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Modeling of non-stationary autoregressive alpha-stable processes by particle filters ☆

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Abstract

In the literature, impulsive signals are mostly modeled by symmetric alpha-stable processes. To represent their temporal dependencies, usually autoregressive models with time-invariant coefficients are utilized. We propose a general sequential Bayesian modeling methodology where both unknown autoregressive coefficients and distribution parameters can be estimated successfully, even when they are time-varying. In contrast to most work in the literature on signal processing with alpha-stable distributions, our work is general and models also skewed alpha-stable processes. Successful performance of our method is demonstrated by computer simulations. We support our empirical results by providing posterior Cramer–Rao lower bounds. The proposed method is also tested on a practical application where seismic data events are modeled.

Keywords: Skewed α-stable distributions; Bayesian estimation techniques; Particle filtering; Time varying autoregressive processes

1. Introduction

In the literature, most processes are assumed to have Gaussian distributions [1–3]. This is widely preferred, since most parameter estimation techniques can lead to analytically tractable solutions under this assumption [1–3]. Moreover, this assumption has been based on the central limit theorem (CLT) in the literature [1–3]. However, CLT is only valid for processes with finite variances. Therefore, processes having infinite variances cannot be modeled as Gaussian. Such processes are represented by other distributions in the literature [3]. Impulsive signals form a major group of processes with infinite variances and they possess outliers. They are seen in many areas, such as geophysics, meteorology, teletraffic in computer communications, radar and sonar applications and mobile communications. Considering the physical nature of the data, the impulsive signals may correspond to cause of extreme effects, such as a major earthquake; thus such signals should be carefully modeled without ignoring the outliers.

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One possible model for impulsive signals is alpha-stable (α-stable) processes [4–8]. Temporal dependencies of these signals can be expressed in terms of autoregressive (AR), moving-average (MA), autoregressive moving average (ARMA) [6–10] or non-linear AR models [11]. Among these, AR structure is used the most. This structure can also be used to parameterize a channel in telecommunications and can vary over time if the communications is performed in a wireless environment [12]. In this work, AR modeling of general α-stable processes is considered, where the α-stable distribution can be either skewed ($\beta \neq 0$), or symmetric ($\beta = 0$). In the physical world, skewed α-stable processes are encountered in many areas, such as earth sciences [5], astrophysics [13], teletraffic data in computer communications [9] and textures in image processing [14]. Depending on the nature of the parameters, four classes of estimation problems arise:

(a) AR parameters may be either time-invariant or time-varying.
(b) Distribution parameters of the alpha-stable process may be either time-invariant or time-varying.

The case of time-invariant AR coefficients and distribution parameters are studied extensively in the literature, where iteratively reweighted least squares [8], generalized Yule–Walker [6] and Markov chain Monte Carlo (MCMC) based methods [15] are proposed to estimate the unknown parameters. Mostly, processes are assumed to be symmetric [6,8,15]. Very limited research has been conducted to model time-varying AR (TVAR) symmetric α-stable processes. In [16], Thavaneswaran and Peiris propose a penalized minimum dispersion method in the case of a known shape parameter α of the symmetric α-stable process which is taken to be larger than one ($\alpha > 1$). In [16], it should be noted that only TVAR coefficients are estimated, assuming that the distribution parameters are known. In [17,18], particle filtering has been utilized to estimate the parameters of TVAR processes in the case of known distribution parameters. Recently, we have proposed another technique, where particle filtering is used for the estimation of the TVAR coefficients, while a hybrid Monte Carlo method is proposed to find the unknown, but constant distribution parameters, namely α and γ, of the symmetric alpha-stable ($S\alpha S$) process [19].

In this work, we propose a more general modeling methodology where both unknown AR coefficients and unknown distribution parameters are estimated, even if all of them are time-varying. In particle filtering, sequential Bayesian estimation is performed by expressing the problem in terms of a state-space formulation [20,21]. Usually, unknown parameters are modeled by state variables and sequential importance sampling is performed to estimate them. In particle filter applications, a well-defined state equation that governs the time evolution of states need to be available [17, p. 866]. In [22], for the signal enhancement problem, TVAR coefficients of a *Gaussian* process embedded in an $S\alpha S$ noise were estimated; moreover, time-variations of these TVAR coefficients are assumed to be known.

On the other hand, in a modeling problem, we can only observe samples of the process and usually we have no information about the time-variations of the unknown state variables [17]. In these cases, an artificial state-transition equation must be used to model TVAR processes by particle filtering. For this purpose, Djuric et al. proposed an efficient method by discounting old measurements [17,18]. They successfully modeled a TVAR process driven by a non-Gaussian process, even if time-variations of the state variables (AR coefficients) are not known. This method has been proposed to model non-Gaussian processes, whose probability density functions (p.d.f.'s) can be expressed analytically. Moreover, the distribution parameters of these driving processes are assumed to be known. Here, our objective is to bring a more general solution, based on particle filters, to the modeling problem. Therefore, we propose a novel methodology to model TVAR processes even if they are driven by non-Gaussian processes having analytically inexpressible p.d.f.'s with unknown distribution parameters. It is known that α-stable distributions are typical examples of this group [6,7]. Here, we present a technique to estimate the unknown AR coefficients and unknown distribution parameters of a general α-stable process; where all parameters can be *time-varying* and the α-stable driving process can have a *skewed* distribution. The results of the proposed method are very promising and we suggest that this method is able to handle the most general modeling schemes where the impulsive signals are involved.

Paper is organized as follows: First, the problem is stated formally in Section 2 with background information on α-stable processes. A brief description of particle filters is given in Section 3. In Section 4, the proposed method is presented which is followed by a brief background information on posterior Cramer–Rao lower bound (PCRLB). Finally, experiments and conclusions are given in Sections 6 and 7, respectively.

2. TVAR alpha-stable processes

2.1. Alpha-stable processes

CLT states that the sum of many random variables is Gaussian as the number of terms goes to infinity [1–3]. However, a condition of the theorem implies that each random variable in the sum is of finite variance. If this condition is not met, we must rely on the generalized CLT [6]. In this case, the limiting distribution is an α-stable distribution. α-stable distributions are defined in terms of their characteristic functions, since their p.d.f. cannot be obtained analytically, except for some limited cases ($\alpha = 2$, Gaussian; $\alpha = 1$, $\beta = 0$, Cauchy; $\alpha = 0.5$, $\beta = -1$, Lévy) [6, p. 18]. The characteristic function of α-stable distributions is given as follows:

$$\varphi(\zeta) = \exp\{j\mu\zeta - \gamma|\zeta|^{\alpha}[1 + j\beta\,\mathrm{sign}(\zeta)\omega(\zeta,\alpha)]\}; \tag{1}$$

$j = \sqrt{-1}$ and ζ denotes a dummy variable. Above, $\mathrm{sign}(\tau) = 1$ if $\tau > 0$, $\mathrm{sign}(\tau) = 0$ if $\tau = 0$ and $\mathrm{sign}(\tau) = -1$ if $\tau < 0$. In (1), parameters α, β, γ and μ are defined within the following intervals: $-\infty < \mu < \infty$, $\gamma > 0$, $0 < \alpha \leqslant 2$ and $-1 \leqslant \beta \leqslant 1$. Furthermore, the function $\omega(\zeta,\alpha)$ is defined as follows:

$$\omega(\zeta,\alpha) = \begin{cases} \tan\frac{\alpha\pi}{2} & \text{if } \alpha \neq 1; \\ \frac{2}{\pi}\log|\zeta| & \text{if } \alpha = 1. \end{cases} \tag{2}$$

As shown above, an α-stable distribution is defined by four parameters and will be represented by $S_{\alpha}(\gamma,\beta,\mu)$. Among these α, γ, β, μ are known as the characteristic exponent, dispersion, symmetry and location parameters, respectively. For a detailed information on stable distributions, the reader is referred to [7].

2.2. Problem statement: Modeling TVAR alpha-stable processes

The main contribution of our methodology is the estimation of both *time-varying* AR and distribution parameters of a general α-stable process, which can be expressed as a time series:

$$y_t = \sum_{k=1}^{K} \phi_t(k)\, y_{t-k} + n_t, \tag{3}$$

where y_t denotes the observed process and $\phi_t(k)$ represents the autoregressive coefficients. In (3), n_t demonstrates the α-stable driving process which is illustrated by the following notation: $n_t \sim S_{\alpha_t}(\gamma_t,\beta_t,\mu_t)$. In this work, the objective is to jointly estimate the TVAR coefficients, $\phi_t(k)$, and the distribution parameters of the α-stable process, which are shown by $\alpha_t, \gamma_t, \beta_t, \mu_t$. It should be noted that all unknown quantities here are time-varying.

3. Particle filters

Particle filters are known as sequential Monte Carlo methods, where the optimal Bayesian solution is approximated sequentially and the posterior distribution of the hidden variables in a non-Gaussian and/or non-linear state-space modeling system can be provided. Such a system can be given by the following equations:

$$\boldsymbol{\theta}_t = f_t(\boldsymbol{\theta}_{t-1}, \mathbf{v}_t), \tag{4}$$

$$\boldsymbol{y}_t = h_t(\boldsymbol{\theta}_t, \mathbf{n}_t), \tag{5}$$

where $\boldsymbol{\theta}_t$ represents the hidden state vector and y_t denotes the observed data at time t. The process and observation noises are denoted by $\mathbf{v}_t$ and $\mathbf{n}_t$, respectively. The functions f_t and h_t are known as the process and observation functions which may be non-linear. Also, the noise processes in (4) and (5) are modeled to be non-Gaussian. Posterior distribution of the state variables is represented by $p(\boldsymbol{\theta}_{0:t} \mid y_{1:t})$, where $y_{1:t}$ denotes the observed data from time 1 to time t. Some non-Gaussian distributions cannot be expressed analytically. In this case, they are approximated by samples, which are called the *particles*. The posterior p.d.f. can be approximated as $p(\boldsymbol{\theta}_{0:t} \mid y_{1:t}) \approx \sum_{i=1}^{N} \tilde{w}_t^{(i)} \delta(\boldsymbol{\theta}_{0:t} - \boldsymbol{\theta}_{0:t}^{(i)})$ where $\boldsymbol{\theta}_{0:t}^{(i)}$ denote the particles for $(i = 1,\ldots,N)$. Here, $\tilde{w}_t^{(i)}$ represent their normalized importance weights

[20,21] and are defined as $\tilde{w}_t^{(i)} = \frac{w(\boldsymbol{\theta}_{0:t}^{(i)})}{\sum_{j=1}^{N} w(\boldsymbol{\theta}_{0:t}^{(j)})}$. Particles are drawn by the *importance sampling* method and their unnormalized importance weights are obtained as follows:

$$w_t^{(i)} = \frac{p(\boldsymbol{\theta}_{0:t}^{(i)} \mid \mathbf{y}_{1:t})}{q(\boldsymbol{\theta}_{0:t}^{(i)} \mid \mathbf{y}_{1:t})}. \tag{6}$$

In (6), $q(.)$ function is called the *importance function*. It is easier to draw samples from $q(.)$ than from the original distribution [20,21]; however, importance sampling shown in (6), can be used in batch processing techniques and should be modified as follows for the sequential applications:

$$\tilde{w}_t^{(i)} \propto \tilde{w}_{t-1}^{(i)} \frac{p(\mathbf{y}_t \mid \boldsymbol{\theta}_t^{(i)}) p(\boldsymbol{\theta}_t^{(i)} \mid \boldsymbol{\theta}_{t-1}^{(i)})}{q(\boldsymbol{\theta}_t^{(i)} \mid \boldsymbol{\theta}_{0:t-1}^{(i)}, \mathbf{y}_{1:t})}. \tag{7}$$

Ideally, particles should be sampled from their optimal importance function, $q(\boldsymbol{\theta}_t^{(i)} \mid \boldsymbol{\theta}_{0:t-1}^{(i)}, \mathbf{y}_{1:t})$. Generally, these are very difficult to form and sample from; thus, simpler approximations are utilized. Here, we will use Bootstrap particle filtering [20,21] where the optimal importance function is approximated by *a priori* state transition p.d.f.'s as: $q(\boldsymbol{\theta}_t^{(i)} \mid \boldsymbol{\theta}_{0:t-1}^{(i)}, \mathbf{y}_{1:t}) = p(\boldsymbol{\theta}_t^{(i)} \mid \boldsymbol{\theta}_{t-1}^{(i)})$. These can be easily formed if the *true state-transition equation is known*. Provided that this importance function is used, calculation of the unnormalized importance weights reduces to the likelihood evaluation at the drawn sample values as shown below

$$w_t^{(i)} \propto p\big(y_t \mid \tilde{\boldsymbol{\theta}}_t^{(i)}\big), \tag{8}$$

where $\tilde{\boldsymbol{\theta}}_t^{(i)}$ denotes the particle drawn from the importance function. This is demonstrated by $\tilde{\boldsymbol{\theta}}_t^{(i)} \sim p(\boldsymbol{\theta}_t \mid \boldsymbol{\theta}_t^{(i)})$. Later, importance weights are normalized and resampling is performed by the replacement of N particles [20]. After resampling, N equally weighted particles are obtained; thus, $w_{t-1}^{(i)}$ is omitted in (8) [21].

4. The proposed method

A TVAR process of order K is expressed by (3). This expression can be shown by the following vectorial notation:

$$y_t = \mathbf{y}_{t-1}^T \boldsymbol{\phi}_t + n_t, \tag{9}$$

where $(.)^T$ denotes transposition and the vectors are defined as follows: $\mathbf{y}_{t-1} = [y_{t-1}, \ldots, y_{t-K}]^T$ and $\boldsymbol{\phi}_t = [\phi_1(t), \ldots, \phi_K(t)]^T$. The driving process is represented by n_t and the kth TVAR coefficient is denoted by $\phi_t(k)$. Driving process is modeled by an α-stable process, as shown below:

$$n_t \sim S_{\alpha_t}(\gamma_t, \beta_t, \mu_t). \tag{10}$$

In (9) and (10), the index t denotes the time dependency of the AR coefficients and the distribution parameters.

For the joint estimation of the vector $\boldsymbol{\phi}_t$ and the distribution parameters $(\alpha_t, \gamma_t, \beta_t, \mu_t)$, we propose to use Bootstrap particle filter. The state vector to be estimated is formed by augmenting the unknown TVAR coefficient vector with the unknown distribution parameters, and is denoted by $\boldsymbol{\theta}_t = [\boldsymbol{\phi}_t, \alpha_t, \gamma_t, \beta_t, \mu_t]^T$ and is of size $K' = K + 4$. In this modeling, $\varphi = \log \gamma$ is used since the dispersion parameter should always take positive values.

Since we have no information regarding the transition of the state variables, a random walk is used to model the time evolution of the state variables, which is given below

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \mathbf{v}_t \tag{11}$$

where the process noise vector represented by $\mathbf{v}_t = [\mathbf{v}_\theta^T, v_\alpha, v_\gamma, v_\beta, v_\mu]^T$, is modeled by Gaussian distribution, $\mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{\mathbf{v}_t})$. Since *a priori* information about the states is not sufficient to construct a good approximation for the optimal importance function, we can model the state transitions in such a way that the observation information is exploited implicitly rather than explicitly. The implicit exploitation of the observation can be achieved by modeling the process noise as Gaussian with a time-varying covariance matrix, which enables discounting of old measurements during the learning process of the TVAR coefficients [17,18]. On the other hand, the variances of the last four terms of the process noise vector are modeled by constants, since no closed form expressions can be obtained for these terms

to discount the old measurements as in [17]. Following this brief information, the covariance matrix of the process noise is taken as: $\mathbf{\Sigma}_{\mathbf{v}_t} = \text{diag}(\sigma^2_{1,t}, \ldots, \sigma^2_{K,t}, \sigma^2_{\alpha,t}, \sigma^2_{\gamma,t}, \sigma^2_{\beta,t}, \sigma^2_{\mu,t})$, where diag(.) indicates a diagonal matrix. Here, the first K components of the main diagonal correspond to the variances of the elements of vector $\mathbf{v}_\theta$, while the last four components denote the variances of v_α, v_γ, v_β and v_μ, respectively. In the light of aforementioned discussions, the elements of this covariance matrix are chosen as shown below:

$$\sigma^2_{k,t} = \left(\frac{1}{\xi} - 1\right)\text{var}\big(\phi_{t-1}(k)\big), \quad k = 1, \ldots, K,$$
$$\sigma^2_{\alpha,t} = \text{constant}, \qquad \sigma^2_{\gamma,t} = \text{constant}, \qquad \sigma^2_{\beta,t} = \text{constant}, \qquad \sigma^2_{\mu,t} = \text{constant}. \tag{12}$$

Here, ξ denotes the forgetting factor which is chosen between 0 and 1 and $\text{var}(\phi_{t-1}(k))$ represents the variance of the particles corresponding to the kth AR coefficient at time $(t-1)$. The latter quantity can be calculated as follows from the particles:

$$\text{var}\big(\phi_{t-1}(k)\big) = \frac{1}{N}\sum_{i=1}^{N}\left(\phi^{(i)}_{t-1}(k) - \frac{1}{N}\sum_{n=1}^{N}\phi^{(n)}_{t-1}(k)\right)^2, \quad k = 1, \ldots, K, \tag{13}$$

where N denotes the total number of particles used in the particle filter. By the procedure given by (11) through (13), the state transition model is obtained; resulting in the following state-space formulation of the problem:

$$\boldsymbol{\phi}_t = \boldsymbol{\phi}_{t-1} + \mathbf{v}_{\theta_t},$$
$$\alpha_t = \alpha_{t-1} + v_{\alpha_t},$$
$$\varphi_t = \varphi_{t-1} + v_{\varphi_t},$$
$$\beta_t = \beta_{t-1} + v_{\beta_t},$$
$$\mu_t = \mu_{t-1} + v_{\mu_t} \tag{14}$$
$$y_t = \mathbf{y}^T_{t-1}\boldsymbol{\phi}_t + n_t. \tag{15}$$

After the state transition model is formed, particles corresponding to each state variable can be drawn by using (14). The alleged particle drawing operation translates into the following choice of importance function:

$$q\big(\boldsymbol{\theta}^{(i)}_t \mid \boldsymbol{\theta}^{(i)}_{0:t-1}, \mathbf{y}_{1:t}\big) \approx p\big(\boldsymbol{\theta}^{(i)}_t \mid \boldsymbol{\theta}^{(i)}_{t-1}\big) \tag{16}$$

which implies that the new particles are drawn from the following p.d.f.: $\boldsymbol{\theta}^{(i)}_t \sim \mathcal{N}(\boldsymbol{\theta}^{(i)}_{t-1}, \mathbf{\Sigma}_{\mathbf{v}_t})$ for $i = 1, \ldots, N$. Given a state-transition model as specified by (11)–(14) and with the proposal density function (16), the importance weight of each particle can be calculated using the likelihood function (8). However, this likelihood cannot be evaluated since the p.d.f. of an α-stable distributed driving process cannot be expressed analytically, unlike those in [17,18]. Therefore, we propose to calculate this value by taking the inverse Fourier transform (IFT) of the characteristic function as shown below

$$p(n_t \mid \alpha_t, \gamma_t, \beta_t, \mu_t) = \frac{1}{2\pi}\int_{-\infty}^{\infty}\exp\big(j\mu_t\zeta - \gamma_t|\zeta|^{\alpha_t}\big[1 + j\beta_t\,\text{sign}(\zeta)\omega(\zeta,\alpha_t)\big]\big)\exp(jn\zeta)\,\mathrm{d}\zeta, \tag{17}$$

where $j = \sqrt{-1}$. Above, IFT can be calculated numerically; one possible solution is given in [23]. By using (9) and (17), (8) takes the form:

$$w^{(i)}_t \propto p\big(\mathbf{y}_t \mid \boldsymbol{\theta}^{(i)}_t\big) = \frac{1}{2\pi}\int_{-\infty}^{\infty}\exp\big(j\mu^{(i)}_t\zeta - \gamma^{(i)}_t|\zeta|^{\alpha^{(i)}_t}\big[1 + j\beta^{(i)}_t\,\text{sign}(\zeta)\omega\big(\zeta,\alpha^{(i)}_t\big)\big]\big)$$
$$\times\exp\big(j\big(y_t - \mathbf{y}^T_{t-1}\boldsymbol{\phi}^{(i)}_t\big)\zeta\big)\,\mathrm{d}\zeta$$

for the calculation of the importance weight pertaining to the ith particle. The weights are normalized and then resampling is performed to avoid the degeneracy problem. Residual resampling [24] is used, since we have not observed significant performance variations due to the choice of the resampling scheme. The pseudo-code description of the proposed method is given in Table 1.

Table 1
Pseudo-code

For $i = 1$ *to* N

1. Initiation

Draw samples from the initial distributions of the state variables: $\boldsymbol{\phi}_0^{(i)} \sim \mathcal{N}(\mathbf{m}_\phi, \mathbf{P}_\phi)$, $\alpha_0^{(i)} \sim \mathcal{U}(0,2]$, $\beta_0^{(i)} \sim \mathcal{U}[-1,1]$, $\varphi_0^{(i)} \sim \mathcal{N}(m_\varphi, P_\varphi) \longrightarrow \sigma_0^{(i)} = \exp(\varphi_0^{(i)})$, $\mu_0^{(i)} \sim \mathcal{N}(m_\mu, P_\mu)$, where $\mathcal{U}(.)$ denotes uniform distribution and $\mathbf{m}$ and $\mathbf{P}$ represent the mean and covariance matrices of Gaussian distributions. ($\mathbf{P}_\phi$ is a diagonal matrix whereas P_φ and P_μ are positive scalars.)

For $t = 1$ *to* T *(*T *denotes the data length)*

2. State transitions

Calculate the variance of each AR coefficient:

$$\operatorname{var}\bigl(\phi_{t-1}(k)\bigr) = \frac{1}{N}\sum_{i=1}^{N}\left(\phi_{t-1}^{(i)}(k) - \frac{1}{N}\sum_{n=1}^{N}\phi_{t-1}^{(n)}(k)\right)^2, \quad k = 1,\ldots,K.$$

Calculate the time-varying variances of the state-transition density and form $\boldsymbol{\Sigma}_{\mathbf{v}_t}$ matrix using (12):

$$\sigma_{k,t}^2 = \left(\frac{1}{\xi} - 1\right)\operatorname{var}\bigl(\phi_{t-1}(k)\bigr), \quad k = 1,\ldots,K,$$

$$\sigma_{\alpha,t}^2 = \text{constant}, \qquad \sigma_{\gamma,t}^2 = \text{constant}, \qquad \sigma_{\beta,t}^2 = \text{constant}, \qquad \sigma_{\mu,t}^2 = \text{constant}.$$

Draw new particles for each state variable by using the proposed state-transition equation:

$$\begin{aligned}
\boldsymbol{\phi}_t &= \boldsymbol{\phi}_{t-1} + \mathbf{v}_{\theta_t},\\
\alpha_t &= \alpha_{t-1} + v_{\alpha_t},\\
\varphi_t &= \varphi_{t-1} + v_{\varphi_t},\\
\beta_t &= \beta_{t-1} + v_{\beta_t},\\
\mu_t &= \mu_{t-1} + v_{\mu_t},\\
\boldsymbol{\theta}_t^{(i)} &\sim \mathcal{N}\bigl(\boldsymbol{\theta}_{t-1}^{(i)}, \boldsymbol{\Sigma}_{\mathbf{v}_t}\bigr), \quad \text{for } i = 1,\ldots,N,
\end{aligned}$$

where the following condition must be satisfied during the transition of states, namely α_t and β_t:

$$p(\alpha_t \mid \alpha_{t-1}) = \mathcal{N}\bigl(\alpha_{t-1}, \sigma_{\alpha,t}^2\bigr)\mathbb{I}_{(0,2]}(\alpha_t), \qquad p(\beta_t \mid \beta_{t-1}) = \mathcal{N}\bigl(\beta_{t-1}, \sigma_{\beta,t}^2\bigr)\mathbb{I}_{[-1,1]}(\beta_t),$$

where $\mathbb{I}$ denotes the indicator function:

$$\mathbb{I}_{[a,b]}(x) = \begin{cases} 1, & \text{if } x \in [a,b];\\ 0, & \text{if } x \notin [a,b]. \end{cases}$$

3. Calculate the importance weight of each particle

$$\begin{aligned}
w_t^{(i)} \propto p\bigl(\mathbf{y}_t \mid \boldsymbol{\theta}_t^{(i)}\bigr) = \frac{1}{2\pi}\int_{-\infty}^{\infty} &\exp\bigl(j\mu_t^{(i)}\zeta - \gamma_t^{(i)}|\zeta|^{\alpha_t^{(i)}}\bigl[1 + j\beta_t^{(i)}\operatorname{sign}(\zeta)\omega\bigl(\zeta,\alpha_t^{(i)}\bigr)\bigr]\bigr)\\
&\times \exp\bigl(j\bigl(y_t - \mathbf{y}_{t-1}^T\boldsymbol{\phi}_t^{(i)}\bigr)\zeta\bigr)\,\mathrm{d}\zeta.
\end{aligned}$$

4. Normalize the weights

$$\tilde{w}_t^{(i)} = \frac{w_t^{(i)}}{\sum_{j=1}^{N} w_t^{(j)}}.$$

5. Resample

6. Go to step 2

End

End

5. Posterior Cramer–Rao lower bound

In this section, PCRLB's are estimated to provide a benchmark for the performance analysis of our methodology. These values provide lower bounds for the mean squared estimation error of each parameter. In [25,26], CRLB is obtained for a general dynamical system which is represented by the state-space equations (4) and (5). This bound is called posterior CRLB since the state dynamics is modeled with a non-zero process noise [25]. CRLB is defined by the following expression [25,26]:

$$E\big((\hat{\boldsymbol{\theta}}_{t|t}-\boldsymbol{\theta}_t)(\hat{\boldsymbol{\theta}}_{t|t}-\boldsymbol{\theta}_t)^T\big)\geqslant \mathbf{J}_t^{-1}, \tag{18}$$

where $\hat{\boldsymbol{\theta}}_{t|t}$ denotes an unbiased estimate of the state vector $\boldsymbol{\theta}_t$ which is obtained by using the measurements $Y_t = \{y_1,\ldots,y_t\}$ and the initial prior density of the states. Above, $E(.)$ denotes the expectation and $\mathbf{J}_t$ represents the Fisher information matrix, which is equal to the inverse of CRLB [26]. Fisher information matrix can be estimated recursively, as follows [25,26]:

$$\mathbf{J}_{t+1}=\mathbf{D}_t^{22}-\mathbf{D}_t^{21}\big(\mathbf{J}_t+\mathbf{D}_t^{11}\big)^{-1}\mathbf{D}_t^{12},\quad t>0, \tag{19}$$

where

$$\mathbf{D}_t^{11}=-E\big(\nabla_{\theta_t}\big(\nabla_{\theta_t}\log p(\boldsymbol{\theta}_{t+1}\mid\boldsymbol{\phi}_t)\big)^T\big), \tag{20}$$

$$\mathbf{D}_t^{21}=-E\big(\nabla_{\theta_t}\big(\nabla_{\theta_{t+1}}\log p(\boldsymbol{\theta}_{t+1}\mid\boldsymbol{\theta}_t)\big)^T\big), \tag{21}$$

$$\mathbf{D}_t^{12}=-E\big(\nabla_{\theta_{t+1}}\big(\nabla_{\theta_t}\log p(\boldsymbol{\theta}_{t+1}\mid\boldsymbol{\theta}_t)\big)^T\big)=\big(\mathbf{D}_t^{21}\big)^T, \tag{22}$$

$$\mathbf{D}_t^{22}=-E\big(\nabla_{\theta_{t+1}}\big(\nabla_{\theta_{t+1}}\log p(\boldsymbol{\theta}_{t+1}\mid\boldsymbol{\theta}_t)\big)^T\big)-E\big(\nabla_{\theta_{t+1}}\big(\nabla_{\theta_{t+1}}\log p(y_{t+1}\mid\boldsymbol{\theta}_{t+1})\big)^T\big). \tag{23}$$

In (20) through (22), expectations are taken with respect to $\boldsymbol{\theta}_t$ and $\boldsymbol{\theta}_{t+1}$, whereas in (23) they are taken with respect to $\boldsymbol{\theta}_t$, $\boldsymbol{\theta}_{t+1}$ and y_{t+1}. Above, operator ∇ is defined as follows: $\nabla_{\theta_t}=(\frac{\partial}{\partial\theta_t(1)},\ldots,\frac{\partial}{\partial\theta_t(K')})^T$. It should be noted that (20) through (22) and the first term in (23) can be easily calculated, since the state transition p.d.f. has a Gaussian distribution. The second term in (23) is calculated numerically, since the measurement process has an α-stable distribution.

6. Experiments and discussions

In this section, performance of the proposed method is demonstrated by computer simulations, where different experiments are performed with respect to the time-variation of the AR coefficients and the distribution parameters. In these experiments, 100 realizations of first order TVAR α-stable processes are synthetically generated by (9) and (10) and ensemble averaged results are illustrated showing the estimations of the AR coefficients and the distribution parameters, for each scenario. For the sake of completeness, the scenario is expressed as follows:

$$y_t=y_{t-1}^T\phi_t+n_t, \tag{24}$$

where the objective is to estimate the time waveforms of the following state variables: $\boldsymbol{\theta}_t=[\theta_1(t),\theta_2(t),\theta_3(t),\theta_4(t),\theta_5(t)]=[\phi_t,\alpha_t,\gamma_t,\beta_t,\mu_t]^T$. To measure the estimation performance numerically, the normalized mean square error (NMSE) of each state variable is also estimated by the following equation:

$$NMSE(t)=\frac{\sum_{r=1}^{R}(\hat{\theta}_{p,r}(t)-\theta_{p,r}(t))^2}{\sum_{r=1}^{R}\sum_{t=1}^{M}\theta_{p,r}^2(t)},\quad p=1,2,3,4,5;\ r=1,\ldots,100, \tag{25}$$

where $\hat{\theta}$ denotes the estimate and r represents the member index of the waveform in the ensemble of R realizations. In all experiments, M represents the length of the observed data, which is taken to be 3000. The number of particles is taken to be $N=100$ which is observed to be sufficient. Forgetting value is chosen to be $\xi=0.9$ in each experiment. State-transition drift parameters (variance values in (12)) and the details of each experiment are given in Table 2. First two experiments A1 and A2 analyze the performance of the proposed method on modeling TVAR $S\alpha S$ processes. In A1, all unknown parameters are chosen as piecewise continuous. However, in A2, dispersion parameter is taken as a sine waveform to test the performance on slowly varying parameters. Ensemble means of each unknown parameter and their corresponding NMSE values are illustrated in Fig. 1 for experiment A1 and in Fig. 2 for experiment A2. In

Table 2
Experimental scenarios: A1 and A2

A1	A2
$\phi_t = \begin{cases} 0.9, & t < M/2; \\ 0.5, & t \geqslant M/2 \end{cases}$	$\phi_t = \begin{cases} 0.9, & t < M/2; \\ 0.5, & t \geqslant M/2 \end{cases}$
$\sigma^2_{1,t} = \left(\frac{1}{\xi} - 1\right) \mathrm{var}(\phi_{t-1}(1))$	$\sigma^2_{1,t} = \left(\frac{1}{\xi} - 1\right) \mathrm{var}(\phi_{t-1}(1))$
$\alpha_t = \begin{cases} 1.5, & t < M/2; \\ 1.1, & t \geqslant M/2 \end{cases}$	$\alpha_t = \begin{cases} 1.5, & t < M/2; \\ 1.1, & t \geqslant M/2 \end{cases}$
$\sigma^2_{\alpha,t} = 5 \times 10^{-4}$	$\sigma^2_{\alpha,t} = 5 \times 10^{-4}$
$\beta_t = 0$	$\beta_t = 0$
$\gamma_t = \begin{cases} 1.5, & t < M/2; \\ 5, & t \geqslant M/2 \end{cases}$	$1.5 + \sin\left(\frac{2\pi t}{M}\right)$
$\sigma^2_{\varphi,t} = 5 \times 10^{-4}$	$\sigma^2_{\varphi,t} = 5 \times 10^{-3}$
$\mu_t = 0$	$\mu_t = 0$

Figs. 1–4, first columns illustrate the ensemble means of parameters and the second columns show their corresponding NMSE curves. In experiment B1, a TVAR skewed α-stable process, with a time varying β parameter is modeled by the proposed method; and the results are presented in Fig. 3. In experiment B2; we included an additional unknown μ parameter to the state vector to be estimated. This is the most general case where all unknown parameters of a TVAR α-stable process are modeled. Its performance analysis results are illustrated in Fig. 4. The simulations verify that successful estimates of the TVAR and distribution parameters can be obtained by the proposed method. It can be concluded that, the tracking capability of the proposed particle filtering scheme is good enough to model instantaneously and smoothly changing distribution parameters. Moreover, it is observed that the parameters are tracked with a high estimation quality.

Next, to demonstrate the efficiency of our estimators, we provide PCRLB values calculated at different parameter values. First, these are calculated for different AR coefficients given the true values of $\alpha = 1.5$, $\beta = 0$, $\gamma = 1.5$, $\mu = 0$. Next, PCRLB values are plotted for different α parameters, given the true values of $\phi = 0.9$, $\beta = 0$, $\gamma = 1.5$, $\mu = 0$. Finally, corresponding curve for the γ parameter is illustrated where $\phi = 0.9$, $\alpha = 1.5$, $\beta = 0$, $\mu = 0$ is taken. Performance of the proposed method is demonstrated by '*stars*' on the relevant figures. These stars correspond to the empirical variance values of each estimated parameter which are calculated by the results obtained in experiment A1. From Fig. 5, it is observed that the empirical results are close to their PCRLB values.

Finally, we test our proposed method on a practical application where we model earthquake data in time. In the literature, earthquake data were modeled by α-stable distributions successfully [5]. However, a batch modeling was utilized in [5] by a maximum likelihood (ML) approach and temporal information could not be modeled.

The earthquake magnitude data for this application is taken from the Southern California Seismic Network Catalog (http://www.data.scec.org) pertaining to the Northridge earthquake which happened on January 17, 1994. It was measured to be 6.7 on the Richter scale. The data we used is composed of 3000 samples which includes 1000 preceding and 2000 succeeding samples from the mainshock. In Fig. 6, magnitude data and the results of our method are illustrated. We model this earthquake data by a TVAR α-stable process and estimate its time-varying parameters. From Fig. 6a, it is observed that the 6.7 main-shock occurs at the 1162nd sample. At that point, we can observe that all α distribution parameters change suddenly. α drops suddenly, indicating that an impulsive event has occurred. (A similar drop is also observed around the 562nd sample, since an outlier close to zero is observed.) On the other hand, skewness, dispersion, and location change, too. A sudden change in the AR coefficient is also observed which indicates a variation in correlation of the process. In addition to these, a slow decay in the location parameter is observed after a sudden increase which occurs during the mainshock. We also fit a ML α-stable model [27] to the same earthquake data for comparison. We found the following point estimates for the whole data: $[\alpha, \beta, \gamma, \mu] = [1.9, 1, 0.4949, 1.9651]$. It is seen that a single point estimate is found for each parameter which characterizes the whole data. Therefore a single

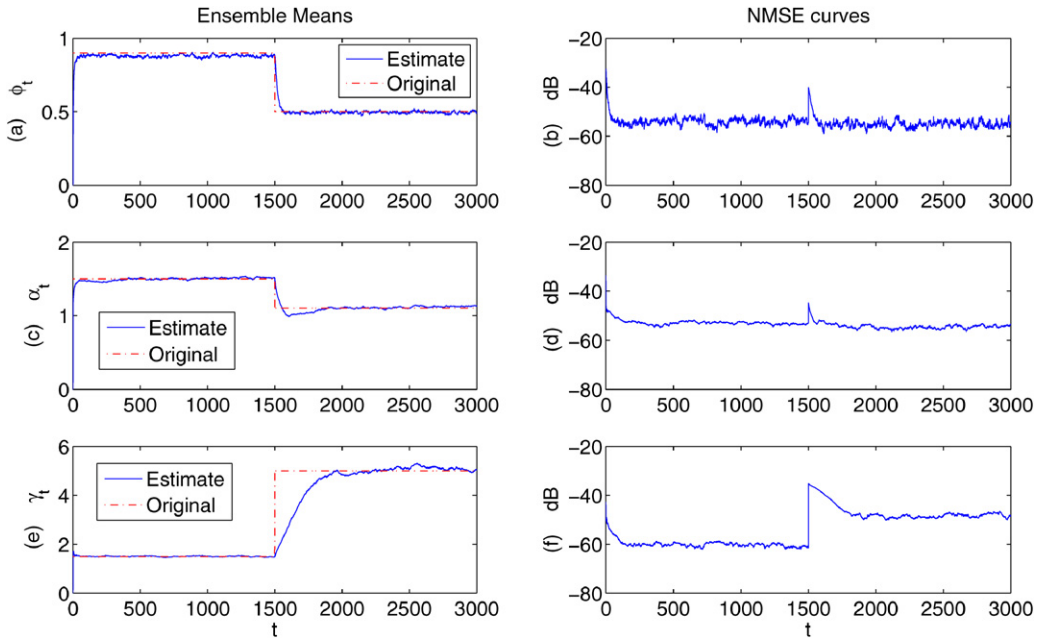

Fig. 1. Experiment A1: TVAR $S\alpha S$ process: Abrupt changes. (a) Estimation of TVAR coefficient, (b) NMSE curve of TVAR estimate, (c) estimation of the shape parameter, (d) NMSE curve of the shape parameter estimation, (e) estimation of the dispersion parameter, (f) NMSE curve of the dispersion parameter estimation.

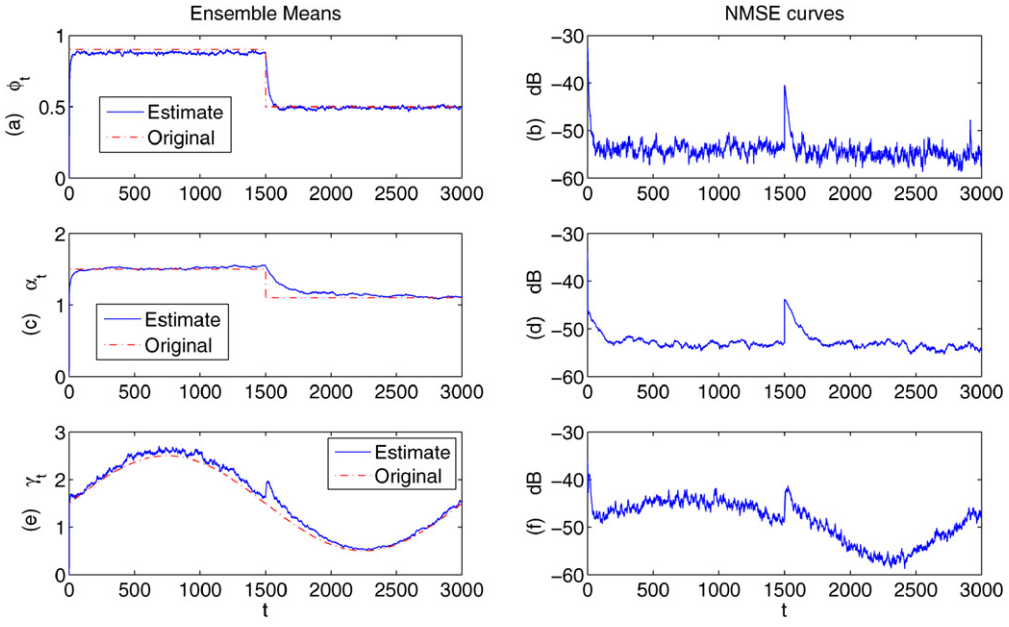

Fig. 2. Experiment A2: TVAR $S\alpha S$ process: Abrupt and smooth changes. (a) Estimation of TVAR coefficient, (b) NMSE curve of TVAR estimate, (c) estimation of the shape parameter, (d) NMSE curve of the shape parameter estimation, (e) estimation of the dispersion parameter, (f) NMSE curve of the dispersion parameter estimation.

model is fit to the whole data including a major earthquake and its aftershocks. So, we did not characterize data at each time instant.

It is known that a major earthquake is followed by a number of aftershocks in that region with a specific characteristics: The graph of the cumulative number of aftershocks at each magnitude versus that magnitude has a specific

Table 3
Experimental scenarios: B1 and B2

B1	B2
$\phi_t = \begin{cases} 0.9, & t < M/2; \\ 0.5, & t \geqslant M/2 \end{cases}$	$\phi_t = \begin{cases} 0.9, & t < M/2; \\ 0.5, & t \geqslant M/2 \end{cases}$
$\sigma^2_{1,t} = \left(\frac{1}{\xi} - 1\right) \mathrm{var}(\phi_{t-1}(1))$	$\sigma^2_{1,t} = \left(\frac{1}{\xi} - 1\right) \mathrm{var}(\phi_{t-1}(1))$
$\alpha_t = \begin{cases} 1.5, & t < M/2; \\ 1.1, & t \geqslant M/2 \end{cases}$	$\alpha_t = \begin{cases} 1.5, & t < M/2; \\ 1.1, & t \geqslant M/2 \end{cases}$
$\sigma^2_{\alpha,t} = 5 \times 10^{-4}$	$\sigma^2_{\alpha,t} = 5 \times 10^{-4}$
$\beta_t = \begin{cases} 0.5, & t < M/2; \\ -0.5, & t \geqslant M/2 \end{cases}$	$\beta_t = \begin{cases} 0.5, & t < M/2; \\ -0.5, & t \geqslant M/2 \end{cases}$
$\sigma^2_{\beta,t} = 5 \times 10^{-3}$	$\sigma^2_{\beta,t} = 5 \times 10^{-3}$
$\gamma_t = 1.5 + \sin\left(\frac{2\pi t}{M}\right)$	$\gamma_t = \begin{cases} 2, & t < M/2; \\ 1, & t \geqslant M/2 \end{cases}$
$\sigma^2_{\varphi,t} = 5 \times 10^{-3}$	$\sigma^2_{\varphi,t} = 5 \times 10^{-4}$
$\mu_t = 0$	$\mu_t = \begin{cases} 1, & t < M/2; \\ -1, & t \geqslant M/2 \end{cases}$
	$\sigma^2_{\mu,t} = 5 \times 10^{-3}$

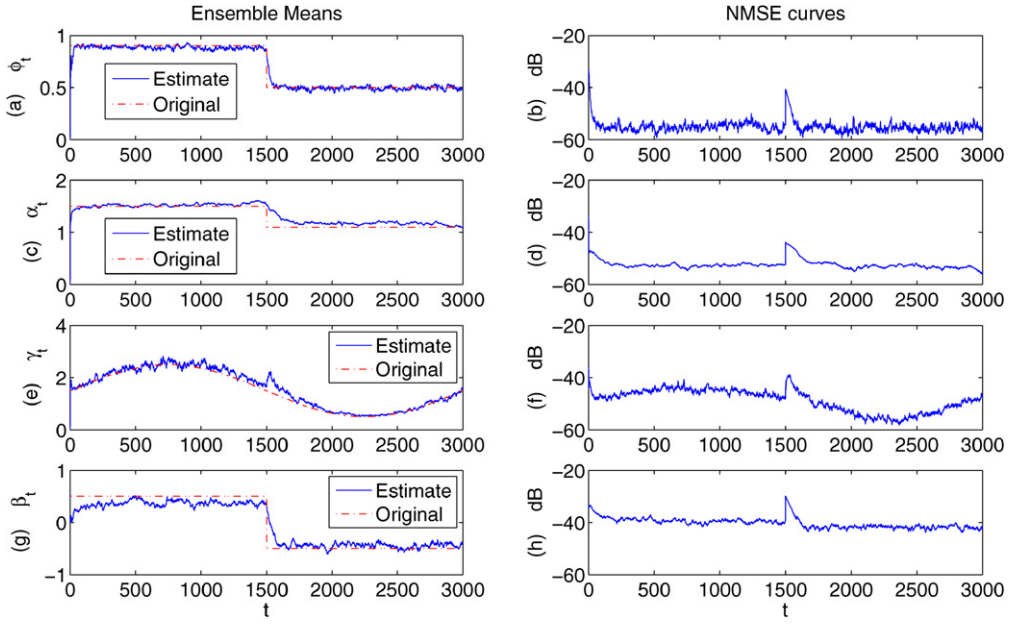

Fig. 3. Experiment B1: TVAR *Skewed* α-stable process: Abrupt and smooth changes. (a) Estimation of TVAR coefficient, (b) NMSE curve of TVAR estimate, (c) estimation of the shape parameter, (d) NMSE curve of the shape parameter estimation, (e) estimation of the dispersion parameter, (f) NMSE curve of the dispersion parameter estimation, (g) estimation of the skewness parameter, (h) NMSE curve of the skewness parameter estimation.

slope [28]. To justify the correctness of our model estimation, we make use of this property of earthquakes. First we plot this graph for the original 2000 aftershocks. Then we reconstruct the earthquake magnitude data with the estimated parameters and plot the graph with the reconstructed data. The result is illustrated in Fig. 7, showing that they have almost the same characteristics.

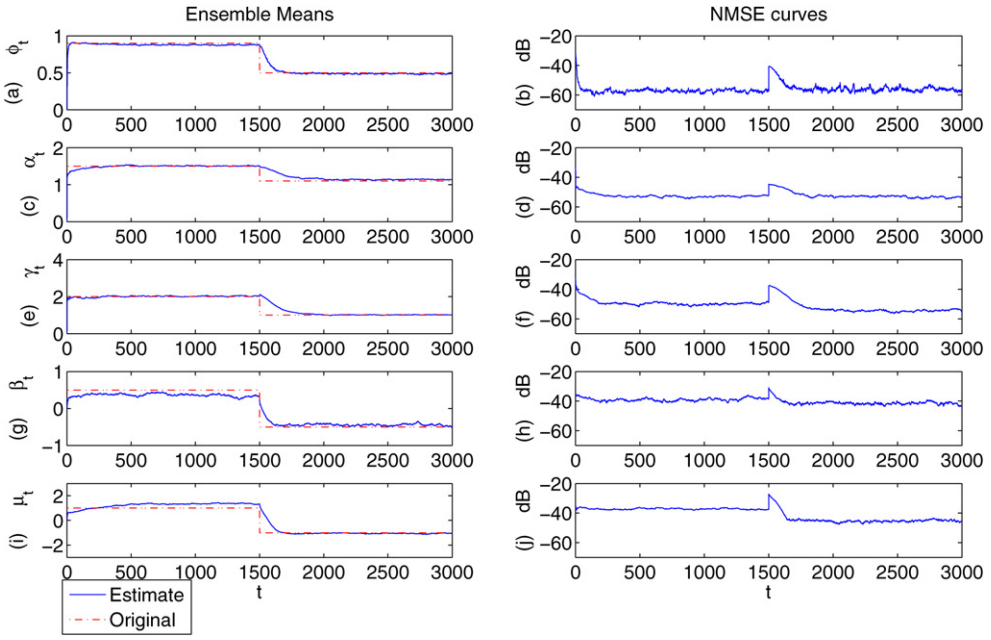

Fig. 4. Experiment B2: TVAR *Skewed* α-stable process: Location parameter is also estimated. (a) Estimation of TVAR coefficient, (b) NMSE curve of TVAR estimate, (c) estimation of the shape parameter, (d) NMSE curve of the shape parameter estimation, (e) estimation of the dispersion parameter, (f) NMSE curve of the dispersion parameter estimation, (g) estimation of the skewness parameter, (h) NMSE curve of the skewness parameter estimation, (i) estimation of the location parameter, (j) NMSE curve of the location parameter estimation.

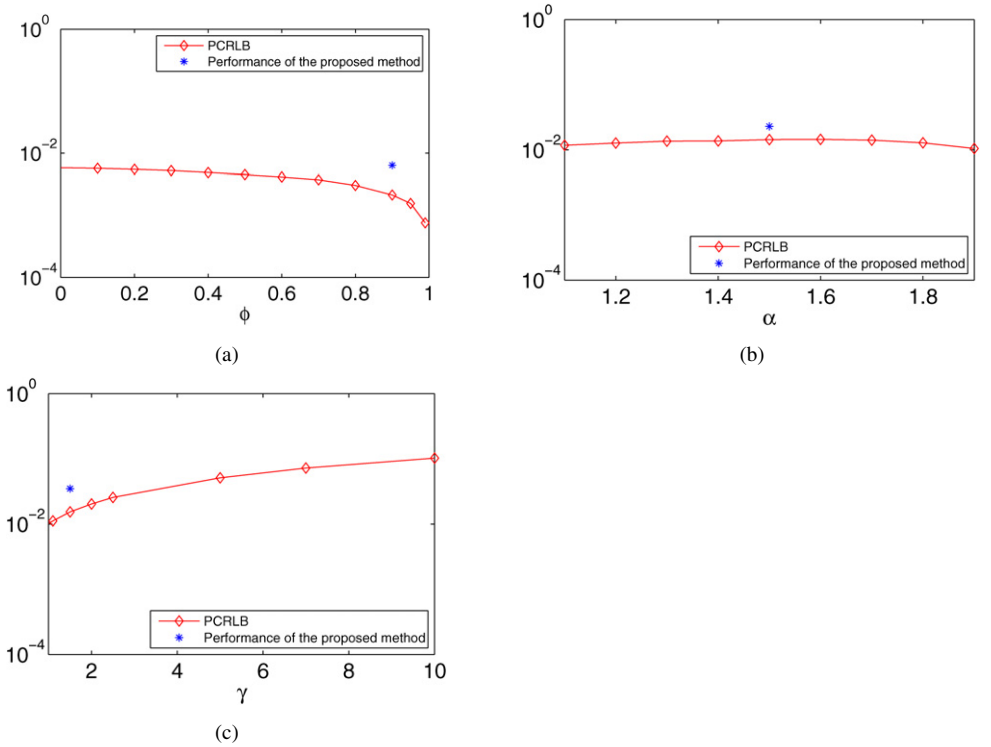

Fig. 5. PCRLB and the performance of the proposed method: (a) of AR coefficient given α and γ, (b) of α parameter given ϕ and γ, (c) of γ parameter given ϕ and α.

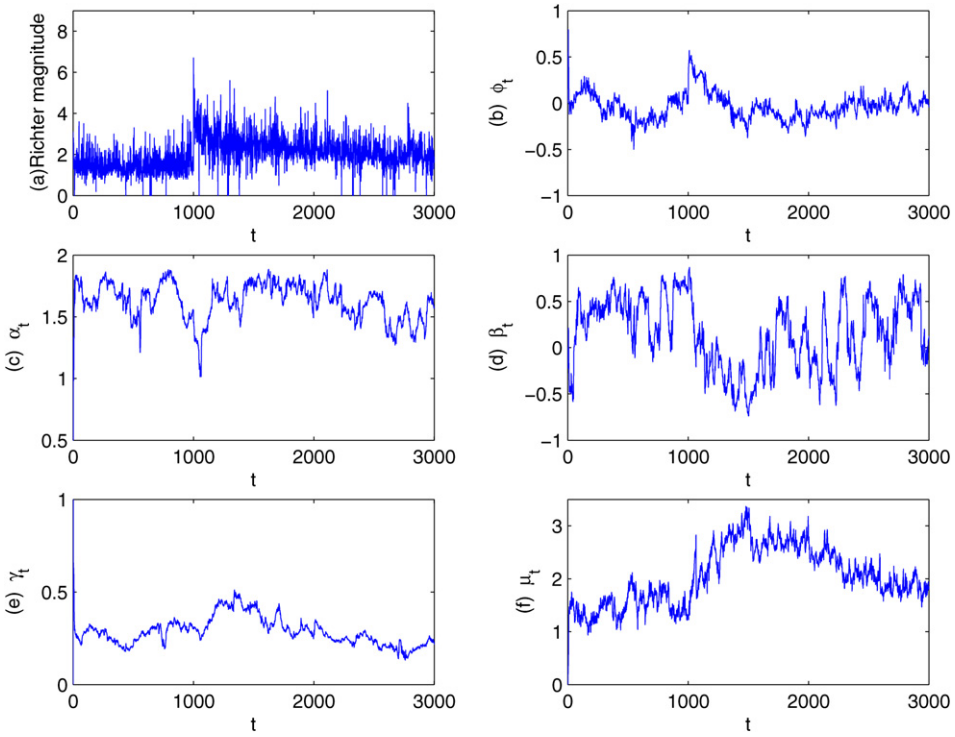

Fig. 6. Sequential Bayesian modeling of an earthquake data: (a) Richter magnitude data, (b) TVAR estimate, (c) α_t estimate, (d) β_t estimate, (e) γ_t estimate, (f) μ_t estimate.

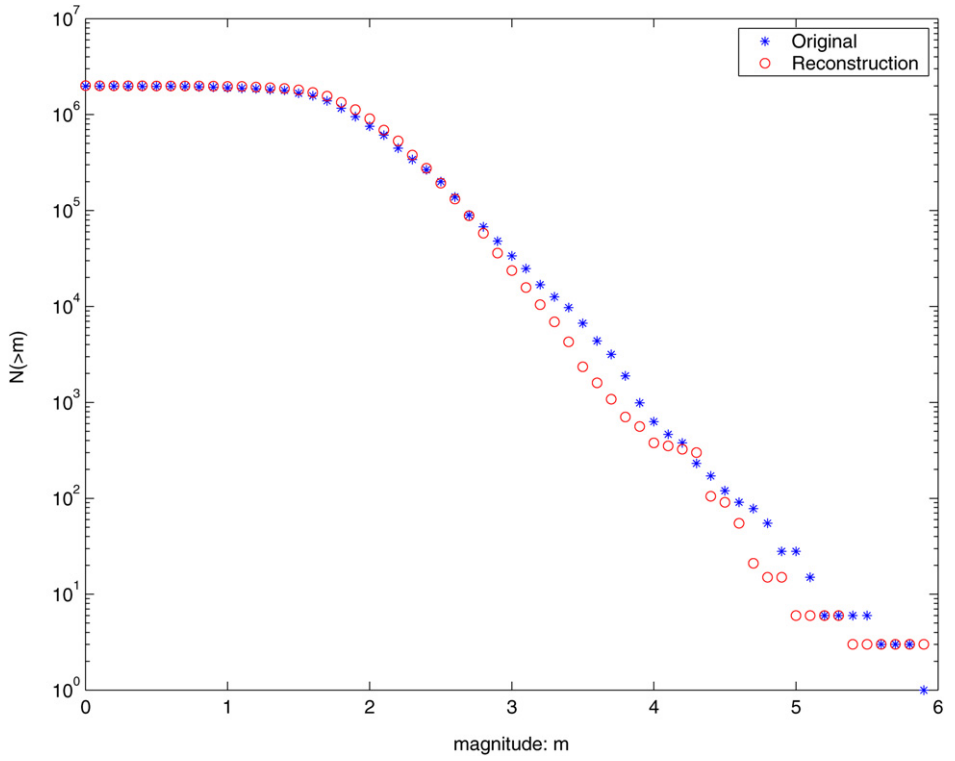

Fig. 7. Cumulative numbers of aftershocks of the Northridge earthquake with magnitudes greater than m.

7. Conclusions

In this work, a novel method is proposed to estimate jointly the TVAR coefficients and the time-varying distribution parameters of a general α-stable process by a particle filter. Skewed α-stable processes with time-varying AR and distribution parameters can also be estimated by the proposed method. The proposed algorithm is composed of a particle filter where the time-varying AR coefficients and the distribution parameters are modeled by a state vector and state-transitions are represented as a random walk model in order to approximate the optimal importance function. Empirical results are verified by PCRLB values. The successful performance of our general method is an innovative contribution in the modeling of time-varying impulsive signals, which are frequently seen in many areas, such as geophysics, teletraffic in computer communications, radar and sonar applications and mobile communications.

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