope of this paper, but the interested reader is referred to Ryu et al [2006] for further details. For the sake of understanding the algorithm in this paper, it is sufficient to know that each posterior distribution $p(x_t|Z^t)$ is represented by a collection of M particles $\{\omega_t^{(i)}, i = 1, 2, ..., M\}$. It allows that properties of the posterior distribution can be estimated directly from the collection of particles.

Suppose we have two conditional probabilities relating to detection of the obstacle given that all we know is range and angle as follows:

$$p(X^t|Z^t_{Range}) \tag{2}$$
$$p(X^t|Z^t_{Angle}) \tag{3}$$

We can combine the evidence from Equation (2) and (3) and apply Bayes' rule on them. Since it is very difficult to estimate conditional probability for evidence combination, we simplify the application of Bayes' rule to add one evidence at a time, which is called *Bayesian updating.*

The first statement of Equation (4) can be read as the probability of the current state (i.e., detection of obstacle) at time t given that all we know is the range and angle from sensor. Therefore, we can reformulate the above equations as follows:

$$\begin{aligned} p(x_t|Z^t_{range}, Z^t_{angle}) &= \frac{p(x_t|Z^t_{angle})p(Z^t_{range}|Z^t_{angle}, x_t)}{p(Z^t_{range}|Z^t_{angle})} \\ &= \frac{p(x_t)p(Z^t_{angle}|x_t)p(Z^t_{range}|x_t)}{p(Z^t_{range})p(Z^t_{range}|x_t)} \\ &= \alpha p(x_t)p(Z^t_{angle}|x_t)p(Z^t_{range}|x_t) \end{aligned} \tag{4}$$

where α is normalization factor, $p(x_t)$ prior for the transition model, and $p(Z^t_{angle}|x_t)p(Z^t_{range}|x_t)$ observation model. Equation (4) basically is derivation of the following rules: conditional independence of each added observation and Bayesian updating rule. It is noted that this simplified form of Bayesian updating only works when the conditional independence relationships hold.

1.1 Observation Likelihood Model

The observation likelihood is probabilities that provide a representation for expressing the certainty about active cell (i,j). Therefore, we must have a function, which transfers a laser scanner reading into appropriate probability for each active cell. The following equations are a set of functions which quantify the observation models of Equation (4) into probabilities.

$$
\begin{aligned}
p(Z^t_{angle}|x_t) &= 1 - (\frac{\theta}{A_{max}})^2 \\
p(Z^t_{range}|x_t) &= 1 - (\frac{r}{R_{max}})^2
\end{aligned}
\tag{5}
$$

where R_{max} and A_{max} are the maximum detection range and the scanning angle, respectively. Equation (5) indicates that the higher the observation likelihood is, the closer the obstacles is to the acoustic axis and likewise the nearer the active cell (i,j) is to the origin of the laser scanner.

1.2 Dynamic Model

The prior probability for characteristics of the environment, $p(x_t)$, should be expressed as the transition model (i.e., prediction). Since we know that Markovian dynamics is inherently embedded in the prior. We can derive the prior probability as follows:

$$p(x_t, x_{t-1}) = \int_{t-1} p(x_t|x_{t-1})p(x_{t-1}|Z^{t-1}_{r,a})dx_{t-1} \tag{6}$$

2. COMPUTING STEERING DIRECTION

Polar obstacle density consists of the probability value since each certainty value is computed based on the observation model. If we only regenerate the particles over the polar obstacle density according to the prediction model, we can complete the particle filtering procedure and result in choosing the most traversable valley in Figure 1.

The similarity measure D is derived based on the Bhattacharyya similarity coefficient and can be defined as follows Ryu et al [2006]:

$$D[\gamma, \delta_t] = \sqrt{1 - \sum_{i=1}^{N} \sqrt{\gamma_i \delta_{i,t}}} \tag{7}$$

where γ and δ are discrete probability distribution of reference features and candidate features, respectively. As a result, the smaller D is, the more similar the two distributions are. In the context of the particle filter, we use the normal gaussian distribution to evaluate the likelihood between them as follows:

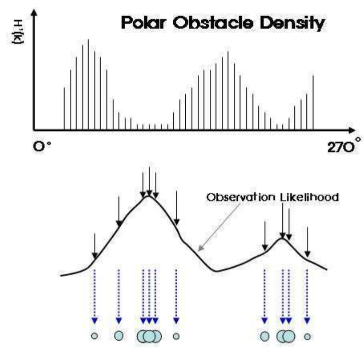

Fig. 1. Transaction from polar obstacle density to observation likelihood

$$\pi(D) = \frac{1}{\sqrt{2\pi}\sigma}\epsilon^{-\frac{D^2}{2\sigma^2}} \tag{8}$$

where the width of the likelihood is controlled by the variance parameter σ^2 in the function of D.

3. CONCLUSION

This paper presents the probabilistic control for the mobile robot integrated with the Vector Field Histogram. In order to impart a decision making control to the mobile robot, the particle filtering approach is derived given the two evidences. Since the VFH inherently generates the 1D polar obstacle density, we are able to compute the similarity measurement without modifying the standard particle filter approach.

REFERENCES

David C. Conner. *Sensor Fusion, Navigation, and Control of Autonomous Vehicles.* Mather Thesis, Virginia Polytechnic Institute and State University, July 2000.

Guilherme A.S. Pereirea, Lucian C.A. Pimenta, Luiz Chaimowicz, Alexandre R. Fonseca, daniel S.C de Almeida, Leonardo De Q. Corr, Renato C. Mesquita, and Mario F.M. Campos. *Robot Navigation in Multi-Terrain Outdoor Environment.* 10th International Symposium on Experimental Robotics, July 2006.

HwangRyol Ryu and Manfred Huber *A Particle Filter Approach for Multi-Target Tracking.* Technical Report, The University of Texas at Arlington, May 2006.

Johann Borenstein and Yoram Koren. *The Vector Field Histogam-Fast Obstacle Avoidance for Mobile Robots* IEEE Int. Conf. Robotics Automat., Vol. 7, No. 3, June 1991.

Robin R. Murphy. *Introduction to AI Robotics* The MIT Press, London, 2002.

Roozbeh Mottaghi and Richard Vaughan. *An Integrated Particle Filter and Potential Field Method Applied to Cooperate Multi-Robot Target Tracking.* IEEE Int. Conf. Robotics Automat., No. 1342-1347, May 2006.

Ulrich and Borensein. *VFH+: Reliable Obstacle Avoidance for Fast Mobile Robots.* IEEE Int. Conf. Robotics Automat., pp. 1572-1577, 1998.