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# Sequential Monte Carlo Methods for Dynamic Systems

Jun S. LIU and Rong CHEN

We provide a general framework for using Monte Carlo methods in dynamic systems and discuss its wide applications. Under this framework, several currently available techniques are studied and generalized to accommodate more complex features. All of these methods are partial combinations of three ingredients: importance sampling and resampling, rejection sampling, and Markov chain iterations. We provide guidelines on how they should be used and under what circumstance each method is most suitable. Through the analysis of differences and connections, we consolidate these methods into a generic algorithm by combining desirable features. In addition, we propose a general use of Rao-Blackwellization to improve performance. Examples from econometrics and engineering are presented to demonstrate the importance of Rao-Blackwellization and to compare different Monte Carlo procedures.

KEY WORDS: Blind deconvolution; Bootstrap filter; Gibbs sampling; Hidden Markov model; Kalman filter; Markov chain Monte Carlo; Particle filter; Sequential imputation; State-space model; Target tracking.

## 1. INTRODUCTION

Dynamic modeling is an important statistical analysis tool that has attracted much attention from researchers in different fields. One widely used dynamic model, the linear state-space model, has long been an active subject in studying time series data and control systems (Harvey 1989; West and Harrison 1989). Despite their computational complexities, nonlinear/non-Gaussian state-space models are also important in various applications. A partial list of references is given in Example 2.

Models of dynamic nature have also been used in various situations, such as updating and learning in graphical models or *probabilistic expert systems* (Kong, Liu, and Wong 1994; Spiegelhalter and Lauritzen 1990), simulating protein structures (Leach 1996; Vasquez and Scherago 1985), genetics (Irwing, Cox, and Kong 1994), and combinatorial optimizations (Wong and Liang 1997). An example of expert system updating can be found in Berzuini et al. (1997).

In this article we study Monte Carlo computation methods for *real time* analysis of dynamic systems. Such a system can be abstractly defined as follows.

*Definition 1.* A sequence of evolving probability distributions  $\pi_t(\mathbf{x}_t)$ , indexed by discrete time  $t = 0, 1, 2, \dots$ , is called a *probabilistic dynamic system*. The state variable  $\mathbf{x}_t$  can evolve in the following three ways

- increasing dimension:  $\mathbf{x}_{t+1}$  has one more component than  $\mathbf{x}_t$ ; that is,  $\mathbf{x}_{t+1} = (\mathbf{x}_t, x_{t+1})$ , where  $x_{t+1}$  can be a multidimensional component.

- discharging:  $\mathbf{x}_{t+1}$  has one fewer component than  $\mathbf{x}_t$ ; that is,  $\mathbf{x}_t = (\mathbf{x}_{t+1}, d_t)$ .
- no change:  $\mathbf{x}_{t+1} = \mathbf{x}_t$ .

Most of this article will be devoted to the first situation of increasing dimension, whereas the other two situations can be handled similarly. Throughout the article,  $\pi(\cdot)$  always refers to the target distribution of the dynamic system, and  $p(\cdot)$  is a generic symbol for probability distributions.

In most applications, the difference between  $\pi_{t+1}$  and  $\pi_t$  is caused by the incorporation of new information in the analysis. Of interests in these systems are usually

- prediction:  $\pi_t(x_{t+1})$  (i.e., when  $\pi_t$  can be “extended” to a new component  $x_{t+1}$ , the best prediction of  $x_{t+1}$  before new information arrives is via  $\pi_t$ )
- updating (smoothing):  $\pi_{t+1}(\mathbf{x}_t)$  (i.e., revision of the previous state given new information)
- new estimation:  $\pi_{t+1}(x_{t+1})$  (i.e., what we can say about  $x_{t+1}$  in light of new information).

The following two examples are typical dynamic systems, and they will be referred to repeatedly throughout this article.

*Example 1: Bayesian Missing-Data Problem.* Suppose that  $z_1, \dots, z_n$  are iid from model  $p(z|\theta)$ , but some  $z$ 's are only partially observed. Let  $z_i = (y_i, x_i)$ , where  $y_i$  is the observed part and  $x_i$  is the missing part. Let  $\mathbf{y}_t = (y_1, \dots, y_t)$  and  $\mathbf{x}_t = (x_0, x_1, \dots, x_t)$ , where  $x_0 = \theta$ . The dynamic system in this case is  $\pi_t(\mathbf{x}_t) = p(\mathbf{x}_t|\mathbf{y}_t)$ . Of interest is usually the posterior distribution  $\pi_n(x_0) = \int \pi_n(\mathbf{x}_n) dx_1 \cdots dx_n$ . When  $\theta$  (i.e.,  $x_0$ ) can be explicitly integrated out from  $p(\mathbf{x}_t, \mathbf{y}_t) = p(y_1, \dots, y_t, x_1, \dots, x_t|\theta)p(\theta)$ , such as in the case of multivariate normal data with missing components (Kong et al. 1994), a good approach is to draw  $x_1, \dots, x_n$  from  $\pi_n(x_1, \dots, x_n)$  and then use Rao-Blackwellization to approximate  $\pi_n(\theta)$ .

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*Example 2: State-Space Model.* Such a model consists of two parts: observation equation, which can be formulated as  $y_t \sim f_t(\cdot|x_t, \phi)$ , and state equation, which can be represented by a Markov process as  $x_t \sim q_t(\cdot|x_{t-1}, \theta)$ . The  $y_t$  are observations and the  $x_t$  are referred to as the (unobserved) states. Of interest at any time  $t$  is the posterior distribution of  $\mathbf{x}_t \equiv (\phi, \theta, x_1, \dots, x_t)$ . Hence the target distribution at time  $t$  is

$$\begin{aligned} \pi_t(\mathbf{x}_t) &= \pi_t(\phi, \theta, x_1, \dots, x_t) = p(\phi, \theta, x_1, \dots, x_t | \mathbf{y}_t) \\ &\propto p(\theta, \phi) \prod_{s=1}^t f_s(y_s | x_s, \phi) q_s(x_s | x_{s-1}, \theta), \end{aligned}$$

where the initial distribution  $q_1(x_1|x_0, \theta)$  is assumed known. When the parameters  $\theta$  and  $\phi$  are given (such as in many engineering problems),  $\mathbf{x}_t$  represents  $(x_1, \dots, x_t)$ . In practice, the  $x$ 's can be the unobserved true signals in signal processing (Liu and Chen 1995), the actual words in speech recognition (Rabiner 1989), the target characteristics (e.g., location, velocity) in a multitarget tracking problem (Avitzour 1995; Gordon, Salmon, and Smith 1993; Gordon, Salmon, and Ewing 1995), the image characteristics in computer vision (Isard and Blake 1996), the gene indicator in a DNA sequence analysis (Churchill 1989), or the underlying volatility in an economical time series (Pitt and Shephard 1997). The applications of dynamic state-space model in DNA and protein sequence analysis are often referred to as *hidden Markov models* (Krogh, Brown, Mian, Sjolander, and Haussler 1994; Liu, Neuwald, and Lawrence 1997).

Except for a few special cases, closed-form analysis of dynamical systems is usually formidable. Recently, there has been a surge of interest in designing Monte Carlo methods for the analysis of these models. In fact, most of the references given in Example 2 use Monte Carlo or iterative methods. To implement Monte Carlo for a dynamic system, we need, at any time  $t$ , random samples either drawn from  $\pi_t(\mathbf{x}_t)$  directly, or drawn from another distribution, say  $g_t(\mathbf{x}_t)$ , and weighted properly (importance sampling). Static methods—for example, most of the popular Markov Chain Monte Carlo (MCMC) schemes (Carlin, Polson, and Stoffer 1992; Carter and Kohn 1994)—achieve this end by treating each  $\pi_t$  separately and repeating same kind of iterative processes. In other words, all of the results (i.e., random draws) obtained at time  $t$  are discarded when the system evolves from  $\pi_t$  to  $\pi_{t+1}$ .

However, when the system is slowly varying [i.e., the  $L^2$  distance between  $\pi_t(\mathbf{x}_t)$  and  $\pi_{t+1}(\mathbf{x}_t)$  is small], random samples obtained at time  $t$  can be “reused” to help construct random samples at time  $t + 1$  so as to improve efficiency. Imagine that we have a sample  $S_t = \{\mathbf{x}_t^{(j)}, j = 1, \dots, m\}$  drawn from  $\pi_t$ . When the system evolves to  $\pi_{t+1}$ , it is desirable to keep those  $\mathbf{x}_t^{(j)}$  and attach to each of them one or several  $x_{t+1}^{(j)}$  drawn from some appropriate distribution  $g_{t+1}(\cdot|x_t^{(j)})$ . Let  $H_{t+1}$  denote the sample space of  $x_{t+1}$ . Then the foregoing idea is equivalent to drawing a sample from the product space  $S_t \otimes H_{t+1}$ . Very often the evolved sample  $\mathbf{x}_{t+1}^{(j)} = (\mathbf{x}_t^{(j)}, x_{t+1}^{(j)})$  needs to be reweighted or re-

sampled to accommodate  $\pi_{t+1}$ . This is the basic principle behind almost all available sequential Monte Carlo methods (see e.g., Berzuini, Best, Gilks, and Larizza 1997, Gordon et al. 1993, Hendry and Richard 1990, Kitagawa 1996, Kong et al. 1994, Liu and Chen 1995, MacEachern, Clyde, and Liu 1998, Pitt and Shephard 1997, and West 1992).

To further elaborate on these ideas, in this article we describe a general framework for using sequential Monte Carlo methods in dynamic systems. Under this framework, we extend and unify previously more restrictive methods, study various reweighting and resampling techniques proposed, and discuss connections and comparisons of these approaches. A main message that we want to communicate in this article is that the sequential importance sampling (SIS) setting provides a good framework for understanding many existing methods and for further improving them (via Rao–Blackwellization, collapsing, etc.).

Section 2 describes the general idea of the SIS method and several key implementation issues, such as the choice of sampling distribution, resampling, and Monte Carlo inference. Section 3 discusses several local Monte Carlo methods that are needed when SIS encounters certain difficulties. Section 4 proposes three methods for resampling from  $S_t$  and provides a generic algorithm that combines SIS and resampling. Section 5 brings in Rao–Blackwellization for improving estimation. Section 6 gives three examples to demonstrate the use of Rao–Blackwellization and to compare different procedures. Section 7 concludes with a brief summary.

## 2. SEQUENTIAL UPDATING IN DYNAMIC SYSTEMS

One of the most effective methods for analyzing a complicated probabilistic system (such as a nonlinear state-space model) is the Gibbs sampler (Carlin et al. 1992; Carter and Kohn 1994; Gelfand and Smith 1990; Tanner and Wong 1987). However, the Gibbs sampler is less attractive when one’s interest is in *real time* prediction and updating in a dynamic system. Another situation for the Gibbs sampler to be ineffective is when the states of the resulting samples are very “sticky,” rendering the sampler very difficult to move (MacEachern, Clyde, and Liu 1998). In this case it appears that intelligently choosing a dynamic system for sequential updating can be more efficient (Wong and Liang 1997). We first describe one of such sequential updating strategies, then discuss its several key implementation issues.

### 2.1 Sequential Importance Sampling

A useful way to represent a complicated high-dimensional distribution, such as  $\pi_t(\mathbf{x}_t)$ , is by multiple Monte Carlo samples drawn from it. Multiple imputation (Rubin 1987) is a successful example of such a practice for survey data. In this article we advocate a similar methodology to that of Rubin’s for analyzing dynamic systems.

*Definition 2.* A random variable  $X$  drawn from a distribution  $g$  is said to be *properly weighted* by a weighting function  $w(X)$  with respect to the distribution  $\pi$  if for any

integrable function  $h$ ,

$$E_g\{h(X)w(X)\} = E_\pi\{h(X)\}.$$

A set of random draws and weights  $(x^{(j)}, w^{(j)})$ ,  $j = 1, 2, \dots$ , is said properly weighted with respect to  $\pi$  if

$$\lim_{m \rightarrow \infty} \frac{\sum_{j=1}^m h(x^{(j)})w^{(j)}}{\sum_{j=1}^m w^{(j)}} = E_\pi(h(X)) \tag{1}$$

for any integrable function  $h$ . In a practical sense, we can think of  $\pi$  as being approximated by the discrete distribution supported on the  $x^{(j)}$  with probabilities proportional to the weights  $w^{(j)}$ .

Let  $S_t = \{\mathbf{x}_t^{(j)}, j = 1, \dots, m\}$  denote a set of random draws that are properly weighted by the set of weights  $W_t = \{w_t^{(j)}, j = 1, \dots, m\}$  with respect to  $\pi_t$ . Let  $H_{t+1}$  be the sample space of  $X_{t+1}$ , and let  $g_{t+1}$  be a trial distribution. Then the SIS procedure consists of recursive applications of the following SIS steps for  $j = 1, \dots, m$ :

- A. Draw  $X_{t+1} = x_{t+1}^{(j)}$  from  $g_{t+1}(x_{t+1} | \mathbf{x}_t^{(j)})$ ; attach it to  $\mathbf{x}_t^{(j)}$  to form  $\mathbf{x}_{t+1}^{(j)} = (\mathbf{x}_t^{(j)}, x_{t+1}^{(j)})$ .
- B. Compute

$$u_{t+1}^{(j)} = \frac{\pi_{t+1}(\mathbf{x}_{t+1}^{(j)})}{\pi_t(\mathbf{x}_t^{(j)})g_{t+1}(x_{t+1}^{(j)} | \mathbf{x}_t^{(j)})}; \tag{2}$$

and let

$$w_{t+1}^{(j)} = u_{t+1}^{(j)} w_t^{(j)}.$$

Here  $u_t$  is called an ‘‘incremental weight.’’ It is easy to show that  $(\mathbf{x}_{t+1}^{(j)}, w_{t+1}^{(j)})$  is a properly weighted sample of  $\pi_{t+1}$ . Thus the SIS can be applied recursively for  $t = 1, 2, \dots$ , to accommodate an ever-changing dynamical system.

The SIS method is also useful in non-Bayesian computation, such as evaluating likelihood functions. Applications in this direction have been discussed by Hendry and Richard (1991) and Irwing et al. (1994). Briefly, suppose that we are interested in evaluating the likelihood function  $L(\theta) = p(y_1, \dots, y_t; \theta)$  in the missing-data problem (Example 1). Then for each fixed  $\theta$  value, we apply the SIS procedure to impute  $(x_1, \dots, x_t)$  sequentially with  $g_1(x_1) = p(x_1 | y_1; \theta)$  and

$$g_s(x_s | x_1, \dots, x_{s-1}) = p(x_s | \mathbf{x}_{s-1}, \mathbf{y}_s; \theta), \quad s = 2, 3, \dots$$

Kong et al. (1994) showed that  $\sum_{j=1}^m w_t^{(j)} / m$  is an unbiased estimate of  $L(\theta)$ . In Section 5 we show that Rao–Blackwellization (Casella and Robert 1996; Liu, Wong, and Kong 1994) can be applied to better estimate.

### 2.2 Choice of the Sampling Distribution $g_{t+1}$ in Sequential Importance Sampling

The choice of the sampling distribution  $g_{t+1}$  is directly

related to the efficiency of the proposed SIS method. For Bayesian missing-data problems (Example 1), Kong et al. (1994) suggested using

$$g_{t+1}(x_{t+1} | \mathbf{x}_t) = \pi_{t+1}(x_{t+1} | \mathbf{x}_t) = p(x_{t+1} | \mathbf{y}_{t+1}, \mathbf{x}_t),$$

with the incremental weight  $u_{t+1} \propto p(y_{t+1} | \mathbf{y}_t, \mathbf{x}_t)$ . Note that although the exact value is not easily known,  $u_{t+1}$  can sometimes be computed up to a normalizing constant, which is sufficient for estimation using formula (1). This choice of  $g_{t+1}$  was also used by Liu and Chen (1995). For the state-space model (Example 2) with known  $x_0 = (\theta, \phi)$ , a similar trial distribution is

$$g_{t+1}(x_{t+1} | \mathbf{x}_t) \propto f_{t+1}(y_{t+1} | x_{t+1}, \phi) q_{t+1}(x_{t+1} | x_t, \theta)$$

$$u_{t+1} = \int f_{t+1}(y_{t+1} | x_{t+1}, \phi) q_{t+1} \times (x_{t+1} | x_t, \theta) dx_{t+1}.$$

In the general dynamic system setting, we suggest choosing  $g$  as

$$g_{t+1}(x_{t+1} | \mathbf{x}_t) = \pi_{t+1}(x_{t+1} | \mathbf{x}_t), \quad t = 1, 2, \dots, \tag{3}$$

with the incremental weight

$$u_{t+1} = \frac{\pi_{t+1}(\mathbf{x}_{t+1})}{\pi_t(\mathbf{x}_t)}. \tag{4}$$

Note that  $u_{t+1}$  in (4) does not depend on the value of  $x_{t+1}$ , and this feature is important to several issues discussed later. The reason that drawing  $x_{t+1}$  from  $\pi_{t+1}(x_{t+1} | \mathbf{x}_t)$  is more desirable than drawing it from a more or less arbitrary function  $g_{t+1}(x_{t+1} | \mathbf{x}_t)$  is clear from rewriting the incremental weight (2.1.1) as

$$u_{t+1} = \frac{\pi_{t+1}(\mathbf{x}_t) \pi_{t+1}(x_{t+1} | \mathbf{x}_t)}{\pi_t(\mathbf{x}_t) g_{t+1}(x_{t+1} | \mathbf{x}_t)}.$$

Intuitively, the second ratio is needed to correct the discrepancy between  $g_{t+1}(x_{t+1} | \mathbf{x}_t)$  and  $\pi_{t+1}(x_{t+1} | \mathbf{x}_t)$  when they are different.

Other choices of  $g_{t+1}$  are also possible. For instance, if  $\pi_t(\mathbf{x}_t)$  can be ‘‘extended’’ for  $x_{t+1}$ , then one may use

$$g_{t+1}^*(x_{t+1} | \mathbf{x}_t) = \pi_t(x_{t+1} | \mathbf{x}_t). \tag{5}$$

For Example 1, this corresponds to  $g_{t+1}^*(x_{t+1} | \mathbf{x}_t) = p(x_{t+1} | \mathbf{x}_t, \mathbf{y}_t)$ . The corresponding incremental weight is  $u_{t+1} \propto p(y_{t+1} | \mathbf{y}_t, \mathbf{x}_{t+1})$ . For Example 2, choice (5) corresponds to

$$g_{t+1}^*(x_{t+1} | \mathbf{x}_t) = q_{t+1}(x_{t+1} | x_t, \theta)$$

and  $u_{t+1} \propto f(y_{t+1} | x_{t+1})$ . This was used by Avitzour (1995), Gordon et al. (1993, 1995), and Kitagawa (1996). Note that this trial distribution generates  $x_{t+1}$  using only the state equation.

Compared to (3), distribution (5) is usually easier to use but tends to result in greater Monte Carlo variation (Berzuini et al. 1997). In the state-space model case, it is obvious that (3) is more desirable than (5), because the former

incorporates the most recent information in  $y_{t+1}$ , whereas the latter does not. Using (3) has another advantage in estimation, which we discuss in Section 2.4. In many applications, however, it may not be easy to use (3). Section 3 provides methods for coping with this difficulty.

### 2.3 Resampling in Sequential Importance Sampling

Suppose that  $S_t = \{\mathbf{x}_t^{(j)}, j = 1, \dots, m\}$  is properly weighted by  $W_t = \{w_t^{(j)}, j = 1, \dots, m\}$  with respect to  $\pi_t$ . Let us call each  $\mathbf{x}_t^{(j)}$  a “stream.” Instead of carrying the weight  $W_t$  as the system evolves, it is also legitimate, and sometimes beneficial (Liu and Chen 1995), to insert a resampling step between SIS recursions. This procedure, called SIS with resampling (SISR), is as follows:

1. Sample a new set of streams (denoted as  $S'_t$ ) from  $S_t$  according to the weights  $w_t^{(j)}$ .
2. Assign equal weights to the streams in  $S'_t$ .

It is not immediately clear why one needs resampling at certain stage  $t$ . As much detailed theoretical discussion has been given by Liu and Chen (1995), we mention only a few heuristics on the issue. First, if the weights  $w_t^{(j)}$  are constant (or near constant) for all  $t$  (such a case occurs when one can draw from  $\pi_t$  directly), then resampling only reduces the number of distinctive streams and introduces extra Monte Carlo variation. This suggests that one should not perform resampling when the coefficient of variation,  $cv_t^2$ , for the  $w_t^{(j)}$  is small. As argued by Kong et al (1994), the “effective sample size” is inversely proportional to  $1 + cv_t^2$ . Second, Kong et al. (1994) showed that as the system evolves,  $cv_t^2$  increases stochastically. When the weights get very skewed at time  $t$ , carrying many streams with very small weights is apparently a waste. Resampling can provide chances for the good (i.e., “important”) streams to amplify themselves and hence “rejuvenate” the sampler to produce a better result for *future* states as system evolves, though it does not improve inferences on *current* state  $\mathbf{x}_t$ . Examples in Section 6 illustrate these heuristics.

The resampling schedule (i.e., when to resample) can be either deterministic or dynamic, and the sampling scheme can be either simple random sampling (with weights), residual sampling, or local Monte Carlo resampling (Sec. 4). The methods of Berzuini et al. (1997), Gordon et al. (1993), Hürzeler and Künsch (1995), Kitagawa (1996), and Pitt and Shephard (1997) can all be seen as SIS with special choices of  $g_{t+1}$  and with resampling at every stage.

### 2.4 Inference With Monte Carlo Samples

In dynamic systems, it is often of interest to obtain *on-line* inference on the state variables; that is, estimating  $E_{\pi_t} h(\mathbf{x}_t)$  at time  $t$ . This is straightforward by using (1) when available is a sample  $\{\mathbf{x}_t^{(j)}\}$  properly weighted by  $w_t^{(j)}$ . However, several issues concerning statistical efficiency of the estimates are worth mentioning. Casella (1997) provided a general treatment on this issue.

- Estimation should be done *before* a resampling step, because resampling introduces extra random variation in the *current* sample.
- Rao–Blackwellization can improve the accuracy of the estimation. For example, when weight (2.1.1) does not depend on  $x_{t+1}$ , such as in the case of using the optimal  $g_{t+1}$  in (3), the current state  $x_{t+1}$  should be estimated *before* it is drawn from  $g_{t+1}$ , using

$$\hat{E}_{\pi_{t+1}} h(x_{t+1}) = \frac{\sum_{j=1}^m w_{t+1}^{(j)} E_{\pi_{t+1}}(h(x_{t+1})|\mathbf{x}_t^{(j)})}{\sum_{j=1}^m w_{t+1}^{(j)}}, \quad (6)$$

provided that  $E_{\pi_{t+1}}(h(x_{t+1})|\mathbf{x}_t^{(j)})$  can be calculated easily. In mixture normal state-space models (Example 2 and Sec. 6.3) and other examples, this is indeed achievable.

- Delayed estimation (i.e., estimation of  $E_{\pi_t} h(x_{t-k})$  at time  $t$ ) usually is more accurate than concurrent estimation (estimation  $E_{\pi_{t-k}} h(x_{t-k})$  at time  $t - k$ ), because the estimation is based on more information. However, precautions must be taken with frequent resampling, because resampling reduces distinct *past* samples.

### 2.5 Some Related Methods

The state-space model as described in Example 2 has a special Markovian feature that the more general dynamic models do not possess. With given  $x_0 = (\phi, \theta)$ , Example 2 satisfies the condition

$$p(x_{t+1}|\mathbf{x}_t, \mathbf{y}_t, y_{t+1}) = p(x_{t+1}|x_t, \mathbf{y}_{t+1}) \propto f_{t+1}(y_{t+1}|x_{t+1})p(x_t|\mathbf{y}_t).$$

That is, with given  $x_t$ , previous  $\mathbf{x}_{t-1}$  and  $\mathbf{y}_t$  can be “forgotten.” As in a Kalman filter, the posterior distribution  $p(x_t|\mathbf{y}_t)$  can be obtained recursively, at least in principle. The main difficulty is that analytical formulas for this recursive updating only exist for certain exponential family models (West and Harrison 1989) or finite discrete state-space model (Rabiner 1989).

Because of the popularity and simplicity of the state-space model, several sequential Monte Carlo methods have been proposed to deal with nonlinear/non-Gaussian cases. In particular, Hendry and Richard (1991) noted the potential use of the SIS in such models. West (1992) suggested using a mixture distribution to approximate  $p(x_t|\mathbf{y}_t)$  at each time  $t$ , and then proceeding with an adaptive importance sampling strategy to produce a mixture approximation of  $p(x_{t+1}|\mathbf{y}_t)$  at time  $t + 1$ . Difficulties with this approach are that finding good mixture approximations for every  $t$  can be time-consuming, and that it can be difficult to implement when the dimensionality of  $x_t$  is high.

Gordon et al. (1993) and Kitagawa (1996) have proposed using importance resampling to obtain a discrete approximation of  $p(x_{t+1}|\mathbf{y}_{t+1})$ , with a given set of samples drawn from  $p(x_t|\mathbf{y}_t)$ . They called such a procedure the *bootstrap filter* or *particle filter*. The method has been successfully applied to multiple target tracking (Avitzour 1995; Gordon

et al. 1995) and time series analysis (Kitagawa 1996). Their method is essentially an SIS with  $g_{t+1}$  chosen as (5) and resampling at every  $t$ . Estimations were performed *after* resampling, which is less efficient. Hürzeler and Künsch (1995) and Pitt and Shephard (1997) have proposed improved algorithms for the state-space model. We discuss their approaches in detail in Section 3.

### 3. LOCAL MONTE CARLO METHODS FOR SEQUENTIAL IMPORTANCE SAMPLING

As we have discussed in Section 2.3, a favorable choice of the recursive sampling distribution is  $g_{t+1}(x_{t+1}|\mathbf{x}_t) = \pi_{t+1}(x_{t+1}|\mathbf{x}_t)$ . However, drawing  $x_{t+1}$  from  $\pi_{t+1}(x_{t+1}|\mathbf{x}_t)$  may not be directly achievable, and the incremental weight  $w_{t+1}$  may not be easy to compute. Under such a premise, methods have been developed to overcome this difficulty for the state-space model. (see, e.g., Berzuini et al. 1997, Hürzeler and Künsch 1995, and Pitt and Shephard 1997). We propose here to extend their methods to our general SIS setting for simultaneously estimating the new weight  $w_{t+1}$  and drawing  $x_{t+1}$ . We refer to these methods as “local Monte Carlo methods” for SIS.

#### 3.1 The Basic Idea

As usual, we let  $S_t = \{\mathbf{x}_t^{(j)}, j = 1, \dots, m\}$  and  $W_t = \{w_t^{(j)}, j = 1, \dots, m\}$ . The central idea of this section is to regard  $\pi_t$  as being represented by the Monte Carlo sample  $S_t$  with weights  $W_t$ . Thus at stage  $t+1$ ,  $\mathbf{x}_t$  can be treated as a random variable with this discrete a priori distribution. To simplify notation, we introduce a random variable  $J$ , which takes values in the set  $\{1, \dots, m\}$ , to indicate the streams in  $S_t$ . Pitt and Shephard (1997) also used such a formulation, and called  $J$  the auxiliary variable.

Let the joint distribution of  $J$  and  $x_{t+1}$  be

$$p(J, x_{t+1}) \propto \frac{\pi_{t+1}(\mathbf{x}_t^{(J)}, x_{t+1})}{\pi_t(\mathbf{x}_t^{(J)})} w_t^{(J)}. \tag{7}$$

Then the marginal distribution of  $x_{t+1}$  from (7) is

$$\hat{\pi}_{t+1}(x_{t+1}) \propto \sum_{j=1}^m \frac{\pi_{t+1}(x_{t+1}, \mathbf{x}_t^{(j)})}{\pi_t(\mathbf{x}_t^{(j)})} w_t^{(j)}, \tag{8}$$

which would be a good approximation to the true marginal distribution  $\pi_{t+1}(x_{t+1})$  provided that the Monte Carlo sample size  $m$  is large and the distribution of the  $w_t$  is not too skewed. The marginal distribution of  $J$  is

$$\begin{aligned} P(J = j) &\propto w_t^{(j)} \int \frac{\pi_{t+1}(\mathbf{x}_t^{(j)}, x_{t+1})}{\pi_t(\mathbf{x}_t^{(j)})} dx_{t+1} \\ &= w_t^{(j)} \frac{\pi_{t+1}(\mathbf{x}_t^{(j)})}{\pi_t(\mathbf{x}_t^{(j)})} \\ &= w_t^{(j)} u_{t+1}^{(j)} = w_{t+1}^{(j)}, \end{aligned}$$

which is exactly the new weight at time  $t+1$  for  $\mathbf{x}_t^{(j)}$  according to (2.1.1) and (4).

Hence, if we have a method to draw a sample,  $(j_1, x_{t+1}^{(j_1)}), \dots, (j_\ell, x_{t+1}^{(j_\ell)})$ , of  $(J, x_{t+1})$  from (7), then the SIS step can be achieved as follows:

- B. Estimate  $w_{t+1}^{(j)}$  by  $\hat{f}_j =$  frequency of  $\{J = j\}$  in the sample.
- A. Form  $\mathbf{x}_{t+1}^{(j)} = (\mathbf{x}_t^{(j)}, x_{t+1}^*)$  if  $\hat{f}_j \neq 0$ , where  $x_{t+1}^*$  is any value of  $x_{t+1}$  that is paired with  $J = j$  in the sample.

Several methods for generating samples from (7) are described in the following subsections, and a few remarks are as follows.

*Remark 1.* As long as the estimates of the weights are unbiased, the new sample is properly weighted by  $\hat{f}_j$  with respect to  $\pi_{t+1}$ . An accurate estimation of the weights is *not* necessary. Those  $\mathbf{x}_t^{(j)}$  with  $\hat{f}_j = 0$  can be replaced by a random draw from those with  $\hat{f}_j \neq 0$ . If the estimation of the incremental weight  $w_{t+1}^{(j)}$  is of interest, then one can set  $w(\mathbf{y}) \equiv 1$  for  $\mathbf{y} \in S_t$  in the above calculations.

*Remark 2.* Since the local MC methods provide samples of  $(J, x_{t+1})$  with distribution (7), they achieve resampling effect automatically. See details in Section 4.

*Remark 3.* None of the methods described in this section are necessary when direct sampling from the optimal  $g_{t+1}$  of (3) is achievable.

#### 3.2 Rejection Methods

Suppose that we can draw  $x_{t+1}$  from a trial distribution  $g_{t+1}^*(x_{t+1}|\mathbf{x}_t)$  that is not equal to (3). There are two rejection methods to sample  $(J, x_{t+1})$  from (7): one based on the joint distribution of  $(J, x_{t+1})$  and the other based on the marginal of  $x_{t+1}$ . Let the “covering constant” be

$$c_{t+1} = \sup_{j, x_{t+1}} \frac{\pi_{t+1}(\mathbf{x}_t^{(j)}, x_{t+1})}{\pi_t(\mathbf{x}_t^{(j)}) g_{t+1}^*(x_{t+1}|\mathbf{x}_t^{(j)})}.$$

##### Rejection Method 1.

- Draw  $J = j$  with probability proportional to  $w_t^{(j)}$
- Given  $J = j$ , draw  $x_{t+1}$  from  $g_{t+1}^*(x_{t+1}|\mathbf{x}_t^{(j)})$ .
- Accept  $(j, x_{t+1})$  with probability

$$p = \frac{\pi_{t+1}(\mathbf{x}_t^{(j)}, x_{t+1})}{c_{t+1} \pi_t(\mathbf{x}_t^{(j)}) g_{t+1}^*(x_{t+1}|\mathbf{x}_t^{(j)})}.$$

*Rejection Method 2.* The first two steps are identical to method 1. In step 3, accept  $x_{t+1}$  with probability

$$p = \frac{\sum_{j=1}^m w_t^{(j)} \pi_{t+1}(\mathbf{x}_t^{(j)}, x_{t+1}) / \pi_t(\mathbf{x}_t^{(j)})}{c_{t+1} \sum_{j=1}^m w_t^{(j)} g_{t+1}^*(x_{t+1}|\mathbf{x}_t^{(j)})}.$$

Then the sample  $x_{t+1}$  accepted from using either of the methods follows (8). In method 2, we need to redraw  $J$

with probability

$$P(J = j|x_{t+1}) \propto \frac{\pi_{t+1}(\mathbf{x}_t^{(j)}, x_{t+1})}{\pi_t(\mathbf{x}_t^{(j)})} w_t^{(j)}. \tag{9}$$

Methods 1 and 2 are identical in the state-space model case and are an essential part of the work of Hürzeler and Künsch (1995). Generally, method 2 is a Rao–Blackwellization of method 1 (Casella and Robert 1996) and can be more efficient.

### 3.3 Importance Resampling

Importance resampling method can also be used to generate approximate samples from (7):

- Draw  $J = j$  with probability proportional to  $w_t^{(j)}$ .
- Given  $J = j$ , draw  $x_{t+1}$  from some  $g_{t+1}^*(x_{t+1}|\mathbf{x}_t^{(j)})$ .
- Assign to the sample  $(j, x_{t+1})$  the weight

$$w(j, x_{t+1}) = \frac{\pi_{t+1}(\mathbf{x}_t^{(j)}, x_{t+1})}{\pi_t(\mathbf{x}_t^{(j)}) g_{t+1}^*(x_{t+1}|\mathbf{x}_t^{(j)})}.$$

The obtained sample  $(j, x_{t+1})$  is properly weighted by the  $w(j, x_{t+1})$  with respect to (7). At this point, one has three choices: (a) do resampling to achieve (7) approximately, as implemented by Gordon et al. (1993) and Kitagawa (1996); (b) estimate  $P(J = j) \propto w_{t+1}^{(j)}$  directly using the weighted sample of  $(j, x_{t+1})$ ; or (c) proceed with the newly sampled  $(\mathbf{x}_t^{(j)}, x_{t+1})$  with new weights  $w(j, x_{t+1})$ , as proposed by Pitt and Shephard (1997).

In addition, Pitt and Shephard (1997) suggested using an adjustment multiplier to improve efficiency. Briefly, one can instead draw  $J = j$  with probability proportional to  $w_t^{(j)} a_{t+1}^{(j)}$  and then adjust the weight accordingly. It is conceivable that by carefully choosing  $a_{t+1}^{(j)}$  (a function of  $\mathbf{x}_t^{(j)}$ ) and  $g_{t+1}^*$ , one can achieve good efficiency. This idea can also be applied to rejection sampling and the following MCMC approach.

### 3.4 Hastings Independence Chain Approach

Alternatively, one can also use Hastings *independence chain* approach (Hastings 1970), as suggested by Berzuini et al. (1997) for the state-space model. Here we prescribe a generalization of their method for dynamic systems. Detailed description of the general independence chain method is given in the Appendix.

Suppose that we can draw  $X_{t+1}$  from a trial distribution  $g_{t+1}^*(x_{t+1}|\mathbf{x}_t)$ . Then starting with an arbitrary  $J^0 = j_0$ , we iterate the following steps:

- Draw  $J = j'$  with probability proportional to  $w_t^{(j')}$ .
- Draw  $X_{t+1} = x'_{t+1}$  from  $g_{t+1}^*(x_{t+1}|\mathbf{x}_t^{(j')})$  or from a reversible MCMC step with  $g_{t+1}^*(\cdot|\mathbf{x}_t^{(j')})$  as its invariant distribution. (See the proof of its correctness in the Appendix.)
- Set  $(J^{k+1}, x_{t+1}^{k+1})$  equal to  $(j', x'_{t+1})$  with probability  $p_a$ , and equal to  $(J^k, x_{t+1}^k)$  with probability  $1 - p_a$ ,

where

$$p_a = \min \left\{ 1, \frac{p(j', x'_{t+1}) w_t^{(j')} g_{t+1}^*(x_{t+1}^k | \mathbf{x}_t^{(j')})}{p(J^k, x_{t+1}^k) w_t^{(j')} g_{t+1}^*(x'_{t+1} | \mathbf{x}_t^{(j')})} \right\},$$

where  $p(J, x_{t+1})$  is defined in (7).

The resulting equilibrium distribution of  $(J, x_{t+1})$  is exactly (7). Theoretical properties of the Hastings chain have been studied by Liu (1996), who showed that this method is comparable to the rejection method in terms of statistical efficiency. The second rejection method described in Section 3.3 can also take this MCMC twist. Its detail is omitted here.

The advantages of rejection methods are that no iterations are needed and the resulting sample is “exact,” whereas the disadvantage is that  $c_{t+1}$  must be computed and the resulting scheme can be very inefficient. Liu (1996) provided more detailed comparisons of the three methods. An interesting variation is to combine rejection and importance samplings as suggested by Liu, Chen, and Wong (1998). When the difference between  $\pi_{t+1}(x_{t+1}|\mathbf{x}_t)$  and  $g_{t+1}^*(x_{t+1}|\mathbf{x}_t)$  is large, none of the methods is ideal. To alleviate this problem for the state-space model, Hürzeler and Künsch (1995) proposed some smoothing techniques, and Pitt and Shephard (1997) suggested using mode approximation to find a good adjustment multiplier.

### 3.5 Illustration with the State-Space Model

Suppose that one is interested in estimating the state-space signal  $x_t$  on line (Example 2) with the parameters  $\theta$  and  $\phi$  given. For simplicity, we suppress  $\phi$  and  $\theta$  in all relevant formulas. Thus the dynamic system for the state-space model is  $\pi_t(\mathbf{x}_t) \propto \prod_{s=1}^t f_s(y_s|x_s) q_s(x_s|x_{s-1})$  and

$$\begin{aligned} \pi_{t+1}(x_{t+1}|\mathbf{x}_t) &\propto \frac{\pi_{t+1}(x_{t+1}, \mathbf{x}_t)}{\pi_t(\mathbf{x}_t)} \\ &= f_{t+1}(y_{t+1}|x_{t+1}) q_{t+1}(x_{t+1}|x_t). \end{aligned}$$

Although sampling from  $\pi_{t+1}(x_{t+1}|\mathbf{x}_t)$  can be difficult, one usually can easily draw from the state equation  $g_{t+1}^*(x_{t+1}|\mathbf{x}_t) = q_{t+1}(x_{t+1}|x_t)$ . Rejection methods 1 and 2 are identical in this situation. Let  $c_{t+1} = \sup_{x_{t+1}} f_{t+1}(y_{t+1}|x_{t+1})$ . The procedure is as follows:

- Draw  $J = j$  with probability proportional to  $w_t^{(j)}$ , then draw  $x_{t+1}$  from  $q_{t+1}(x_{t+1}|x_t^{(j)})$ .
- Accept  $(J, x_{t+1})$  with probability  $p = f_{t+1}(y_{t+1}|x_{t+1})/c_{t+1}$ .

All of the samples of  $(J, x_{t+1})$  drawn from this scheme follows the distribution

$$p(J = j, x_{t+1}) \propto w_t^{(j)} f_{t+1}(y_{t+1}|x_{t+1}) q_{t+1}(x_{t+1}|x_t^{(j)}).$$

Similarly, with  $g_{t+1}^* = q_{t+1}(x_{t+1}|x_t)$ , the importance resampling procedure becomes:

- Draw  $J = j$  with probability proportional to  $w_t^{(j)}$ .
- Draw  $x_{t+1}$  from  $q_{t+1}(x_{t+1}|x_t^{(j)})$ .
- Assign weight to the sample  $(j, x_{t+1})$  as  $f_{t+1}(y_{t+1}|x_{t+1})$ .

The procedure of Gordon et al. (1995) and Kitagawa (1996) is exactly this, with an additional step of resampling from the obtained sample using the assigned weight. In addition to the use of  $g_{t+1}^* = q_{t+1}(x_{t+1}|x_t)$ , Pitt and Shephard (1997) incorporated an adjustment multiplier  $a_{t+1}^{(j)} = f_{t+1}(y_{t+1}|\mu_{t+1}^{(j)})$ , where  $\mu_{t+1}^{(j)}$  can be the mode, the mean, or another likely value of  $x_{t+1}^{(j)}$ . Thus the resulting weight for the obtained sample is  $w(j, x_{t+1}) = f_{t+1}(y_{t+1}|x_{t+1}^{(j)})/f_{t+1}(y_{t+1}|\mu_{t+1}^{(j)})$ .

In the independence chain approach with the same  $g_{t+1}^*$  as before, the rejection probability can be computed as

$$p_a = \min \left\{ 1, \frac{f_{t+1}(y_{t+1}|x'_{t+1})w_t^{(J_k)}}{f_{t+1}(y_{t+1}|x_{t+1}^k)w_t^{(j')}} \right\},$$

and the rest can be carried out routinely.

#### 4. RESAMPLING AND A GENERIC ALGORITHM

In much of the early work on Monte Carlo methods for the state-space model, resampling has played a major role in evolving the system from time  $t$  to  $t + 1$  (see, e.g., Gordon et al. 1993 and Kitagawa 1996). In this section we describe three resampling methods, discuss possible resampling schedules, and then prescribe a generic Monte Carlo algorithm for dynamic systems.

##### 4.1 Resampling Methods

**4.1.1 Simple Random Sampling.** In this procedure one samples from  $S_t$  with replacement with probability proportional to the weights in  $W_t$ . Liu and Chen (1995) used this approach to modify the skewed importance weights resulting from the SIS.

In general, a resampling step is inserted between two SIS steps. But when the weight (2.1.1) does not depend on  $x_{t+1}$  (i.e., when sampling distribution (3) is used), the resampling step should be inserted *inside* a SIS step. Specifically, an optimal SISR consists of SIS step B  $\rightarrow$  resampling step  $\rightarrow$  SIS step A. This generates more distinct samples of  $x_{t+1}$  than performing resampling *after* SIS steps A and B.

**4.1.2 Residual Sampling.** The following scheme can replace simple random sampling:

- Retain  $k_j = [mw_t^{(*j)}]$  copies of  $x_t^{(j)}$  for each  $j$ , where  $w_t^{(*j)}$  is the renormalized weight of  $w_t^{(j)}$ . Let  $m_r = m - k_1 - \dots - k_m$ .
- Obtain  $m_r$  iid draws from  $S_t$  with probabilities proportional to  $mw_t^{(*j)} - k_j, j = 1, \dots, m$ .
- Reset the weights to 1.

It is easily shown that the residual sampling dominates the simple random sampling (SRS) in having smaller Monte Carlo variance and favorable computation time, and it does not seem to have disadvantages in other aspects. A comparison of the two procedures is given in Section 6.2.

**4.1.3 Local Monte Carlo Resampling.** Because the local Monte Carlo methods described in Section 3 provide samples of  $(J, x_{t+1})$  with distribution (7), it appears that these methods achieve the resampling effect automatically. More precisely, let  $(J^k, x_{t+1}^k), k=1, \dots, m^*$  be a set of draws obtained from using either a rejection method or the Hastings method (after burning) in Section 3. Then the set of streams  $S'_{t+1} = \{(x_t^{(J^k)}, x_{t+1}^k), k = 1, \dots, m^*\}$  is a desirable resample. The weights associated with the new streams are equal to 1. Note that  $m^*$  is not necessarily equal to  $m$ . This procedure avoids weight estimation.

##### 4.2 Resampling Schedule

As shown by our earlier arguments and later examples, resampling at every stage is neither necessary nor efficient. It is thus desirable to prescribe a schedule for the resampling step to take place. Two such schedules are available: deterministic versus dynamic. In a deterministic schedule one conducts resampling at time  $t_0, 2t_0, \dots$ , where  $t_0$  depends on difficulty of a particular problem and may require some experimentation. In a dynamic schedule, one gives a sequence of thresholds  $c_1, c_2, \dots$ , and monitors the coefficient of variation of the weights  $cv_t^2$ . When  $cv_t^2 > c_t$  occurs, one invokes resampling. A typical sequence of  $c_t$  can be  $c_t = a + bt^\alpha$ .

##### 4.3 A Generic Monte Carlo Algorithm

We recommend the following algorithm for Monte Carlo computation in dynamic systems:

1. Check the weight distribution: perform one of the following two choices at time  $t$ :
  - Dynamic.* If the weight (or estimated weight) distribution is not too skewed, (i.e.,  $cv_t^2(w) < c_t$ ), go to step 2.
  - Deterministic.* If  $t \neq kt_0$  for some integer  $k$ , go to step 2. Otherwise, go to step 3.
2. Set  $t = t + 1$ . Invoke an SIS step (Sec. 2.1). Sometimes one may need a local Monte Carlo procedure (Sec. 3) to accomplish recursive sampling and weighting. Go to step 1.
3. Set  $t = t + 1$ . Invoke an SISR step (Sec. 2.3). Use residual sampling whenever possible. To avoid weight calculation, use local Monte Carlo resampling methods. Go to step 1.

A noticeable difference between our use of local Monte Carlo procedures and that of others (Berzuini et al. 1997; Hürzeler and Künsch 1995; Pitt and Shephard 1997) is that we decouple the local Monte Carlo outputs into two parts: estimating the new weights for the  $x_t$  and obtaining the draws of  $x_{t+1}$ . Such a decoupling has two advantages: Obtaining an explicit weighting can tell us how different  $\pi_{t+1}$  and  $\pi_t$  are and how well the SIS works, and it provides a means to improve efficiency via the use of residual sampling and delayed resampling. Because the local Monte Carlo procedures are merely used to achieve a good  $g_{t+1}$ , any other means that leads to this end should be considered whenever possible.



### 5. RAO-BLACKWELLIZATION

In all SISR procedures, the discrete representation of  $\pi_{t+s}(\mathbf{x}_t)$ , by a sample of  $\mathbf{x}_t^{(j)}$  with the weight  $w_{t+s}^{(j)}$ , degenerates very rapidly as the number of resamplings increases between  $t$  and  $t + s$ . Consequently, estimating a quantity of interest, such as  $E_{\pi_{t+s}}(h(\mathbf{x}_t))$ , can be very inaccurate.

Take Example 1, for instance. As SISR proceeds with  $t$ , the number of distinctive  $x_0$  (i.e.,  $\theta$ ) values decreases monotonically. This rapidly leads to a degenerate posterior distribution of  $\theta$ . To alleviate this problem, we can apply a variant of Rao-Blackwellization (Casella and Robert 1996; Kong et al. 1994; Liu et al. 1994).

Suppose that, with the Bayesian missing-data setting of Example 1, we have at time  $t$  the observed information  $\mathbf{y}_t$  and multiple draws  $(\theta^{(j)}, \mathbf{x}_t^{(j)})$ ,  $j = 1, \dots, m$ , properly weighted by  $w_t^{(j)}$ . If the number of distinctive values of the  $\theta^{(j)}$  is too small, we can fragment each stream  $(\theta^{(j)}, \mathbf{x}_t^{(j)})$  by drawing  $\theta^{(j1)}, \dots, \theta^{(jk)}$  from the complete-data posterior distribution  $p(\theta|\mathbf{x}_t^{(j)}, \mathbf{y}_t)$ . When the posterior distribution of  $\theta$  is continuous, we will have  $km$  distinctive  $\theta$  values after Rao-Blackwellization. The weight associated with each  $(\theta^{(j\ell)}, \mathbf{x}_t^{(j)})$  is  $w_t^{(j)}$ . (This is the consequence of the fact that after a few steps of MCMC transition with respect to which the target distribution  $\pi_t$  is invariant, the sample is still properly weighted with respect to  $\pi_t$  (see MacEachern et al. 1998). To retain constant total number of streams  $m$ , one can either set  $k = 1$  or resample  $m$  streams from the  $km$  streams according to their corresponding weight. Rao-Blackwellization as described earlier results in a sampling distribution that is closer to the target distribution, because it uses more information.

If at time  $t$  we want  $p(\theta|\mathbf{y}_t)$ , we can use the Rao-Blackwellized estimate,

$$\hat{p}(\theta|\mathbf{y}_t) = \frac{\sum_{j=1}^m w_t^{(j)} p(\theta|\mathbf{x}_t^{(j)}, \mathbf{y}_t)}{\sum_{j=1}^m w_t^{(j)}}$$

instead of the weighted histogram of the sampled  $\theta^{(j)}$ .

To compute the likelihood function  $L(\theta|\mathbf{y}_t)$ , we can first draw  $\theta$  uniformly (if the parameter space is bounded; otherwise, one need to combine the flat prior with some data) and apply the SIS to draw multiple copies  $(\theta^{(j)}, \mathbf{x}_t^{(j)})$  with weight  $w^{(j)}$ . Then the Rao-Blackwellized estimate of the likelihood function is

$$\hat{L}(\theta|\mathbf{y}_t) \approx \frac{\sum_{j=1}^m w^{(j)} p(\theta|\mathbf{x}_t^{(j)}, \mathbf{y}_t)}{\sum_{j=1}^m w^{(j)}}$$

where  $p(\theta|\mathbf{x}_t^{(j)}, \mathbf{y}_t)$  is the complete-data posterior distribution of  $\theta$  with flat prior.

Berzuini et al. (1997) noticed that when some form of conditional independence is present (e.g., in a missing-data problem when a parameter  $\theta$  is involved conditional on which the missing data are independent of each other), one may sometimes “disengage” those early observation  $y$ 's and early imputations. For instance, in Example 1  $p(x_{t+1}, y_{t+1}|\theta, \mathbf{x}_t, \mathbf{y}_t) = p(x_t, y_t|\theta)$ . Hence all of the  $\mathbf{x}_t$  and

$\mathbf{y}_t$  can be “disengaged.” Similarly in Example 2, the  $\mathbf{x}_{t-1}$  and  $\mathbf{y}_{t-1}$  can be “disengaged.” The advantage of doing this is obvious; it saves memory and may speed up computation.

However, when disengagement is implemented, Rao-Blackwellization is no longer directly applicable. A remedy is to represent the information contained in the disengaged components as a mixture distribution of the  $\theta$  (via Rao-Blackwellization) and then proceed in combination with resampling. A numerical experiment on this method is under investigation.

### 6. EXAMPLES

#### 6.1 Econometric Disequilibrium Model

Initially proposed by Fair and Jaffee (1972), this class of models has attracted much attention from econometrics researchers in past few decades. It provides a theoretical foundation for the philosophical arguments (generally called *Keynesian theory*, named after the economist J. M. Keynes, who attacked the dominant paradigm of economics in 1930s) against the postwar mainstream approach to economics, the equilibrium methods (for reviews and discussions see Quandt 1982, 1988). Here we only look at a special dynamic disequilibrium model of Hendry and Richards (1990). Almost all components other than the relevant lagged variables, such as prices and other environmental exogenous variables, are excluded for the sake of simplicity. We illustrate an improvement in estimation by using Rao-Blackwellization.

Let  $q'_t = (q_{1t}, q_{2t})$  be bivariate normal random variables with

$$E(q_{i(t+1)}|q_t) = \alpha_i q_{it}; \quad \text{var}(q_{t+1}|q_t) = \mathbf{I},$$

for  $t = 0, \dots, T - 1$ , where  $\mathbf{I}$  is the identity matrix. The observed data for this model are  $y_t = \min\{q_{1t}, q_{2t}\}$ , for  $t = 1, \dots, T$ . For simplicity in presentation, the initial states  $q_{10}$  and  $q_{20}$  were taken to be 0 and assumed known. Of interest is the likelihood function or posterior distribution of  $(\alpha_1, \alpha_2)$ .

Let  $\lambda_t = \max\{q_{1t}, q_{2t}\}$ , let  $\delta_t$  be  $i$  if  $y_t = q_{it}$ , and let  $\theta = (\alpha_1, \alpha_2)$ . If we write  $x_t = (\lambda_t, \delta_t)$ , then the distribution involved in sequential sampling is  $g_{t+1}(x_{t+1}|\mathbf{x}_t) = p(x_{t+1}|\theta, \mathbf{x}_t, \mathbf{y}_t, y_{t+1})$ , and that involved in weight updating is  $w_{t+1} \propto p(y_{t+1}|\theta, \mathbf{x}_t, \mathbf{y}_t)$ . Detailed computations are given in the Appendix.

For each fixed  $\theta$ , Hendry and Richard (1991) used SIS to evaluate the likelihood  $L(\theta|\mathbf{y}_T)$  based on equation (8) of Kong et al. (1994). Putting a flat prior on  $\theta$ , we can treat the likelihood computation as a Bayesian computation and use the SIS method to simulate weighted samples of  $(\theta, \mathbf{x})$  jointly. Rao-Blackwellization can be applied to improve the efficiency.

We simulated 50 data observations  $y_1, \dots, y_{50}$  from the model with  $\alpha_1 = \alpha_2 = .6$ , and initial value  $q_{11} = q_{21} = 0$ . Assuming that we know that  $\alpha_1 = \alpha_2 = \alpha$ , we used the SIS method with  $m = 10,000$  to obtain the likelihood function for  $\alpha$ , as shown in Figure 1. It took 8.16 seconds on a Silicon Graphics workstation with R10000 microprocessor,

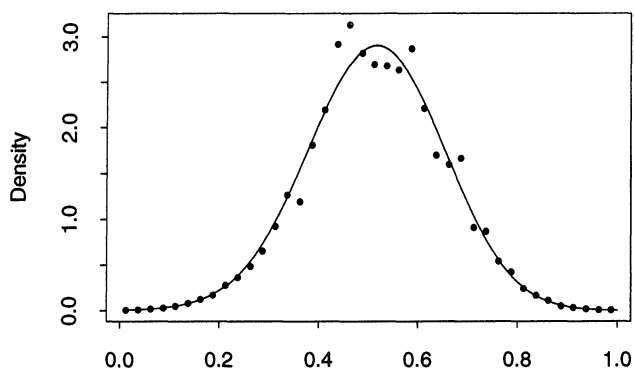


Figure 1. The Posterior Distribution of  $\alpha_1$  After the 50 Observations With Uniform Prior. —, Result from Rao-Blackwellization; ···, result from the standard SIS.

and the  $cv^2$  at the end of the SIS is 5.13. The smooth curve is the result from the Rao-Blackwellization.

### 6.2 Blind Deconvolution

The moving-average system,  $y_t = \sum_{i=1}^q \phi_i x_{t-i} + \varepsilon_t$ , is often seen in digital communication. The input signal  $x_t$  takes value from a known set of discrete states and  $\varepsilon_t \sim N(0, \sigma^2)$ . By observing the blurred signals  $y_1, \dots, y_n$ , it is of interest to reconstruct the  $x_t$  and to estimate the system coefficients  $\phi_i$ . (More references can be found in Liu and Chen 1995.)

We took a simulated example from Chen and Li (1995) in which the system equation is

$$y_t = x_t + .8x_{t-1} - .4x_{t-2} + \varepsilon_t.$$

The input signals  $x_t$  were iid uniform on  $\{0, 1, 3\}$ . The signal-to-noise ratio was controlled at 15 dB, which gives a standard deviation of .3 for the noise. The  $\phi_i$  in this case can be easily integrated out with a normal prior, and all of the sampling and weighting calculations have been given by Liu and Chen (1995). A direct SIS without using a local Monte Carlo procedure applies.

A total of  $n = 200$  signal sequences were simulated, each with 200 sequential observations from the system. Our interest was in testing the simple SIS with different resampling schedules and with the two resampling methods; that is, simple random sampling (s) versus residual sampling (r). One thousand streams ( $m = 1,000$ ) were carried in the SIS procedure. We estimated the input signal  $x_t$  by MAP

using the weight at time  $t + 3$ . Table 1 shows the number of misclassification of signals in 200 simulations, each with 200 sequential signals. Here resampling frequency  $t_0$  means procedures (s) or (r) were applied at  $t_0, 2t_0, 3t_0, \dots$  (so  $t_0 = 200$  implies no resampling). For dynamic scheduling, the resampling procedure is applied whenever the effective sample size (defined as  $m/(1 + cv^2(w))$ ) is less than 3. In our example, this dynamic schedule leads to 5–15 resamplings in processing 200 signals.

Table 1 shows that resampling either too often ( $t_0$  small) or too rare ( $t_0$  large) tends to produce a large number of misclassifications. When resampling too rare, (e.g.,  $t_0 = 200$ ), there are numerous instances when the Monte Carlo method is never on the right track, resulting in disastrous estimations. In the reasonable range of  $t_0$  (between 4 and 20), the residual sampling method seems to be slightly better than simple random sampling.

### 6.3 Target Tracking in Clutter

Tracking multiple targets in clutter is of interest to engineers and computer scientists. The problem has received much attention recently and many solutions have been proposed, among which the method of Avitzour (1995) and Gordon et al. (1995) is most closely related to the method described in this article. As has been mentioned earlier, their algorithm uses the sampling distribution (5). Here we use the example of Avitzour (1995) to show that using sampling distribution (3) can produce better tracking results.

The tracking problem of Avitzour (1995) can be formulated as a state-space model with state variable  $x_t = (x_t^{(1)}, x_t^{(2)})$ , where  $x_t^{(1)}$  is the location of the target on a straight line and  $x_t^{(2)}$  is the target velocity. The  $z_t$  are location observations. They evolve in the following way:

$$x_{t+1}^{(1)} = x_t^{(1)} + x_t^{(2)} + \frac{1}{2} w(t + 1),$$

$$x_{t+1}^{(2)} = x_t^{(2)} + w(t + 1),$$

and

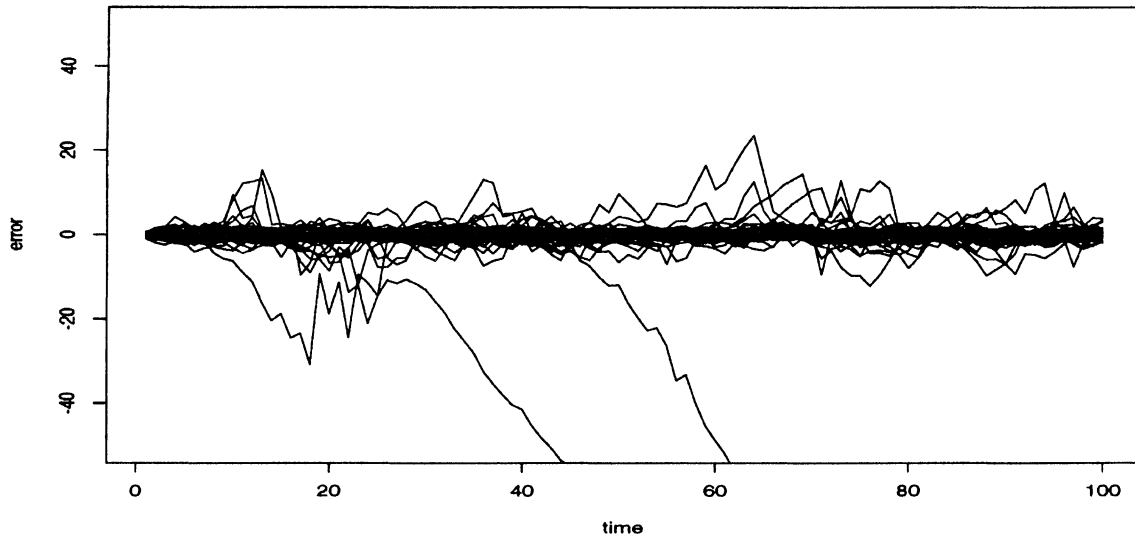
$$z_{t+1} = x_{t+1}^{(1)} + v(t + 1),$$

where  $w(t) \sim N(0, q^2)$  and  $v(t) \sim N(0, r^2)$  are independent. We further assume that we have only probability  $p_d$  to make the location observation  $z_t$ . The rate of false

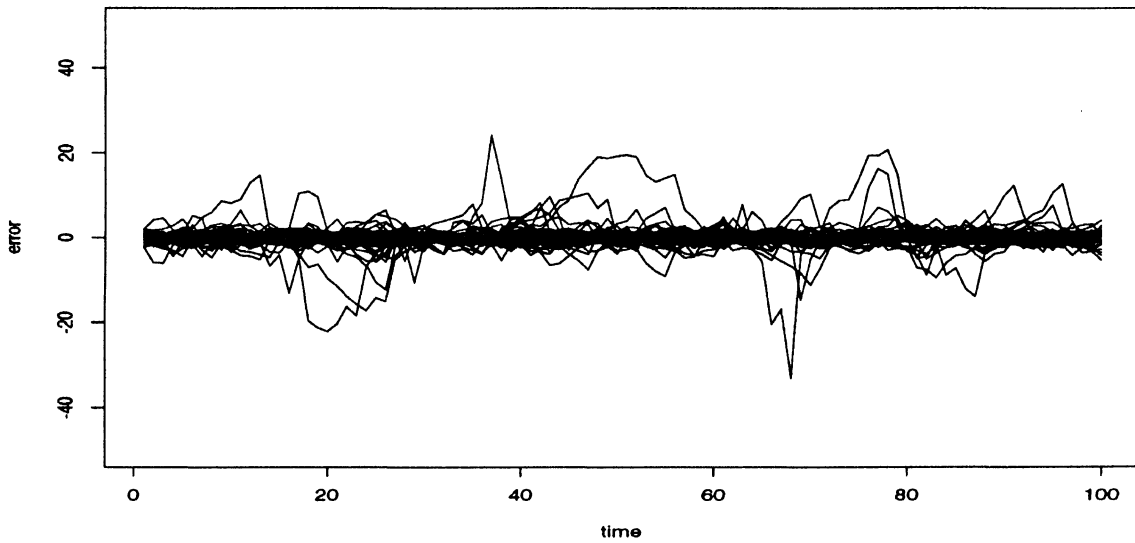
Table 1. Demonstration of the Numbers of Misclassified Signals (First Column) in a Total of 200 Simulations, Each With 200 Sequential Signals

Error	Deterministic resampling frequency $n/t_0$												Dynamic schedule	
	1		5		20		50		100		200		s	r
	s	r	s	r	s	r	s	r	s	r	s	r		
0–2	11	5	7	13	13	13	7	10	1	0	0	0	11	12
3–5	49	49	46	53	61	65	53	49	28	28	7	7	69	58
6–8	41	43	50	52	72	70	57	58	59	58	12	12	66	67
9–11	23	20	27	30	38	38	52	48	43	44	47	47	29	41
12–15	10	9	13	7	8	6	17	20	33	32	44	44	16	8
16–25	11	10	14	11	8	8	14	15	35	35	84	84	6	11
16–50	4	10	8	9	0	0	0	0	1	3	6	6	1	1
>50	51	54	35	25	0	0	0	0	0	0	0	0	2	2

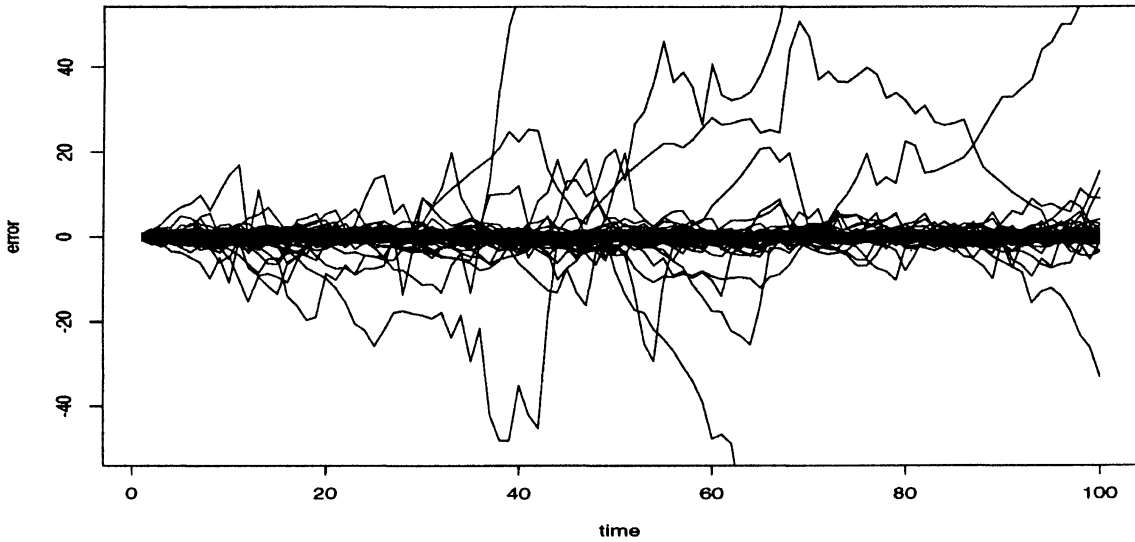
NOTE. All of the columns except the first are results from different combinations of SIS strategies; "s" and "r" represent simple random sampling and residual sampling, respectively.



(a)



(b)



(c)

Figure 2. Tracking Results From Using Three Different Sequential Monte Carlo Methods. We used  $m = 500$  and resampled at every step. The y-axis is the distance between the estimated and true positions of the target. (a) Results from using  $g_{t+1}$  prescribed by (3); (b) results from using the collapsing procedure; (c) results from using (5).

signal clutter is  $\alpha\Delta$ , with  $\Delta$  being the width of  $4r$  detection region. Therefore, the actual observation  $y_t$  is a vector of length  $m_t$  among which at most one is the true observation. The distribution of  $m_t$  is Bernoulli( $p_d$ ) + Poisson ( $\lambda\Delta$ ). The false signals are uniformly distributed in the detection region.

In this case the sampling distribution  $\pi_{t+1}(x_{t+1}|y_{t+1}, \mathbf{x}_t)$  in (3) can be easily shown to be a mixture of  $m_{t+1}$  normal distributions, with means and variances being functions of  $y_{t+1}$  and  $x_t$ . (More details are given in the Appendix.) Resampling is conducted *before* each  $x_{t+1}$  is drawn, and concurrent estimation of  $E_{\pi_{t+1}}(x_{t+1})$  is done using Rao-Blackwellization (6).

Another trick that we can play with this example is to integrate out the state variable  $x_t$  and use Monte Carlo to impute an indicator variable that tells which component of  $y_t$  is the true signal. With the true signal identified, it is trivial to estimate the true location of the target. This *collapsing procedure* produces an even better result.

Figure 2 shows the plots of tracking errors (estimated location – true location) of 50 simulated runs, with  $r^2 = 1.0$ ,  $q^2 = .1$ ,  $p_d = .9$ , and  $\lambda = .1$ . Five hundred streams ( $m = 500$ ) were used, with resampling done at every step. Figure 2(a) resulted from using the optimal sampling distribution (3); 2(b), from using the collapsing procedure. Figure 2(c) shows the result from using a less-optimal sampling distribution  $g_{t+1} = q(x_{t+1}|x_t)$ , following Avitzour (1995). Figure 2(a) has 13 runs with absolute value of tracking errors exceeding 10 at least once, 2(b) has 16, and 2(c) has 20. Similarly, Figure 2(a) has four runs exceeding the 20 limit, 2(b) has four, 2(c) has eight.

The foregoing parameter combination is slightly different from that of Avitzour (1995), with smaller clutter density but larger state equation variance. With their configuration, the results are similar, but the differences between different procedures are smaller.

### 7. SUMMARY

In this article we have proposed a general framework for on-line Monte Carlo computations for dynamic systems. It is clear that almost all of the available sequential Monte Carlo procedures can be unified under this framework. This general setting provides a common ground for understanding and improving various similar methods developed for specific models. It also provides a general guidance on how such procedures should be used in practice and how different “tricks” developed for specific problems can be combined to achieve maximum efficiency. In particular, we discussed several key issues in implementing sequential Monte Carlo methods; namely, choices of the recursive sampling distribution  $g_{t+1}$ , advantages and disadvantages of resampling and their scheduling, efficient use of Monte Carlo samples, and Rao-Blackwellization.

Besides the obvious application of sequential Monte Carlo in the state-space models, there are many other problems that can be formulated as a dynamic system and solved using techniques described in this article. For example, the SIS procedure can be built into a MCMC scheme to produce

a more efficient transition proposal chain. The Hastings rejection procedure described in the Appendix can be used in combination. This type of Monte Carlo methods (sometimes called “configuration-biased Monte Carlo”) have been tested effective for simulating biopolymers (Leach 1996). (See Irwing et al. 1994; Kong et al. 1994; Wong and Liang 1997). We hope that the results reported here can stimulate more interest and effort from other researchers on this type of problem.

### APPENDIX: THE INVARIANT DISTRIBUTIONS OF THE HASTINGS INDEPENDENCE CHAIN

This scheme was first discussed by Hastings (1970, sec. 2.5) as one way to do importance sampling. Tierney (1994) generalized the discussion under the term “independence chains,” and it was called “Metropolized independence sampling” by Liu (1996). The general scheme can be stated as follows.

Suppose that  $\pi(x)$  is known up to a normalizing constant, and we are able to draw independent samples from  $g(x)$ . A Markov chain  $\{X_1, X_2, \dots\}$  can be constructed with the transition function

$$K(x, y) = \begin{cases} g(y) \min\{1, \frac{w(y)}{w(x)}\}, & \text{if } y \neq x \\ 1 - \int_{z \neq x} g(z) \min\{1, \frac{w(z)}{w(x)}\} dz, & \text{if } y = x, \end{cases}$$

where  $w(x) = \pi(x)/g(x)$  is called the *importance ratio* (or *importance weight*). Intuitively, the transition from  $X_n = x$  to  $X_{n+1} = y$  is accomplished by generating an independent sample from  $g(\cdot)$  and then “thinning” it down based on a comparison of the corresponding importance ratios  $w(y)$  and  $w(x)$ . It can be shown that  $\pi$  is an invariant distribution of the constructed Markov chain. Note that the foregoing scheme is only a special example, that more serious Metropolis-Hastings algorithms most commonly make dependent local moves instead of independent global jumps. An eigenanalysis of this chain was provided by Liu (1996).

Suppose that we cannot directly sample from  $g(x)$  but have a reversible MCMC procedure (a condition that most single-step MCMC schemes satisfy), with transition function  $A(x, y)$ , that has  $g(x)$  as its invariant distribution. Then we have  $g(x)A(x, y) = g(y)A(y, x)$ . Hence if we conduct a Metropolis step with  $A(x, y)$  as the proposal chain and  $\pi(x)$  as the target distribution, then the rejection probability can be computed as

$$\begin{aligned} p_a &= \min\left\{1, \frac{\pi(y)A(y, x)}{\pi(x)A(x, y)}\right\} = \min\left\{1, \frac{\pi(y)g(x)}{\pi(x)g(y)}\right\} \\ &= \min\left\{1, \frac{w(y)}{w(x)}\right\}. \end{aligned}$$

Hence the procedure described in Section 3.4 is still valid but can no longer be called an “independence chain” approach.

#### A.1 Computations Involved in the Example (Section 6.1)

For computing the weights, we must compute

$$p(y_t|\theta, \mathbf{x}_{t-1}, \mathbf{y}_{t-1}) = \phi(y_t - \alpha_1 q_{1(t-1)})[1 - \Phi(y_t - \alpha_2 q_{2(t-1)})] + \phi(y_t - \alpha_2 q_{2(t-1)})[1 - \Phi(y_t - \alpha_1 q_{1(t-1)})],$$

and for imputing missing data, we need

$$\begin{aligned} p(\delta_t = 1|\theta, \mathbf{x}_{t-1}, \mathbf{y}_{t-1}, y_t) &= \frac{\phi(y_t - \alpha_1 q_{1(t-1)})[1 - \Phi(y_t - \alpha_2 q_{2(t-1)})]}{p(y_t|\theta, \mathbf{x}_{t-1}, \mathbf{y}_{t-1})} \\ p(\lambda_t|\delta_t = 1, y_t, \theta, \mathbf{x}_{t-1}, \mathbf{y}_{t-1}) &= \frac{\phi(\lambda_t - \alpha_2 q_{2(t-1)})}{1 - \Phi(y_t - \alpha_2 q_{2(t-1)})} \end{aligned}$$

and

$$p(\lambda_t | \delta_t = 2, y_t, \theta, \mathbf{x}_{t-1}, \mathbf{y}_{t-1}) = \frac{\phi(\lambda_t - \alpha_1 q_{1(t-1)})}{1 - \Phi(y_t - \alpha_1 q_{1(t-1)})}$$

Suppose that the prior distribution for  $\theta$  is  $p_0(\alpha_1, \alpha_2)$ ; then given complete observations, the posterior

$$p(\theta | q_1, \dots, q_T) \propto p_0(\theta) \times \exp \left\{ - \sum_{t=2}^T \frac{(q_{1t} - \alpha_1 q_{1(t-1)})^2 + (q_{2t} - \alpha_2 q_{2(t-1)})^2}{2} \right\}.$$

Without loss of generality, we take  $p_0(\theta)$  to be uniform on  $[0, 1]^2$ . Then the posterior distribution is simplified as

$$p(\theta | q_1, \dots, q_T) \propto \exp \left\{ - \frac{(\alpha_1 - a_1)^2}{2b_1^2} - \frac{(\alpha_2 - a_2)^2}{2b_2^2} \right\}, \quad 0 \leq a_1, a_2 < 1,$$

where

$$b_1 = \left( \sum_{t=2}^T q_{1(t-1)}^2 \right)^{-1/2},$$

$$a_1 = b_1^2 \sum_{t=2}^T q_{1t} q_{1(t-1)},$$

$$b_2 = \left( \sum_{t=2}^T q_{2(t-1)}^2 \right)^{-1/2},$$

and

$$a_2 = b_2^2 \sum_{t=2}^T q_{2t} q_{2(t-1)}.$$

To sample from the truncated normal distribution  $X \sim \phi(x)$  with  $X > c$ , where  $\pi(x)$  is standard normal density, we use the following strategy. When  $c < 0$ , we simply conduct a simple normal random number generation and do rejection until we have a sample satisfying  $X > c$ . For  $c > 0$ , especially when  $c$  is large we use an exponential random variable with the rejection method.

Suppose that the exponential distribution  $\lambda_0 e^{-\lambda_0 x}$  is to be used as an envelop function; then we need to find the minimum constant  $b$  so that

$$\frac{\phi(x+c)}{1 - \Phi(c)} \leq b \lambda_0 e^{-\lambda_0 x}, \quad x \geq 0.$$

This gives us the best solution for  $b$ :

$$b = \frac{\exp\{(\lambda_0^2 - 2\lambda_0 c)/2\}}{\sqrt{2\pi}\lambda_0(1 - \Phi(c))}.$$

The acceptance rate for using this exponential distribution is then  $1/b$ . To achieve the minimum rejection rate, we further find that the best choice for  $\lambda_0$  is

$$\lambda_0 = (c + \sqrt{c^2 + 4})/2.$$

With this choice of  $\lambda_0$  and  $b$ , we implement the rejection method of von Neumann (1951). The rejection rate for this scheme decreases as  $c$  increases, and this rate is very small for moderate to large  $c$  (e.g., for  $c = 0, 1, 2$ , the rejection rates are .24, .12, and .07).

### A.2 Computations for Target Tracking (Section 6.3)

Let  $y_{t+1} = (y_{t+1(1)}, \dots, y_{t+1(m_{t+1})})$  be the observed signals at

time  $t + 1$ . Then

$$f(y_{t+1} | x_{t+1}) = (1 - p_d) \left[ \frac{1}{\Delta} \frac{e^{-\lambda \Delta} (\lambda \Delta)^{m_{t+1}}}{m_{t+1}!} \right] + p_d \left[ \frac{1}{m_{t+1}} \sum_{i=1}^{m_{t+1}} \frac{1}{\Delta^{m_{t+1}-1}} \phi_r(y_{t+1(i)} | x_{t+1}) \right] \times \frac{e^{-\lambda \Delta} (\lambda \Delta)^{m_{t+1}-1}}{(m_{t+1}-1)!} = \left[ p_d \sum_{i=1}^{m_{t+1}} \phi_r(y_{t+1(i)} | x_{t+1}) + (1 - p_d) \lambda \right] \times \frac{e^{-\lambda \Delta} \lambda^{m_{t+1}-1}}{m_{t+1}!}$$

for  $t = 0, 1, 2, \dots$ , where  $\phi_r$  refers to the normal density with variance  $r^2$ . Furthermore,

$$\phi_r(y_{t+1(i)} | x_{t+1}) q(x_{t+1} | \mathbf{x}_t) = \frac{1}{\pi q r} \exp \left\{ - \frac{(y_{t+1(i)} - x_{t+1}^{(1)})^2}{2r^2} - \frac{(x_{t+1}^{(1)} - x_t^{(1)} - x_t^{(2)})^2}{2(q/2)^2} \right\} = \frac{c}{\sqrt{2\pi}\sigma_{t+1}} \exp \left\{ - \frac{(x_{t+1}^{(1)} - \mu_{t+1})^2}{2\sigma_{t+1}^2} \right\},$$

where

$$\sigma_{t+1}^2 = \frac{r^2 q^2}{q^2 + 4r^2}, \quad \mu_{t+1} = \left[ \frac{y_{t+1(i)}}{r^2} + \frac{x_t^{(1)} + x_t^{(2)}}{(q/2)^2} \right] \sigma_{t+1}^2$$

and

$$c = \frac{2\sigma_{t+1}}{\sqrt{2\pi} r q} \exp \left\{ - \frac{1}{2} \left[ \frac{y_{t+1(i)}^2}{r^2} + \frac{x_t^{(1)} + x_t^{(2)}}{(q/2)^2} - \frac{\mu_{t+1}^2}{\sigma_{t+1}^2} \right] \right\}.$$

Hence  $f(y_{t+1} | x_{t+1}) q(x_{t+1} | \mathbf{x}_t)$  is a mixture of  $m_{t+1}$  normal distributions.

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