

# Contents

<b>1</b>	<b>Continuous Probability Densities</b>	<b>1</b>
1.1	Continuous Probability Densities . . . . .	1
1.2	Gaussian Densities . . . . .	2
1.3	Bayes Nets and Mixture Models . . . . .	3
1.4	Continuous Measurement Models . . . . .	4
1.5	Continuous Motion Models . . . . .	5
<b>2</b>	<b>Monte Carlo Inference</b>	<b>6</b>
2.1	Simulating from a Continuous Bayes Net . . . . .	6
2.2	Sampling as an Approximate Representation . . . . .	7
2.3	Importance Sampling . . . . .	9
2.4	Particle Filters and Monte Carlo Localization . . . . .	9
2.4.1	Resampling-based MCL . . . . .	10
2.4.2	Mixture-density MCL . . . . .	11
2.4.3	Implementation . . . . .	12
2.5	Connection with the Elimination Algorithm* . . . . .	13
2.6	Importance Sampling and Gibbs Sampling in Bayes Nets* . . . . .	14
2.6.1	Importance sampling . . . . .	14
2.6.2	Gibbs Sampling . . . . .	14

## 1 Continuous Probability Densities

### Motivation

In real robots we often deal with continuous variables and continuous state spaces. Hence, we need to extend the notion of probability to continuous variables.

### 1.1 Continuous Probability Densities

In robotics we typically need to model a belief over continuous, multivariate random variables  $x \in \mathbb{R}^n$ . We do this using **probability density functions** (PDFs)  $p(x)$  over the variables  $x$ , satisfying

$$\int p(x)dx = 1. \tag{1}$$

In terms of notation, for continuous variables we use lowercase letters for random variables, and uppercase letters to denote sets of them. We drop the notational conventions of making distinctions between random variables  $X$  and their realized values  $x$ , which helped us get used to thinking about probabilities, but will get in the way of clarity below.

A **unimodal** density has a single maximum, its **mode**. In general, however, a density can have multiple modes, in which case we speak of a **multimodal** density. The **mean** of a density is defined as

$$\mu = E_p[x] = \int xp(x)dx$$

irrespective of whether the density is unimodal or multimodal. Above, the notation  $E_p[.]$  stands for “the expectation of . with respect to the density  $p$ ”.

## 1.2 Gaussian Densities

A Gaussian probability density on a scalar  $x$  given **mean**  $\mu$  and **variance**  $\sigma^2$  is given by

$$\mathcal{N}(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{1}{2} \left( \frac{x - \mu}{\sigma} \right)^2 \right\}. \quad (2)$$

This density is also known as the “bell curve”. This density is very popular in robotics because it is so simple: it is just the negative exponential of a quadratic around  $\mu$ . In a Bayesian probability framework we interpret densities as knowledge, and the **standard deviation**  $\sigma$  indicates the uncertainty we have about the quantity  $x$ .

The other reason of the Gaussian’s popularity derives from the **central limit theorem**. This theorem says that the probability of the sum of a number of random variables, no matter what the density is on them, will tend to a Gaussian density. And, it does not have to be many random variables either: summing 4 random variables distributed randomly over an interval yields a cubic density, which already matches a Gaussian quite nicely.

A **multivariate Gaussian density** on  $x \in \mathbb{R}^n$  is obtained by extending the notion of a quadratic to multiple dimensions. We define the squared **Mahalanobis distance**,

$$\|x - \mu\|_{\Sigma}^2 \triangleq (x - \mu)^{\top} \Sigma^{-1} (x - \mu) \quad (3)$$

where  $\mu \in \mathbb{R}^n$  is the mean. The quantity  $\Sigma$  is an  $n \times n$  **covariance matrix**, a symmetric matrix indicating uncertainty about the mean. The Mahalanobis distance is nothing but a weighted Euclidean distance, and is the multivariate equivalent of the scalar squared distance

$$\|x - \mu\|_{\sigma^2}^2 \triangleq \left( \frac{x - \mu}{\sigma} \right)^2$$

but using the matrix inverse to weight this distance metric in an  $n$ -dimensional space. Armed with this, the equation for the multivariate Gaussian is

$$\mathcal{N}(x; \mu, \Sigma) = \frac{1}{\sqrt{|2\pi\Sigma|}} \exp \left\{ -\frac{1}{2} \|x - \mu\|_{\Sigma}^2 \right\}, \quad (4)$$

where the term  $|2\pi\Sigma|$  in the normalization factor denotes the determinant of  $2\pi\Sigma$ .

Gaussian densities, whether scalar or multivariate, have some nice properties. A Gaussian density is unimodal and the mean  $\mu$  is also its mode. In addition, any scalar marginal of a multivariate Gaussian is also a Gaussian. In fact, the probability density  $P(y)$  of *any* linear combination  $y = Hx$ , with  $y$  an  $m$ -dimensional vector and  $H$  an  $m \times n$  matrix, is also Gaussian with mean  $H\mu$  and covariance  $H\Sigma H^T$ .

### Exercise

1. Given a 2-dimensional density on  $(x, y)$ , with mean  $\mu = (\bar{x}, \bar{y})$  and covariance matrix

$$\Sigma = \begin{bmatrix} \sigma_x^2 & r \\ r & \sigma_y^2 \end{bmatrix}$$

what is the variance of the marginals  $p(x)$  and  $p(y)$ ? Use the linearity property above.

2. Given the same 2D density, what is the mean and variance of the sum  $z = x + y$ ?
3. Deeper thinking: what happens to the density if we push it through a nonlinear function, e.g.,  $z = \sqrt{x^2 + y^2}$ , the Euclidean norm of the vector  $(x, y)$ ? A qualitative answer is asked for.

### 1.3 Bayes Nets and Mixture Models

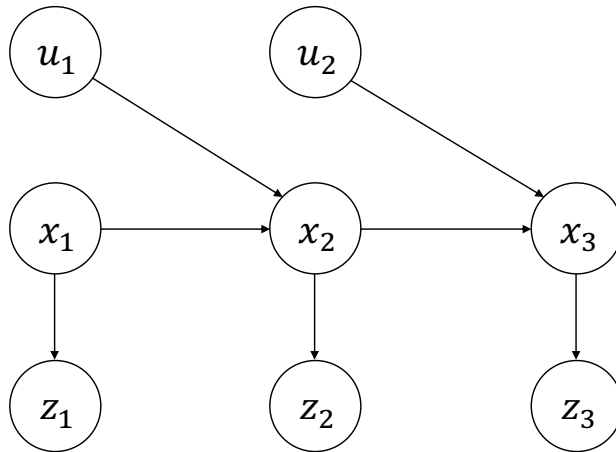


Figure 1: Continuous Bayes net modeling a robot with continuous states  $x_t$ , continuous measurements  $z_t$ , and continuous controls  $u_t$ .

Continuous Bayes nets are exactly like discrete Bayes nets, except with continuous variables. Most of the concepts generalize effortlessly, and we will forego very formal definitions where we can.

An example crucial to the robotics domain is shown in Figure 1, which is the continuous equivalent of the dynamic Bayes net from Part I. In the figure, the continuous Markov chain backbone represents the evolution of the continuous state  $x_t$  over time, conditioned on the **controls**  $u_t$ . Notice we use new terminology here: we say *controls* rather than actions in this new, continuous world. For example, for the Duckiebot, the control  $u$  might be two-dimensional and represent the wheel speeds of the left and right wheels, respectively. Finally, the continuous measurements  $z_t$  at the bottom are conditioned on the states  $x_t$ .

We can mix and match discrete and continuous variables. A particularly simple Bayes net is a **Gaussian mixture model**. The joint density is

$$p(x, C) = p(x|C)P(C)$$

where  $P(C)$  is a PMF on a discrete variable  $C$  that chooses between different Gaussians,  $p(x|C)$  is the corresponding Gaussian mixture component. Even though each Gaussian density is unimodal, the marginal  $p(x)$  is a multimodal density

$$p(x) = \sum_c p(x|C = c)p(C = c)$$

where the sum is over components. An example for a two-component mixture is shown in Figure 2.

Continuous probability densities present a representational challenge. We can no longer specify CPTs: either an equation needs to be available, as with the Gaussian density above, or an arbitrary density has to be somehow approximated. One such approximation is exactly using mixture densities: we can “mix” many simpler densities, like Gaussians, to approximate a more complicated density. This is known as **Parzen window density estimation**.

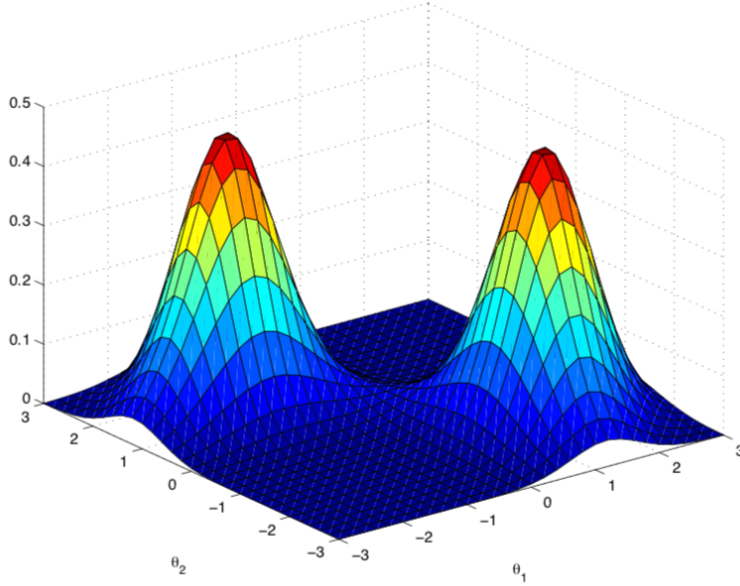


Figure 2: Gaussian mixture density with two components of about equal weight.

#### 1.4 Continuous Measurement Models

In many cases it is both justified and convenient to model measurements as corrupted by zero-mean Gaussian noise. For example, a bearing measurement from a given pose  $x \in SE(2)$  to a given 2D landmark  $l$  would be modeled as

$$z = h(x, l) + \eta, \quad (5)$$

where  $h(\cdot)$  is a **measurement prediction function**, and the noise  $\eta$  is drawn from a zero-mean Gaussian density with **measurement covariance**  $R$ . This yields the following conditional density  $p(z|x, l)$  on the measurement  $z$ :

$$p(z|x, l) = \mathcal{N}(z; h(x, l), R) = \frac{1}{\sqrt{|2\pi R|}} \exp \left\{ -\frac{1}{2} \|h(x, l) - z\|_R^2 \right\}. \quad (6)$$

The measurement functions  $h(\cdot)$  are often nonlinear in practical robotics applications. Still, while they depend on the actual sensor used, they are typically not difficult to reason about or write down. The measurement function for a 2D bearing measurement is simply

$$h(x, l) = \text{atan2}(l_y - x_y, l_x - x_x) - x_\theta, \quad (7)$$

where  $\text{atan2}$  is the well-known two-argument arctangent variant. Hence, the final **probabilistic measurement model**  $p(z|x, l)$  is obtained as

$$p(z|x, l) = \frac{1}{\sqrt{|2\pi R|}} \exp \left\{ -\frac{1}{2} \|\text{atan2}(l_y - x_y, l_x - x_x) - x_\theta - z\|_R^2 \right\}. \quad (8)$$

Note that we will not *always* assume Gaussian measurement noise: to cope with the occasional data association mistake, we can use robust measurement densities, with heavier tails than a Gaussian density.

## 1.5 Continuous Motion Models

For a robot operating in the plane, probabilistic **motion models** are densities of the form  $p(x_{t+1}|x_t)$ , specifying a **probabilistic motion model** which the robot is assumed to obey. This *could* be derived from odometry measurements, in which case we would proceed exactly as described above. Alternatively, such a motion model could arise from known control inputs  $u_t$ . In practice, we often use a conditional Gaussian assumption,

$$p(x_{t+1}|x_t, u_t) = \frac{1}{\sqrt{|2\pi Q|}} \exp \left\{ -\frac{1}{2} \|g(x_t, u_t) - x_{t+1}\|_Q^2 \right\}, \quad (9)$$

where  $g(\cdot)$  is a motion model, and  $Q$  a covariance matrix of the appropriate dimensionality, e.g.,  $3 \times 3$  in the case of robots operating in the plane.

### Summary

We briefly summarize what we learned in this section:

1. Continuous probability densities generalize the notion of probability distributions to continuous random variables.
2. The scalar and multivariate Gaussian densities are useful and relatively simple.
3. Bayes nets generalize as well, and even allow for discrete and continuous variables in the same Bayes net, as in the case of mixture densities.
4. Continuous measurement models typically have a measurement prediction corrupted by noise, often modeled as Gaussian.
5. Continuous measurement models follow a similar pattern, but are conditioned on controls.

## 2 Monte Carlo Inference

### Motivation

With nonlinear dynamics and/or measurement models exact inference is computationally intractable. One way out is to perform approximate inference using sampling. One of the best known such algorithms are particle filters, including Monte Carlo Localization.

### 2.1 Simulating from a Continuous Bayes Net

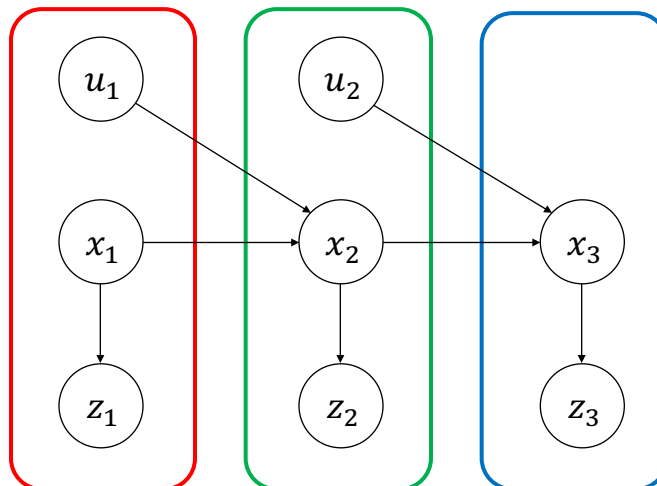


Figure 3: Ancestral sampling in a continuous Bayes net.

Sampling from a continuous Bayes net is done using ancestral sampling, as before: we topologically sort the DAG, and then sample the conditional densities in topological sort order. For the dynamic Bayes net from Figure 1, the topological sort trivially follows the temporal ordering, and we sample first within the red, then green, and then the blue time-slice, as shown in Figure 3.

In each slice, the story is pretty much the same. For example, in the second (green) slice we will

1. Sample the state  $x_2$  from the continuous motion model  $p(x_2|x_1, u_1)$ , by evaluating  $g(x_1, u_1)$ , and adding Gaussian noise with mean  $\mu = 0$  and covariance  $Q$ .
2. Sample the measurement  $z_2$  from the continuous measurement model  $p(z_2|x_2)$ , and adding zero-mean Gaussian noise with measurement covariance  $R$ .
3. Sample a control  $u_2$  that we will use in the next time-slice.

The only exception is the first slice, where the first state  $x_1$  is sampled from the prior  $p(x_1)$ .

To illustrate these concepts we use an example where we use a large appearance-based map to localize a robot in a large known environment. The basic idea, which was detailed in a 1999 CVPR paper, was to generate an image mosaic of the ceiling of the environment in which the robot needs to operate, and use that during operation to localize the robot. An example of such a **ceiling mosaic**

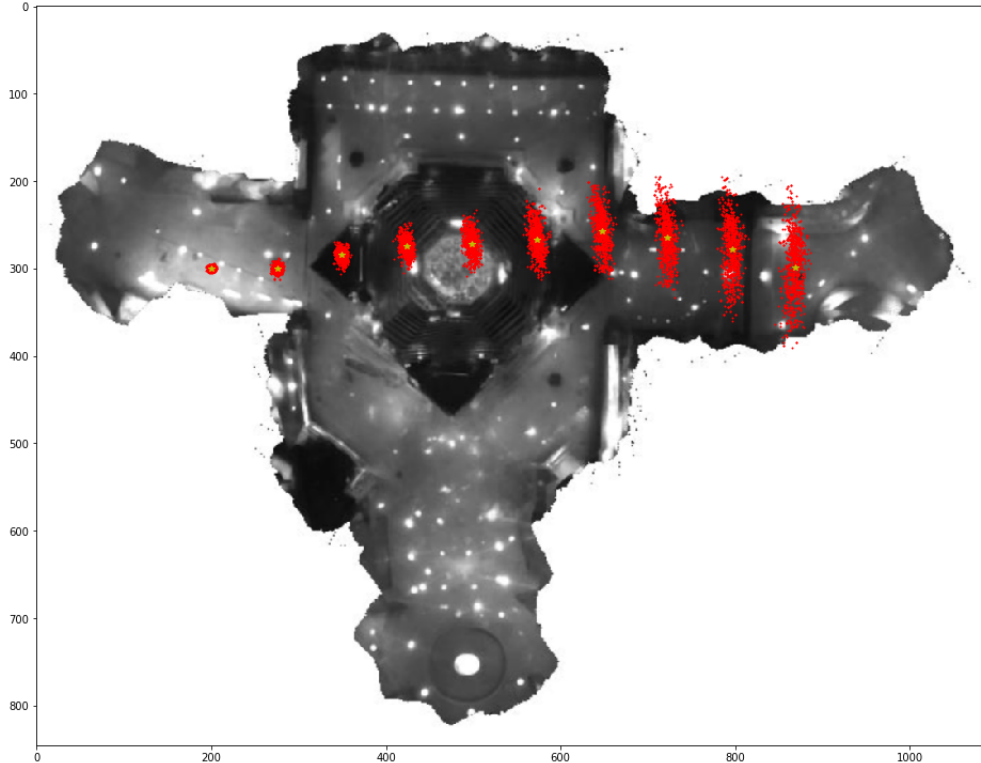


Figure 4: Sampling from the motion-model only, giving rise to so-called “banana-shaped” densities.

from our testbed-application is shown in Figure 4. The figure shows a large portion (40 m. deep by 60 m. wide) of the first floor ceiling of the Museum for American History (MAH), one of the Smithsonians in Washington, DC. The mosaic was generated from 250 images in a mapping phase.

The figure shows the result of sampling from the motion-model only, giving rise to so-called “banana-shaped” densities, shown as red point clouds. In this example, the states are 2D poses  $x = (x_x, x_y, x_\theta)$ , and the control has a forward velocity component  $u_v$  and an angular velocity component  $u_\theta$ . The motion model is then:

$$g(x, u) = (x_x + u_v \cos(x_\theta)\Delta t, x_y + u_v \sin(x_\theta)\Delta t, x_\theta + u_\theta\Delta t)$$

What is happening is mysterious at first, until you realize that the red dots in the figure only show the marginal of the robot position  $(x_x, x_y)$ , not the full 3-dimensional density on the pose. The Gaussian additive noise can make the resulting densities decidedly non-Gaussian after several iterations. The reason is the noise on the heading  $x_\theta$ : this leads to non-linear effects over time.

Note that the Figure does not yet show the result of incorporating the information from the sensor. That will be discussed below.

## 2.2 Sampling as an Approximate Representation

The solution to the robot localization problem is obtained by running a Bayes filter, alternating between prediction and measurement, as we saw before. Depending on how one chooses to represent the **filtering density**  $p(x_t|Z^t)$ , one obtains algorithms with vastly different properties.

If both the motion and the measurement model are linear with additive Gaussian noise, and the initial state is also specified as a Gaussian, then the filtering density  $p(x_t|Z^t)$  will remain Gaussian

at all times. This is the basis of the classical **Kalman filter**. Kalman-filter based techniques are particularly efficient, but in most robotics applications this basic assumption of Gaussian densities is violated. Indeed, for many sensors the likelihood functions are typically complex and multi-modal, as discussed above.

To overcome these disadvantages, different approaches have used increasingly richer schemes to represent uncertainty, moving away from the restricted Gaussian density assumption inherent in the Kalman filter. These different methods can be roughly distinguished by the type of discretization used for the representation of the state space. We have already discussed **Markov localization**, which discretizes the world and can be used in grid worlds and for localizing topological maps. However, in many applications we are interested in a more fine-grained position estimates, e.g., in environments with a simple topology but large open spaces, where accurate placement of the robot is needed. Discretizing the continuous world is powerful, but suffers from the disadvantages of computational overhead and a priori commitment to the size of the state space. For example, the resolution and hence the precision at which they can represent the state has to be fixed in advance.

Finally, one can represent the density by a set of **samples** that are randomly drawn from it. This is the representation we will use in this section. In sampling-based methods one represents the filtering density  $p(x_t|Z^t)$  by a set of  $N$  random samples or particles  $S^t = x_t^{(s)}|s = 1..N$  drawn from it. We are able to do this because of the essential duality between the samples and the density from which they are generated. From the samples we can always approximately reconstruct the density, e.g. using a histogram or a kernel-based density estimation technique.

One nice property of samples as an approximate density is that we can easily compute expected values such as the mean, using a **Monte Carlo approximation**. The name Monte Carlo derives from the city in the south of France, famous for its casinos, where of course a lot of randomness is involved. For the mean, the Monte Carlo approximation is

$$\mu = \int xp(x)dx \approx \frac{1}{N} \sum_r x^{(r)},$$

with  $N$  the number of samples. In fact, we can approximate any expectation of any function of  $x$ :

$$E_p[f(x)] \approx \frac{1}{N} \sum_r f(x^{(r)}),$$

where  $f$  can be a scalar or multivariate function of the random variable  $x$ .

Marginalization of sampled representations is very easy: if we have a set of samples

$$\{(x, y)^{(r)}\} \sim p(x, y)$$

then the sampling-based approximation of the marginal  $p(y)$ , for example, is obtained by just taking the  $y$  component of each sample:

$$\{y^{(r)}\} \sim p(y)$$

If we instantiate these ideas within the context of localization, the goal is then to recursively compute at each time- step  $t$  the set of samples  $S^t$  that is drawn from  $p(x_t|Z^t)$ . A particularly elegant algorithm to accomplish this is the particle filter, which is a Monte Carlo approximation of the Bayes filtering paradigm. Before we go there, however, we need to introduce one more piece of the puzzle in the next section, which is importance sampling.



## Exercise

Prove that the Monte Carlo approximation of  $y = Ax$  is equal to  $A\hat{\mu}$ , where  $\hat{\mu}$  is the approximation of the mean.

## 2.3 Importance Sampling

Sampling from arbitrary densities is not easy in general. Gaussian densities, which are relatively easy to sample from, are the exception rather than the rule.

A simple method is **importance sampling**. Given any **target density**  $p(x)$ , we instead sample from a (hopefully easier) **proposal density**  $q(x)$ , and then produce *weighted samples* with **importance weights**

$$w^{(r)} = \frac{p(x^{(r)})}{q(x^{(r)})}$$

where  $x^{(r)}$  is a sample (with index  $r$ ) from  $q(x)$ . After sampling the required number, the importance weights can be normalized to sum up to 1.

Importance sampling can be used as a simple approximate implementation of Bayes rule. In this case, the target density is  $p(x|z)$ , and we can use the prior  $p(x)$  as the proposal density. Hence, the weights can be computed as

$$w^{(r)} = \frac{p(x^{(r)}|z)}{p(x^{(r)})} \propto \frac{l(x^{(r)}; z)p(x^{(r)})}{p(x^{(r)})} = l(x^{(r)}; z)$$

where we used  $p(x|z) \propto l(x; z)p(x)$ , with  $l(x; z)$  the likelihood of  $x$  given  $z$ . Hence, when implementing Bayes law by proposing from the prior, the weights are simply the measurement likelihoods  $l(x^{(r)}; z)$ .

## 2.4 Particle Filters and Monte Carlo Localization

Recall that localization in robotics can be done via the Bayes filter. For continuous variables, the (exact) **filtering density** associated with a Bayes filter is given by

$$p(x_t|Z^t) \propto l(x_t; z_t) \int_{x_{t-1}} p(x_t|x_{t-1})p(x_{t-1}|Z^{t-1}), \quad (10)$$

where  $Z^t \triangleq \{z_1, z_2 \dots z_t\}$  is shorthand for all measurement up to and including time  $t$ . In other words, the filtering density  $p(x_t|Z^t)$  at time  $t$  is recursively obtained from the filtering density  $p(x_{t-1}|Z^{t-1})$  at time  $t-1$ , by first calculating the **predictive density**

$$p(x_t|Z^{t-1}) = \int_{x_{t-1}} p(x_t|x_{t-1})p(x_{t-1}|Z^{t-1}), \quad (11)$$

and then weighting with the likelihood function  $l(x_t; z_t)$ .

There are two ways to intuitively derive particle filtering, which we discuss one by one in the first two sections below.

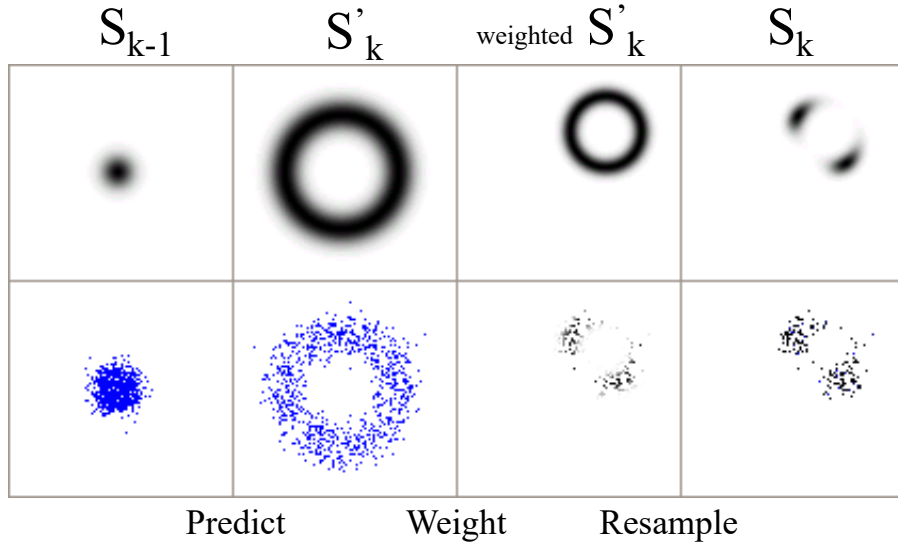


Figure 5: Schematic explanation of resampling-based MCL, see text.

#### 2.4.1 Resampling-based MCL

Let us assume that we have a set of samples on  $X_{t-1}$ , i.e.,  $\{x_{t-1}^{(s)}\} \sim p(x_{t-1}|Z^{t-1})$ . We create a tiny Bayes net,  $x_{t-1} \rightarrow x_t$ , and extend the sample set as in ancestral sampling, obtaining  $\{(x_{t-1}, x_t)^{(s)}\} \sim p(x_{t-1}, x_t|Z^{t-1})$ . We then marginalize to  $\{x_t^{(s)}\} \sim p(x_t|Z^{t-1})$ , weight by the likelihoods  $l(x_t^{(s)}; z_t)$  to obtain  $\{x_t^{(s)}, w_t^{(s)}\} \sim p(X_t|Z^t)$ . Finally, resample to get back to an unweighted set of particles for the next step. In summary, given the approximate posterior at the previous time step  $\{x_{t-1}^{(s)}\} \sim p(x_{t-1}|Z^{t-1})$ , we

1. extend to include the next state to obtain  $\{(x_{t-1}, x_t)^{(s)}\} \sim p(x_{t-1}, x_t|Z^{t-1})$ ;
2. marginalize to obtain the approximate predictive density  $\{x_t^{(s)}\} \sim p(x_t|Z^{t-1})$ ;
3. weight by the likelihoods  $w_t^{(s)} = l(x_t^{(s)}; z_t)$  to obtain  $\{x_t^{(s)}, w_t^{(s)}\} \sim p(x_t|Z^t)$ ;
4. resample to get back an unweighted approximation  $\{x_t^{(r)}\} \sim p(x_t|Z^t)$ .

One iteration of the algorithm is illustrated in 5. Each panel in the top row shows the exact density, whereas the panel below shows the particle-based representation of that density. In panel A, we start out with a cloud of samples  $S_{k-1}$  representing our uncertainty about the robot position. In the example, the robot is fairly localized, but its orientation is unknown. Panel B shows what happens to our belief state when we are told the robot has moved exactly one meter since the last time-step: we now know the robot to be somewhere on a circle of 1 meter radius around the previous location. Panel C shows what happens when we observe a landmark, half a meter away, somewhere in the top-right corner: the top panel shows the likelihood  $p(z_k|x_k)$ , and the bottom panel illustrates how each sample is weighted according to this likelihood. Finally, panel D shows the effect of resampling from this weighted set, and this forms the starting point for the next iteration.

### 2.4.2 Mixture-density MCL

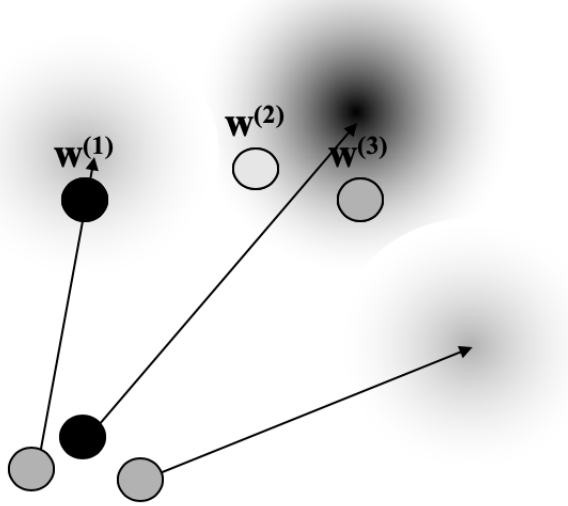


Figure 6: Sampling from the predictive density  $p(x_t|Z^{t-1})$ , approximated by a mixture density  $\sum_r w_{t-1}^{(r)} p(x_t|x_{t-1}^{(r)})$  with 3 components. The middle component happens to be picked twice. After that, the three new samples each get a new likelihood weight  $w^{(s)}$ , as shown.

The second way to view a particle filter is by considering approximating the integral in the predictive density (11) with a sum approximation, i.e.,

$$p(x_t|Z^{t-1}) = \int_{x_{t-1}} p(x_t|x_{t-1})p(x_{t-1}|Z^{t-1}) \approx \sum_r w_{t-1}^{(r)} p(x_t|x_{t-1}^{(r)}) \quad (12)$$

Hence, in this view we start out with a weighted sample approximation for the previous filtering density  $\{x_{t-1}^{(r)}, w_{t-1}^{(r)}\} \sim p(x_{t-1}|Z^{t-1})$ , and then approximate predictive density with a mixture density as in Equation 12. We then sample from it to get  $\{x_t^{(s)}\} \sim p(x_t|Z^{t-1})$ , and then weight the samples using the likelihood:  $\{x_t^{(s)}, w_t^{(s)}\} \sim P(x_t|Z^t)$ , where  $w_t^{(s)} = l(x_t^{(s)}; z_t)$ . In summary, given the approximate posterior using weighted samples  $\{x_{t-1}^{(r)}, w_{t-1}^{(r)}\} \sim p(x_{t-1}|Z^{t-1})$ , we

1. approximate the predictive density as a mixture density  $p(x_t|Z^{t-1}) \approx \sum_r w_{t-1}^{(r)} p(x_t|x_{t-1}^{(r)})$ ;
2. sample from it to get  $\{x_t^{(s)}\} \sim p(x_t|Z^{t-1})$ ;
3. weight the samples using the likelihood:  $\{x_t^{(s)}, w_t^{(s)}\} \sim P(x_t|Z^t)$ , where  $w_t^{(s)} = l(x_t^{(s)}; z_t)$ .

The former derivation is a straight extension of importance sampling as in the previous section, but the resampling step is somewhat magical. The latter derivation shows that the resampling can be interpreted as approximating the predictive density for  $X_t$ . Of course, both derivations lead to the exact same algorithm.

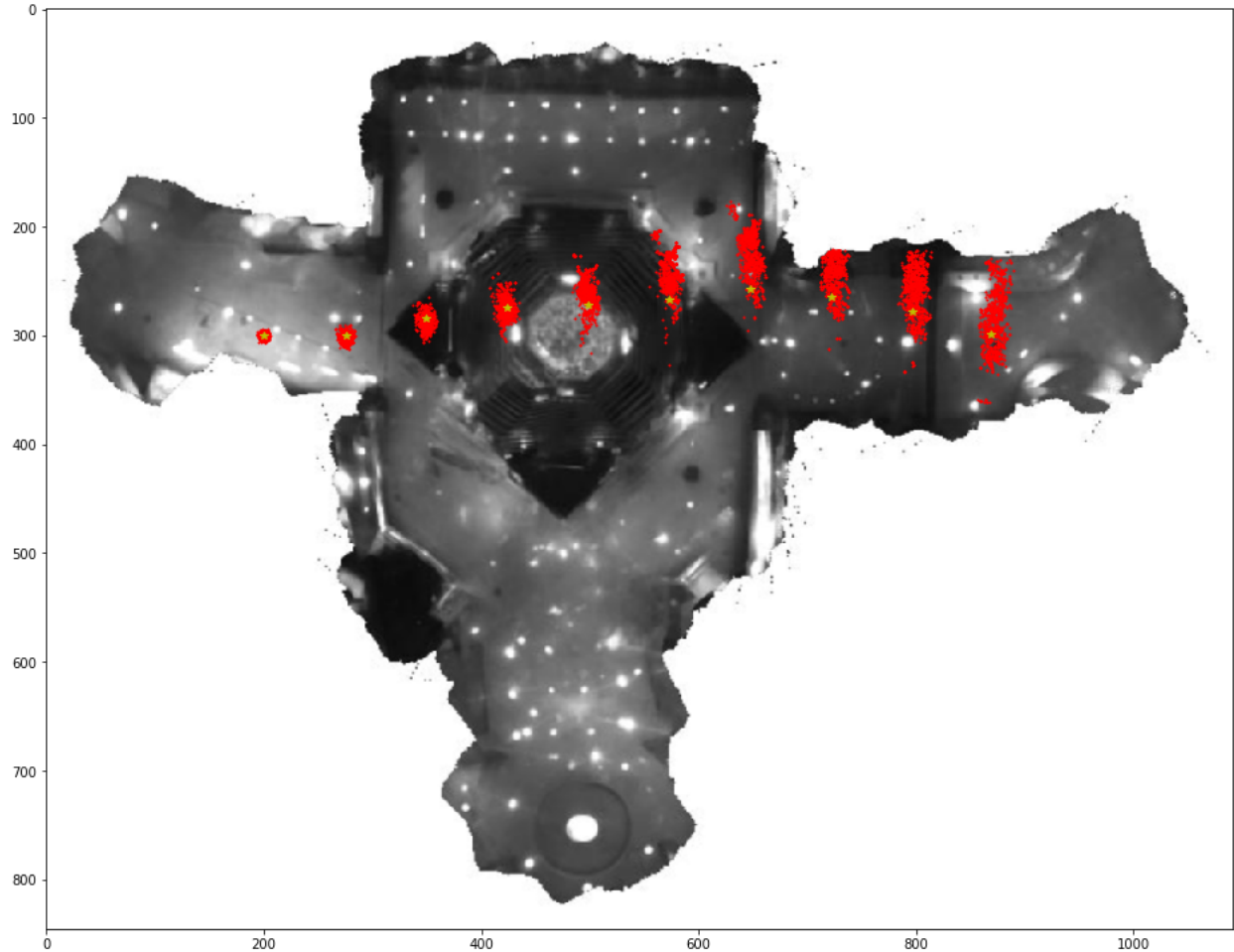


Figure 7: Monte Carlo localization resamples the particles based on weights derived from the sensors. In this case the sensor is simply picking up the grayscale value of the ceiling above the robot.

### 2.4.3 Implementation

Particle filters are very easy to implement. In fact, the inner loop can be done in just three lines of python (provided you have numpy and scipy installed and imported):

```

1 I = numpy.random.choice(N,size=N,p=W)
2 X = numpy.array([np.random.multivariate_normal(g(X[i],u), cov) for i in I])
3 W = scipy.special.softmax([- (h(x)-z)**2 for x in X])

```

Above  $N$  is the number of samples,  $W$  are the weights for the samples  $X$ , and the variable  $cov$  is the motion model covariance  $Q$ . In the code above, the first two lines sample from the predictive mixture density  $p(x_t|Z^{t-1}) \approx \sum_r w_{t-1}^{(r)} p(x_t|x_{t-1}^{(r)})$ , and the last line uses “softmax” to weight each sample using the likelihood  $l(x_t^{(s)}; z_t)$  and then normalize the weights.

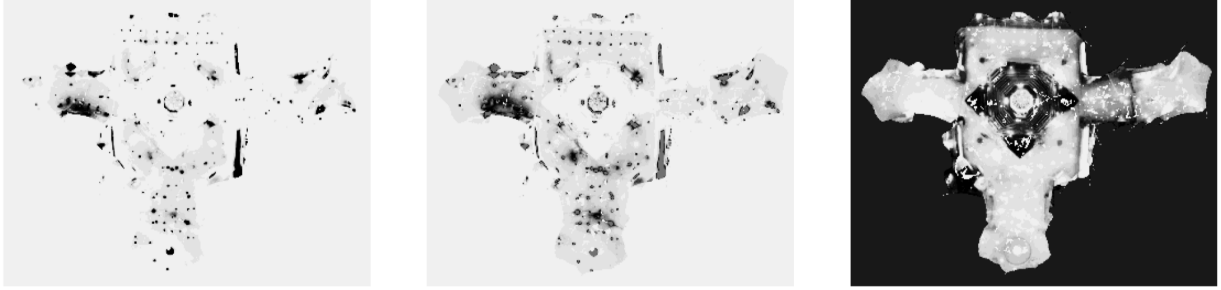


Figure 8: The likelihood functions  $l(x|z)$  of being at a pose  $x$  given a brightness measurement  $z$  for three values of  $z$ . Left: high  $z$  indicates the robot is under a light. Middle: intermediate  $z$ . Right: low  $z$ : not under a light.

An example of this code in action is shown in Figure 7, for the ceiling localization example. In this case, the simulated sensor was simply the grayscale value at the simulated location of the robot. This is not a very informative sensor, but it does focus the distributions more on the correct location, indicated in yellow, as compared to the motion-model only particles from Figure (7). The likelihood functions  $l(x|z)$  associated with this simple sensor model are in general complex and multimodal. To illustrate this, three different likelihood functions are shown in Figure (8), respectively when the robot is under a light, at the border of a light, and not under a light. It is clear that these densities do not resemble anything remotely like a Gaussian density. To see the full results with a real robot, operating in a real environment, please refer to the full 1999 paper.

### Exercise

1. Show that both algorithms are the same.
2. Examine the python code in detail and try to fully understand it.

## 2.5 Connection with the Elimination Algorithm\*

Factor graphs were not harmed in the making of this filter. But, you can interpret the weighted samples as a factor  $f_1(x_{t-1})$  on  $x_{t-1}$ , then add a motion model to  $x_t$  and a likelihood factor on  $x_t$ .

A continuous version of eliminating  $x_{t-1}$ , if this was tractable, would form the product factor

$$\psi(x_{t-1}, x_t) = f_1(x_{t-1})p(x_t|x_{t-1})$$

and try to re-write it as  $p(x_{t-1}|x_t)\tau(x_t)$ . We saw in the discrete sum-product algorithm that this is done by marginalization. Doing this here, we obtain the new factor

$$\tau(x_t) = \sum f_1(x_{t-1})p(x_t|x_{t-1}),$$

which can be recognized as approximating the predictive density  $p(x_t|Z^{t-1})$ . In the elimination step we also usually calculate the conditional  $p(x_{t-1}|x_t)$  but we do not need it here.

Then, eliminating  $x_t$  would form the product  $\tau(x_t)l(x_t; z_t)$ . This is hard if we would like to modify mixture components exactly, but easy if we first sample from them: we just re-weight then with the likelihood, and we are done. Hence, the factor graph interpretation closely aligns with the second derivation above.

## 2.6 Importance Sampling and Gibbs Sampling in Bayes Nets\*

One of the downsides of Bayes filtering schemes is that we only get the posterior  $p(x_t|Z^t)$  on the current state. But what if we are interested in the posterior  $p(X^t|Z^t)$  on the entire trajectory? Below we discuss two schemes: importance sampling and Gibbs sampling.

### 2.6.1 Importance sampling

Importance sampling is easy. We once again partition the variables into unknown variables  $X$  and observed values  $Z$ . Rather than converting to a factor graph, we simply sample from the unknown variables in topological sort order, but whenever we encounter a variable  $z \in Z$  we of course use the known value rather than sample. Then we give a weight to each sample  $X^{(r)}$  equal to  $w^{(r)} = p(Z|X) = \prod_z p(z|\Pi_z)$ , and normalize the weights. Note that in calculating the weight we can omit any conditionals that do not involve unknown variables  $x$ .

As an example, consider again the dynamic Bayes net in Figure 1. If the evidence is all actions and measurements, importance sampling comes down to sampling from the motion model Markov chain, as illustrated in Figure 4, and then weighting by  $\prod p(z_t|x_t)$ . We don't need to bother with the probabilities of the actions, as they do not depend on the states  $\mathcal{X}$  in any way.

However, the variance associated with producing samples from the posterior makes it only useful for small examples. Indeed: we are multiplying many small numbers together, and if the posterior  $p(x|z)$  is very different from the proposal distribution, many of the samples will be wasted. For a large number of variables, almost all samples will be thus wasted.

### 2.6.2 Gibbs Sampling

A theoretically better way to sample from a posterior is using **Gibbs sampling**. For this, we convert to a factor graph with the method we explained before. Then, we start with a random initial estimate for all variables, and then repeat the following simple procedure over and over: for all variables, sample from the conditional density  $p(x|\mathcal{N}_x)$ , where  $\mathcal{N}_x$  is the set of all neighbors of  $x$ , and pretending these neighbors are *known*. We then replace the current value of  $x$  with the sampled value. The conditional density  $p(x|\mathcal{N}_x)$  can be computed by eliminating  $x$ , i.e., forming the product factor. After visiting each variable in turn in each iteration, we produce a large sequence of samples for the set of unknowns  $X$ , one for each iteration of Gibbs sampling.

There are pros and cons to Gibbs sampling, as well. The biggest advantage is that it does not have much of a variance problem as importance sampling does. The disadvantages are three-fold: (a) it might not always be easy to calculate the densities needed, or sample from them; (b) the samples of  $X$  are correlated over time; (c) it could take a long time for this sample to converge to its stationary distribution  $p(X|Z)$ .

## Summary

We briefly summarize what we learned in this section:

1. Simulating Continuous Bayes Nets
2. Sampling as Approximation
3. Importance Sampling
4. Particle Filters and Monte Carlo Localization
5. Monte Carlo Localization & the Elimination Algorithm