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Joint State and Parameter Estimation in Particle Filtering and Stochastic Optimization

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1. Introduction

Dynamic state-space models are useful for describing data in many different areas, such as engineering, finance mathematics, environmental data, and physical science. An important task when analyzing data by state-space models is estimation of the underlying state process based on measurements from the observation process. Bayesian filtering represents a solution of considerable importance for this type of problem definition as demonstrated by many existing algorithms based on the Kalman filter and particle filtering (PF) (Arulampalam 2002, Doucet et al. 2001, Yang et al. 2006). The PF has been extensively studied in the situation where the unknown attributes are time-varying dynamic states. Although PF have been successful in many applications, a main problem with it is how to handle the presence of the unknown static parameters, especially in models with realistically large numbers of fixed parameters.

The estimation of both the dynamic state and static parameters is commonly known in literatures as the dual estimation. Numerous papers have been written on the construction of estimation algorithms based on Markov chain Monte Carlo (MCMC) (Spall 2003). Although such methods may be effective for offline estimation, they are not suitable for online estimation because the MCMC algorithm needs to be restart at each time point. In engineering, a common trick to problem is to include the parameters as part of the state space vector. Berzuini et al. (Berzuini et al. 1997) put this approach into Bayesian estimation. However, the non-dynamics in the parameters cause the degeneracy of the algorithm. Jane and West (Jane & Mike 2001) introduced diversity in the particles by Kernel method, which is similar to replace the original static parameter with an alternative dynamic model. Polson et al (Polson & Stroud 2008) proposed a sequential parameter learning and filtering based on approximating the target posterior by a mixture of fixed lag smoothing distributions. Lee and Chia (Lee & Chia 2002) combined the particle filtering and MCMC to achieve an estimation algorithm in which the measurements are processed sequentially by particle filtering. When the degeneration occurs, the particles are rejuvenated by MCMC. Storvik (Storvic 2002) considered models with sufficient statistics for the parameters and applied particle filters to an augmented vector of states and sufficient statistics. Djuric et al (Djuric & Miguez 2002) proposed an alternative approach for a certain class of state-space model, which suppose that the marginal distribution of parameter can be analytically tractable. However, both algorithms suffer from an accumulation of error over times, albeit more slowly, leading to instability eventually. On the other hand, Andrieu et al (Andrieu et al.

2003, 2004, 2005, Yang et al. 2008) considered maximum likelihood parameter point estimation based on gradient. But in reality the graduate computation is intractable for complex nonlinear system function.

In this chapter, we propose a new algorithm that preserves the static nature of the unknown parameters. The maximum likelihood parameter estimation is performed based on particle filtering and an effective stochastic approximation gradient algorithm is used to optimize cost function. The estimation of static parameters and dynamic state variables is performed simultaneously.

2. Problem formulation

The state-space models have the form

$$
\begin{aligned}
x_t &\sim p(x_t | x_{t-1}, \theta) \\
y_t &\sim p(y_t | x_t, \theta)
\end{aligned}
\tag{1}
$$

where x_t is unobserved state vector at time t, y_t is an observation at time t, $\theta \in R^m$ is m dimensional unknown static parameters vector, and $p(\cdot|\cdot)$ is generic conditional distribution. Optimal filtering consists of estimating recursively in time the sequence of posterior densities function (PDF) $p(x_t | y_{1:t})$ which summarizes all the information about the system states x_t as given by the collection of observations $y_{1:t} = (y_1, \cdots, y_t)$. For non-linear and non-Gaussian dynamic models, the particle filtering can achieve approximated estimation of PDF based on Monte Carlo simulation. Although particle filtering has been successful in many simulation experiments and in analysis of real data, a main problem with it is how to handle the presence of unknown static parameters. In this paper, we present a method referred to as point estimation, i.e. we do not aim to estimating the PDF of θ. We focus rather on the estimation of θ directly by maximum-likelihood (ML) principle. The dynamic state is estimated by particle filtering and static parameter is estimated by recursive ML method online.

Given a set of measurements $y_{0:t}$, the estimation of ML requires maximization of likelihood with respect to parameter θ. Firstly, the cost function is presented, and the likelihood of measurements $y_{0:t}$ is given by

$$
\begin{aligned}
p(y_{0:t}, \theta) &= p(y_t | y_{0:t-1}, \theta) p(y_{0:t-1}, \theta) \\
&= p(y_0, \theta) \prod_{k=1}^{t} p(y_k | y_{0:k-1}, \theta)
\end{aligned}
\tag{2}
$$

where

$$
\begin{aligned}
p(y_k | y_{0:k-1}, \theta) &= \int p(y_k | x_k, \theta) p(x_k | y_{0:k-1}, \theta) dx_k \\
&= \int p(y_k | x_{k-1}, \theta) p(x_{k-1} | y_{0:k-1}, \theta) dx_{k-1}
\end{aligned}
$$

$$
p(y_0, \theta) = \int p(y_0 | x_0, \theta) p(x_0) dx_0
$$

In practice, one uses the log-likelihood which is numerically better behaved and satisfies

$$l(y_{0:t}, \theta) = \log p(y_{0:t}, \theta)$$
$$= \log p(y_0, \theta) + \sum_{k=1}^{t} \log p(y_k | y_{0:k-1}, \theta) \tag{3}$$

To simplify the computation, the cost function is chosen as predicted likelihood, i.e.

$$f(\theta) = p(y_t | y_{0:t-1}, \theta) = \int p(y_t | x_t, \theta) p(x_t | y_{0:t-1}, \theta) dx_t \tag{4}$$

However, except in a few simple cases, it is impossible to compute the optimal filter and the likelihood in closed-form, the numerical approximation schemes are required.

The problem of maximizing the cost function can be translated into finding the zeros of the gradient $\nabla f(\theta)$. A recursion procedure to estimate θ such that $\nabla f(\theta) = 0$ proceeds as follows

$$\theta_t = \theta_{t-1} + \gamma_t \widehat{\nabla} f(\theta_{t-1}) \tag{5}$$

where $\widehat{\nabla} f(\theta_{t-1})$ is the estimation of gradient estimated at the point θ_{t-1} and $\{\gamma_t > 0\}$ denotes a sequence of decreasing step-size. One selects a step-size sequence satisfying $\gamma_t \to 0$, $\sum_{t=1}^{\infty} \gamma_t = \infty$. Under appropriate conditions, the iteration in (5) will converge to the true value of θ in some stochastic sense. The essential part of (5) is how to obtain the gradient estimate, however, it is impossible to compute the closed-form gradient and we must resort to the numerical approximation.

The particle filtering (Gordon 1993, Doucet et al. 2001, Yang et al. 2006) is based on importance sampling where x_t is simulated sequentially from some importance distribution $q(x_t | y_{1:t})$, and the whole trajectory $x_{1:t}$ is given importance weight

$$\omega_t = p(x_t | y_{1:t}) \Big/ q(x_t | y_{1:t})$$

N such sequences are simulated parallel, giving a weighted particle set $(x_t^{(i)}, \omega_t^{(i)}), i = 1, \cdots, N$ at each time point t. The problem with the particle filtering is the degeneracy phenomenon, where the variance of the importance weights can only increase over time, making the estimate unstable (Kong et al. 1994). A common trick to avoid this is to re-sample from particle set with probabilities proportional to the importance weight (Gordon et al. 1993). The convergence result is surveyed in (Crisan & Doucet 2002), where the error in the approximate distribution is stable with increasing the number of particles to infinity. Given a set of weighted particle $(x_{t-1}^{(i)}, \omega_{t-1}^{(i)})$ which approximate $p(x_{t-1} | y_{0:t-1}, \theta)$ and given the estimate of parameter θ_{t-1} at time $t-1$, the cost function can be approximated as follows

$$\hat{f}(\theta_{t-1}) = \hat{p}(y_t | y_{0:t}, \theta_{t-1}) = \sum_{i=1}^{N} \omega_{t-1}^{(i)} p(y_t | \tilde{x}_t^{(i)}, \theta_{t-1}) \tag{6}$$

where the particles $\tilde{x}_t^{(i)} \sim p(x_t | x_{t-1}^{(i)}, \theta_{t-1})$ are obtained using a one-step ahead state evolution prediction.

Stochastic optimization techniques apply in the cases where a closed-form solution to the optimization problem of interest is not available and where the input information into optimization method may be contaminated with noise. One of the techniques that have attracted considerable recent attention for difficult multivariate problems is the simultaneous perturbation stochastic approximation (SPSA) method introduced by Spall (Spall 1987, 1998). SPSA is based on a highly efficient and easily implemented "simultaneous perturbation" approximation to the gradient. The SPSA technique requires all elements of θ to be varied randomly simultaneously to obtain two estimates of the cost function. Only two cost function measurements are required regardless of the dimension of the parameters be optimized. The SPSA has proven to be an effective and easy implemented algorithm and success among other finite difference methods with reduced number of estimates required for convergence (Chan et al. 2003, Doucet & Tadic 2002, Andrieu et al. 2003).

A step-by-step guide to implementation of SPSA for stochastic optimization is presented in (Spall 1998). It is assumed that $f(\theta)$ is a differentiable function of θ and that the minimum point of θ corresponding to a zero point of the gradient. In SPSA, the gradient estimate

$$\widehat{\nabla} f(\theta_{t-1}) = (\widehat{\nabla} f_1(\theta_{t-1}), \cdots, \widehat{\nabla} f_m(\theta_{t-1}))$$

is given by

$$\widehat{\nabla} f_j(\theta_{t-1}) = \frac{\widehat{f}(\theta_{t-1} + c_t \Delta_t) - \widehat{f}(\theta_{t-1} - c_t \Delta_t)}{2 c_t \Delta_{t,j}}$$

where c_t denotes a sequence of positive scalars such that $c_t \to 0$ and $\Delta_t = (\Delta_{t,1}, \Delta_{t,2}, \cdots, \Delta_{t,m})$ is a m-dimensional random perturbation vector. The choice of gain sequences is critical to the performance of SPSA. Careful selection of algorithm parameters a, c, A, α, r and gain sequences is required to ensure convergence. The γ_t and c_t generally take the form of $\gamma_t = \frac{a}{(A + t + 1)^\alpha}$ and $c_t = \frac{c}{(t + 1)^r}$. The practically effective values for α and r are 0.602 and 0.101 respectively. As a rule-of-thumb, it is effective to set c at a level approximately equal to the standard deviation of the measurement noise in $f(\theta)$. The values of a, A can be chosen together to ensure effective practical performance of the algorithm. Each components of Δ_t is usually generated from Bernoulli ± 1 distribution with probability of $\frac{1}{2}$ for each ± 1 independently.

In cases where the gradient has more than one zero point, then the algorithm may only converge to a local minimum, Spall further gives some modifications to the basic SPSA algorithm to allow it to search for the global solution among multiple local solutions[15].

3. Sampling algorithms for combined estimation of parameter and state

We present here how to incorporate maximum-likelihood algorithm within the particle filtering framework. To enhance the global convergence and Robust of the parameter estimate, for each state particle, i.e. a possible state trajectory, we produce a particle of

parameter and resample correspondingly. The ultimate parameter estimate is produced by weighted sum of parameter particles. This process can alleviate the divergence of estimate of parameter. The algorithm proceeds as follows.

Step 1. Initialization:

For $i = 1, \cdots, N$, sample $x_0^{(i)} \sim p(x_0)$ and initial particles of parameters estimate $\theta_0^{(i)}$.

Assign initial important weights as $\omega_0^{(i)} = 1/N$.

The initial estimate of parameter is $\theta_0 = \sum_{i=1}^{N} \omega_0^{(i)} \theta_0^{(i)}$

Step 2. State sampling:

Given a set of weighted state and parameter particles $(x_{t-1}^{(i)}, \theta_{t-1}^{(i)}, \omega_{t-1}^{(i)})$, $i = 1, \cdots, N$ at time $t-1$, sample $\tilde{x}_t^{(i)} \sim p(x_t | x_{t-1}^{(i)}, \theta_{t-1}^{(i)})$ for $i = 1, \cdots, N$.

Step 3. Cost function evaluation:

For each parameter particle $\theta_{t-1}^{(i)}$, generate a m-dimensional simultaneous perturbation vector $\Delta_t^{(i)}$. Compute the perturbed parameter particle $(\theta_{t-1}^{(i)} + c_t \Delta_t^{(i)})$ and $(\theta_{t-1}^{(i)} - c_t \Delta_t^{(i)})$.
For $i = 1, \cdots, N$,

Sample $\tilde{x}^{(i)+} \sim p(x_t | x_{t-1}^{(i)}, \theta_{t-1}^{(i)} + c_t \Delta_t^{(i)})$ and compute the likelihood $p(y_t | \tilde{x}^{(i)+}, \theta_{t-1}^{(i)} + c_t \Delta_t^{(i)})$.

Sample $\tilde{x}^{(i)-} \sim p(x_t | x_{t-1}^{(i)}, \theta_{t-1}^{(i)} - c_t \Delta_t^{(i)})$

Compute the likelihood $p(y_t | \tilde{x}^{(i)-}, \theta_{t-1}^{(i)} - c_t \Delta_t^{(i)})$

Evaluate cost function

$$\hat{f}(\theta_{t-1}^{(i)} + c_t \Delta_t^{(i)}) = p(y_t | \tilde{x}^{(i)+}, \theta_{t-1}^{(i)} + c_t \Delta_t^{(i)})$$

$$\hat{f}(\theta_{t-1}^{(i)} - c_t \Delta_t^{(i)}) = p(y_t | \tilde{x}^{(i)-}, \theta_{t-1}^{(i)} - c_t \Delta_t^{(i)})$$

Step 4. Gradient approximation:

For each parameter particle, the corresponding gradient

$$\widehat{\nabla} f(\theta_{t-1}^{(i)}) = (\widehat{\nabla} f_1(\theta_{t-1}^{(i)}), \cdots, \widehat{\nabla} f_m(\theta_{t-1}^{(i)}))$$

where the components of gradient

$$\widehat{\nabla} f_j(\theta_{t-1}^{(i)}) = \frac{\hat{f}(\theta_{t-1}^{(i)} + c_t \Delta_t^{(i)}) - \hat{f}(\theta_{t-1}^{(i)} - c_t \Delta_t^{(i)})}{2 c_t \Delta_{t,j}^{(i)}},$$

and $\Delta_{t,j}^{(i)}$ denote the j-th component of $\Delta_t^{(i)}$.

Step 5. Parameter update:

For each parameter particle $\theta_t^{(i)} = \theta_{t-1}^{(i)} + \gamma_t \widehat{\nabla} f(\theta_{t-1}^{(i)})$

Step 6. Re-sampling:

For each particle $(\tilde{x}_t^{(i)}, \theta_t^{(i)})$, compute the normalized importance weights as $\tilde{\omega}_t^{(i)} \propto \omega_{t-1}^{(i)} p(y_t | \tilde{x}_t^{(i)}, \theta_t^{(i)})$ at time t .

Multiply/discard particles $(\tilde{x}_t^{(i)}, \theta_t^{(i)})$ with respect to high/low importance weights $\tilde{\omega}_t^{(i)}$.
Re-assign even importance weights $\omega_t^{(i)} = 1/N$.

Step 7. Output:

The obtained weighted particles
$(x_t^{(i)}, \theta_t^{(i)}, \omega_t^{(i)}), i = 1, \cdots, N$ approximate to $p(x_t | y_{0:t}, \theta)$.
The posterior density function of state is approximated as

$$p(x_t | y_{0:t}, \theta) = \sum_{i=1}^N \omega_t^{(i)} \delta(x_t - x_t^{(i)})$$

The estimate of state is $x_t = \sum_{i=1}^N \omega_t^{(i)} x_t^{(i)}$.

The estimate of parameter is $\theta_t = \sum_{i=1}^N \omega_t^{(i)} \theta_t^{(i)}$

$t = t + 1$. Return to step 2.

4. Simulation results

Here, we consider the following set of equations as an illustrative example which has been analyzed before in many publications (Gordon et al. 1993, Doucet et al. 2001, Chan et al. 2003).

$$x_t = \frac{x_{t-1}}{2} + \frac{\theta_1 x_{t-1}}{1 + x_{t-1}^2} + \theta_2 \cos(0.1t) + v_t$$

$$y_t = \frac{x_t^2}{20} + w_t$$

where $x_0 \sim N(0,5)$, v_t and w_t are zero mean Gaussian random variables with variances Q_t and R_t , respectively. We use $Q_t = 10$ and $R_t = 1$. θ_1 is unknown parameter with true value $\theta_1 = 25$ and $\theta_2 = 10$. This example is severely nonlinear, both in the system and the measurement equation. Note that the form of the likelihood $p(y_t | x_t)$ adds an interesting twist to the problem.

We present two algorithms to deal with the unknown parameters. The first algorithm, titled "Augmented State", includes the parameters as part of the state vector (x_t, θ_t) which

proposed in paper (Jane & Mike 2001). θ is replaced by θ_t at time t, then add an independent, zero-mean normal increment increment to the parameter at each time. That is,

$$\theta_t = \theta_{t-1} + \zeta_t$$
$$\zeta_t \sim N(0, W_t)$$

For some specified variance matrix W_t. We use $W_t = 10$ in simulations. The second algorithm is our algorithm, titled "Adaptive estimate", which includes an on-line adaptive estimation of the parameters as proposed in this paper.

We perform 50 independent Monte Carlo runs with $N = 1000$ particles in each run. The initial values of parameters are selected randomly in interval $[0,1]$.

For reference, the true states for the exemplar run are shown in Fig.1 and the measurements in Fig.2. The sequences of parameter θ_1 and θ_2 estimate are illustrated in Fig.3 and Fig.4 respectively where the solid line with the label "adaptive estimation" indicates the estimate by our algorithm, the dashed line with the label "augmented state" indicates the estimate by the first algorithm. Fig.5 shows the RMSE of dynamic state x_t by particle filtering where dashed line represents RMSE with true value of parameters, the solid line represent RMSE with augmented state estimates of parameters by the first algorithm. Fig.6 shows the RMSE of particle filtering where dashed line represents RMSE with true value of parameters, the solid line represent RMSE with adaptive estimates of parameters by our algorithm. From the simulation results, it can be seen that the parameters converge to true values quickly by the proposed algorithm and RMSE of dynamic state with adaptive estimates of parameters diminish with time and approach to RMSE with the true values of parameters.
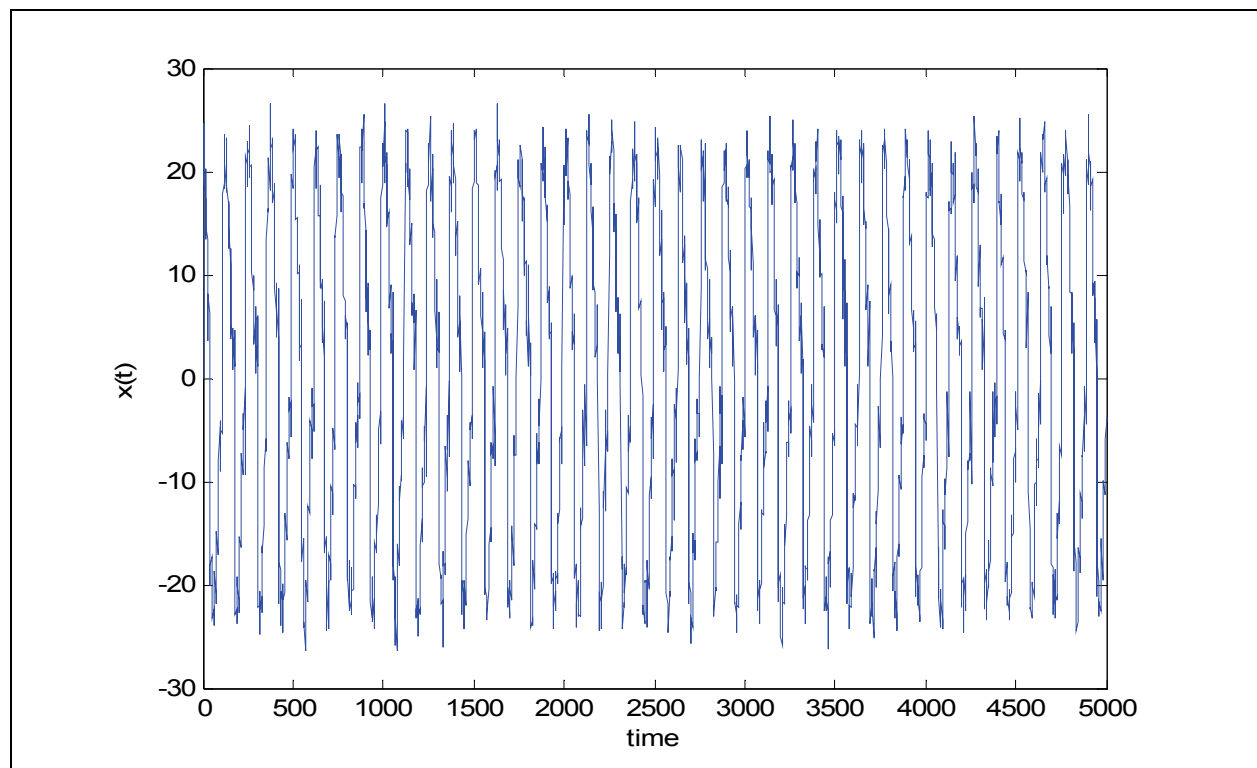

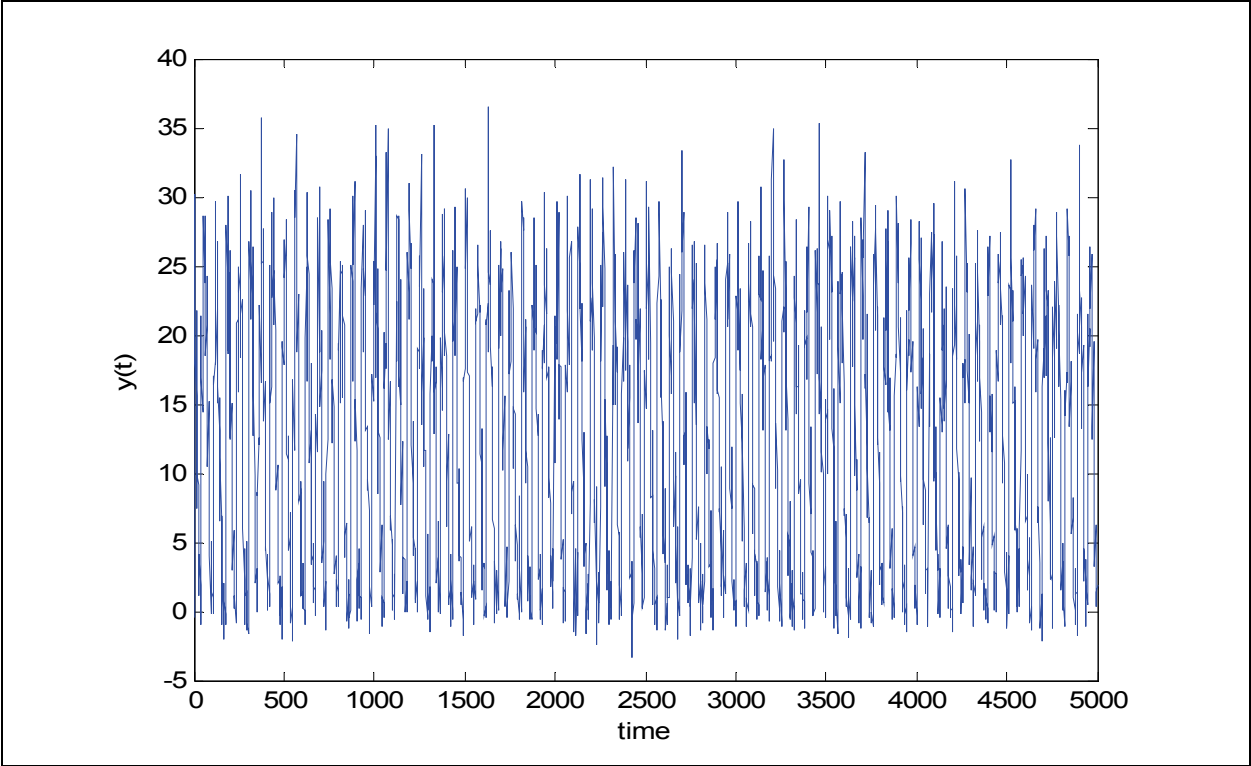Fig. 1. Figure of the true values of state $x(t)$ as ma function of t for the exemplar run

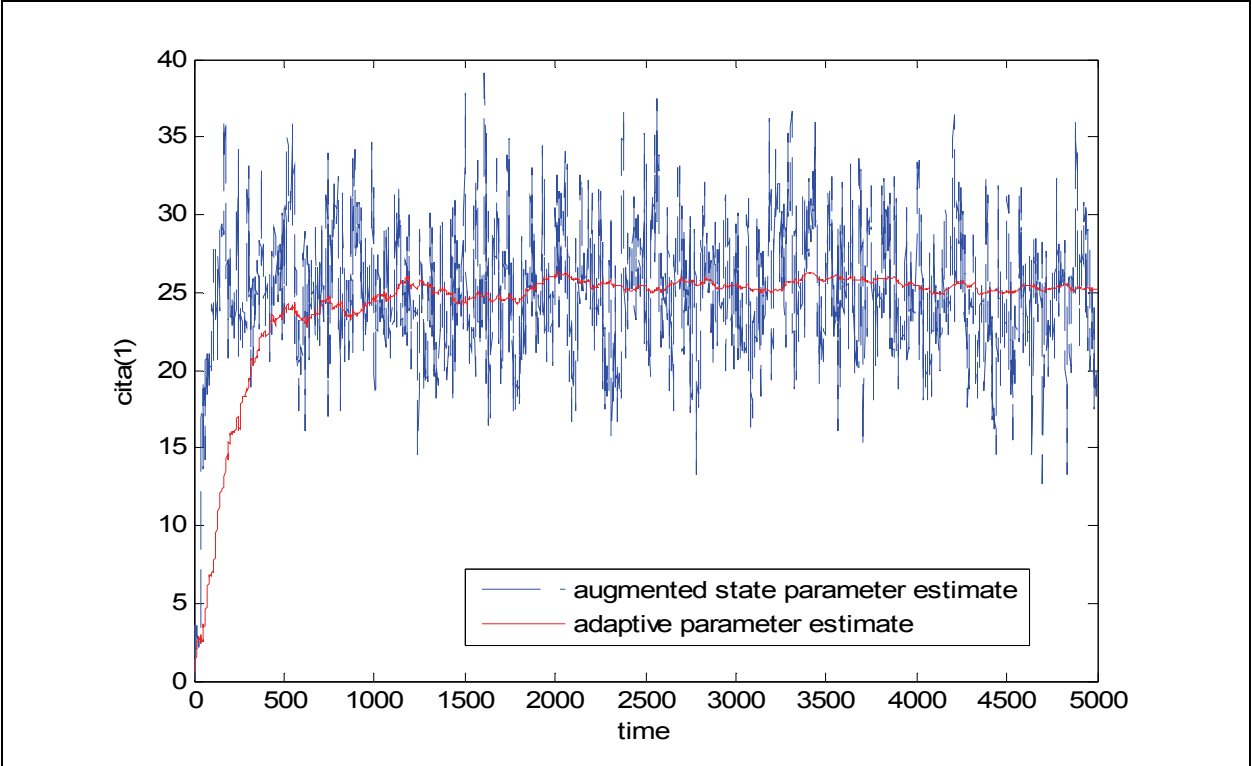Fig. 2. Figure of the measurements $y(t)$ of the states $x(t)$ shown in Fig.1 for the same exemplar run
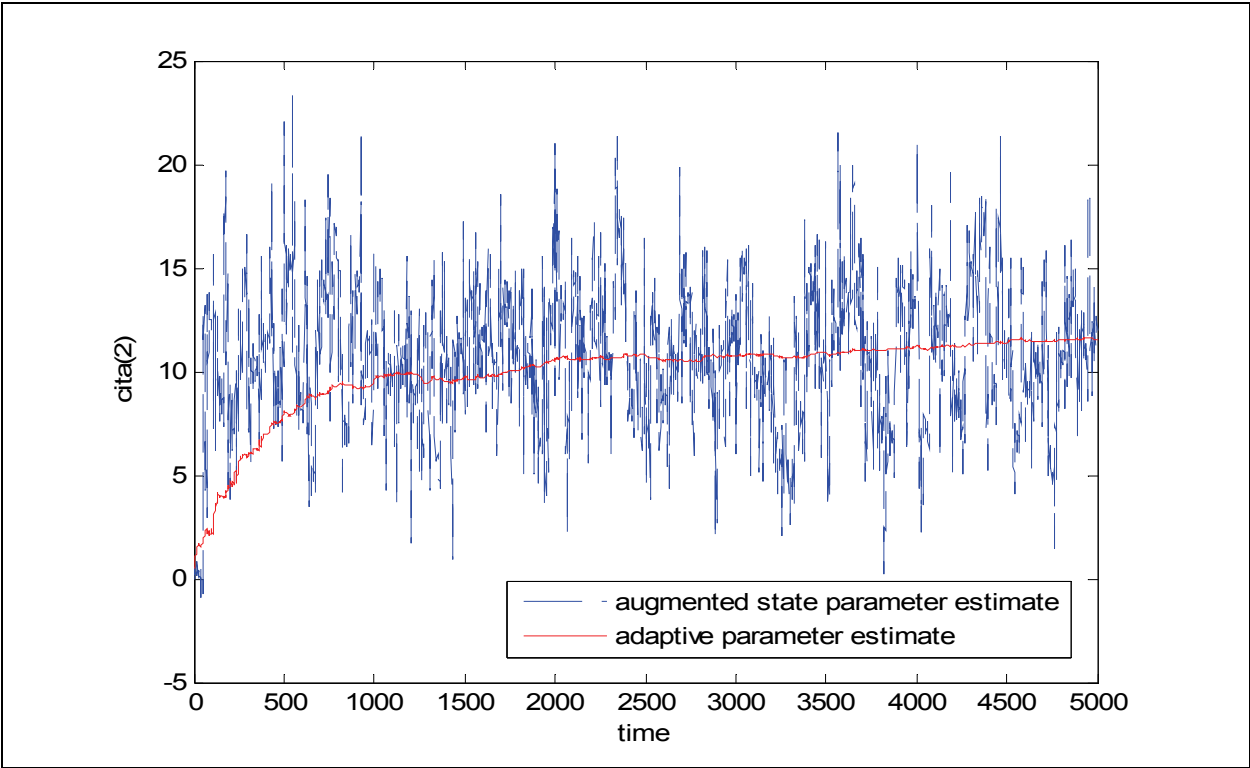

Fig. 3. Sequence of parameter θ_1 estimate over time

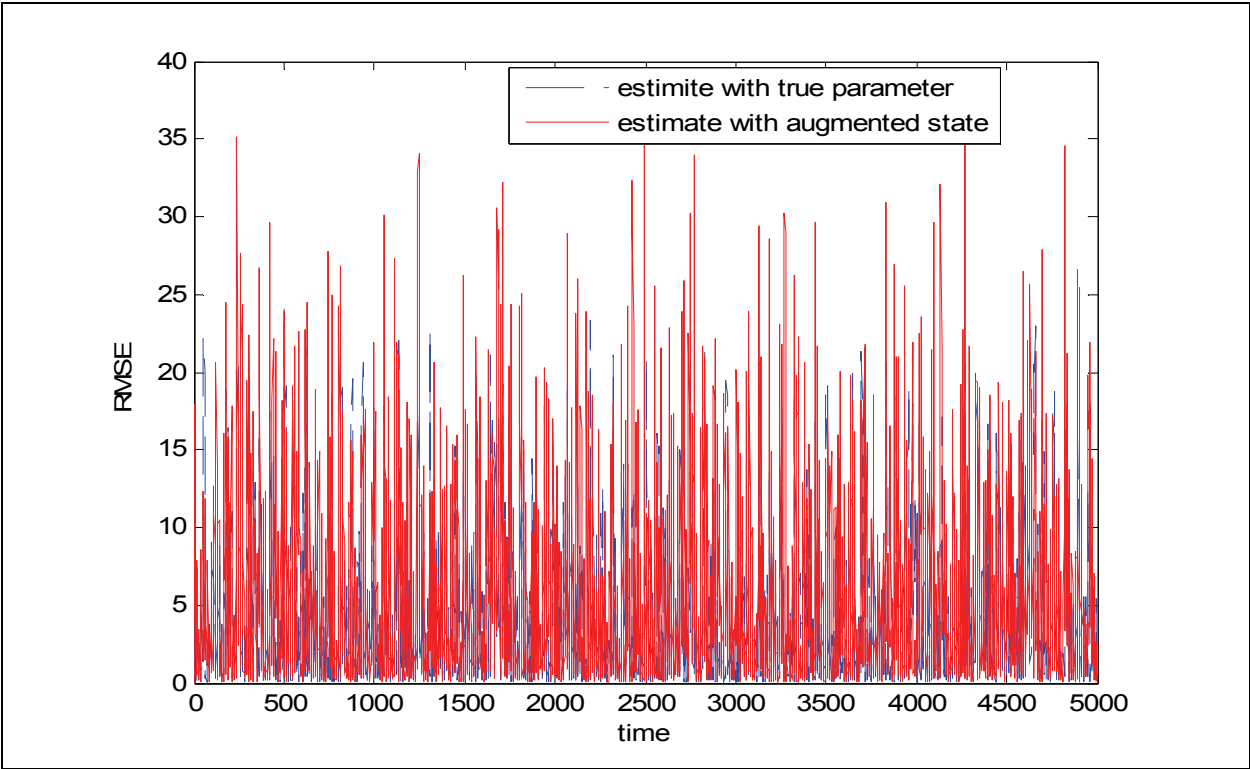Fig. 4. Sequence of parameter θ_2 estimate over time

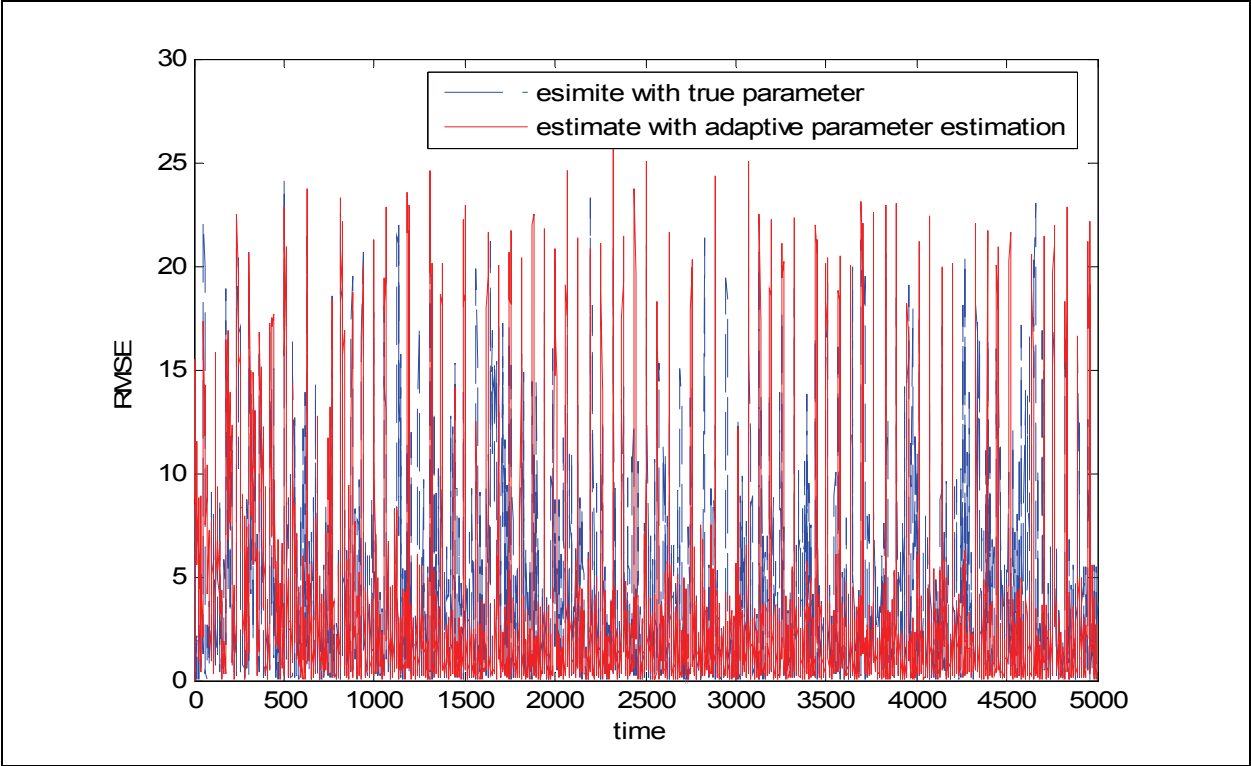Fig. 5. RMSE of state x_t by particle filtering with true parameter and augmented state parameter estimation

Fig. 6. RMSE of state x_t by particle filtering with true parameter and adaptive parameter estimation

We also compare the performance measure of our results with the "augmented state estimate" algorithm. The performance measure is root mean square error as follows:

$$RMS = \sqrt{\frac{1}{MT}\sum_{m=1}^{M}\sum_{t=1}^{T}(\hat{x}(m,t)-x(t))^2}$$

where $\hat{x}(m,t)$ is the estimate of $x(t)$ in the mth Monte Carlo simulation, $M = 50, T = 5000$. The performance of the first algorithm, our algorithm and the particle filtering with true parameter for various number of particles are presented in Table 1.

Algorithm / N	800	1000	2000
Augmented State	0.2017	0.1945	0.1873
Adaptive estimation	0.1005	0.0996	0.0908
True parameter	0.0912	0.0852	0.0803

Table 1. RMS performance measure for the two algorithms

5. Conclusions

In this chapter, we proposed an adaptive estimation algorithm for non-linear dynamic systems with unknown parameters based on combination of particle filtering and SPSA technique. We have demonstrated how to combine the maximum-likelihood parameter

estimation with particle filtering. The estimates of parameters are obtained by state samples and maximum-likelihood estimation within particle filtering. The SPSA is used to approximate the gradient of cost function. The proposed algorithm achieves joint estimation of dynamic state and static parameters.

6. References

Andrieu, C.; Doucet, A.; & Tadic V. B. (2003). Online sampling for parameter estimation in general state space models. *Proceedings of IFAC Symposium on System Identification (SYSID 2003)*, pp.221–225, Netherlands

Andrieu, C.; Doucet, A.; Singh, S. S.; & Tadic, V. B. (2004). Particle methods for change detection, system identification, and control. *Proceeding of the IEEE*, Vol. 92, No. 3，(March, 2004) 32-68

Andrieu, C.; doucet, A.; Tadic, V. (2005). On-Line Parameter Estimation in General State-Space Models. *Proceedings of the 44th IEEE Conference on Decision and Control*, Seville

Arulampalam, M. S. ; Maskell, S.; Gordon, N.; & Clap, T. (2002). A tutorial on particle filters for on-line nonlinear/non-Gaussian Bayesian tracking. *IEEE Transactions on Signal Processing*, Vol. 50, No. 2, (February, 2002) 174–188

Berzuini, C.; Best, N. G.; & Gilks, W. R. (1997). Dynamic conditional independence models and Markov chain Monte Carlo methods. *Journal of the American Statistical Association*, Vol. 92, No.1, 1403-1411

Chan, B. L.; Doucet, A.; & Tadic, V. B. (2003). Optimization of particle filters using simultaneous perturbation stochastic approximation. *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing*, pp.681-684, Hong Kong

Crisan, D.; & Doucet, A. (2002). A survey of convergence results on particle filtering methods for practitioners. *IEEE Transaction on Signal Processing*, Vol. 50, No. 3, (March, 2002) 736-746

Doucet, A.; Freitas, J. & Gordon, N. (2001). *Sequential Monte Carlo Methods in Practice*, Springer-Verlag, ISBN : 0387951466, New York

Doucet, A.; & Tadic, V. B. (2002). On-line optimization of sequential Monte Carlo methods using stochastic approximation. *Proceeding of American Control Conference*. pp.2565–2570, Anchorage

Djuric, P. M.; & Miguez, J. (2002). Sequential particle filtering in the presence of additive Gaussian noise with unkown parameters. *Proceedings of the IEEE*, Vol. 45, No. 2, (March, 2002) 23-47

Gamerman, D. (1998). Markov chain Monte Carlo for dynamic generalized models. *Biometrika*, Vol. 85, No. 1, (January, 1998) 215-227

Gordon, N. J.; Salmond, D. J.; & Smith, A. F. M. (1993). Novel approach to nonlinear/non-Gaussian Bayesian state estimation. *IEE Proceedings-F*, Vol. 140, No. 2, (February, 1993) 107-113

Jane, L.; & Mike, W. (2001). Combined parameter and state estimation in simulation-based filtering. in *Sequential Monte Carlo Methods in Practice*, Doucet, A.; Freitas, J. F. G.; & Gordon, N. J. (Eds.), Springer-Verlag, ISBN: 0387951466, New York

Kong, A.; Liu, J. S.; & Wong, W. H. (1994). Sequential imputations and Bayesian missing data problems. *Journal of the American Statistical Association*, Vol.89, No.5, (May, 1994) 278-288

Lee, D. S.; & Chia, N. K. K. (2002). A particle algorithm for sequential Bayesian parameter estimation and model selection. *IEEE Transactions on Signal Processing*, Vol. 50, No. 2, (February, 2002) 326-336

Polson, N. G.; & Stroud, J. R. (2008). Practical filtering with sequential parameter learning. *Journal of the Royal Statistical Society: Series B*, Vol.70, No. 2 413–428

Spall, J. C. (1987). A stochastic approximation technique for generating maximum likelihood parameter estimates. *Proceedings of the American Control conference*, pp.1161-1167, Chicago

Spall, J. C. (1998). Implementation of the simultaneous perturbation algorithm for stochastic optimization. *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 34, No. 3, 817-823

Spall, J. C. (2003). Estimation via Markov chain Monte Carlo. *IEEE Control System Magazine,* Vol. 23 , No.2, (February, 2003) 34-45

Storvic, G. (2002). Particle filters in state space models with the presence of unknown static parameters. *IEEE Transactions on Signal Processing*, Vol. 90, No. 2, (February, 2002) 281-289

Yang, X.; Pan, Q.; & Wang, R. (2006). Development and prospect of particle filtering. *Control Theory & Applications*, Vol. 23, No. 2, 261– 67

Yang, X.; Xing, k.; & Pan Q. (2008). Joint Parameter and State Estimation in Particle Filtering and Stochastic Optimization. Journal of Control Theory & Application, Vol.6, No.2, 215-220
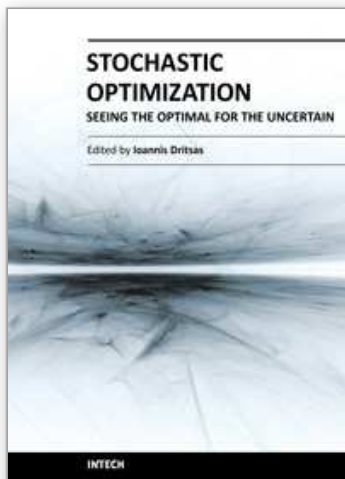
Stochastic Optimization - Seeing the Optimal for the Uncertain

Edited by Dr. Ioannis Dritsas

Stochastic Optimization Algorithms have become essential tools in solving a wide range of difficult and critical optimization problems. Such methods are able to find the optimum solution of a problem with uncertain elements or to algorithmically incorporate uncertainty to solve a deterministic problem. They even succeed in â€œfighting uncertainty with uncertaintyâ€. This book discusses theoretical aspects of many such algorithms and covers their application in various scientific fields.

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