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Editorial

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In most problems of sequential signal processing, measured or received data are processed in real time. Typically, the data are modeled by state-space models with linear or nonlinear unknowns and noise sources that are assumed either Gaussian or non-Gaussian. When the models describing the data are linear and the noise is Gaussian, the optimal solution is the renowned Kalman filter. For models that deviate from linearity and Gaussianity, many different methods exist, of which the best known perhaps is the extended Kalman filter.

About a decade ago, Gordon et al. published an article on nonlinear and non-Gaussian state estimation that captured much attention of the signal processing community [1]. The article introduced a method for sequential signal processing based on Monte Carlo sampling and showed that the method may have profound potential. Not surprisingly, it has incited a great deal of research, which has contributed to making sequential signal processing by Monte Carlo methods one of the most prominent developments in statistical signal processing in the recent years.

The underlying idea of the method is the approximation of posterior densities by discrete random measures. The measures are composed of samples from the states of the unknowns and of weights associated with the samples. The samples are usually referred to as particles, and the process of updating the random measures with the arrival of new data as particle filtering. One may view particle filtering as exploration of the space of unknowns with random grids whose nodes are the particles. With the acquisition of new data, the random grids evolve and their nodes are assigned weights to approximate optimally the desired densities. The assignment of new weights is carried out recursively and is based on Bayesian importance sampling theory.

The beginnings of particle filtering can be traced back to the late 1940s and early 1950s, which were followed in the last fifty years with sporadic outbreaks of intense activity [2]. Although its implementation is computationally intensive, the widespread availability of fast computers and the amenability of the particle filtering methods for parallel implementation make them very attractive for solving difficult signal processing problems.

The papers of the special issue may be arranged into four groups, that is, papers on (1) general theory, (2) applications of particle filtering to target tracking, (3) applications of particle filtering to communications, and (4) applications of particle filtering to speech and music processing. In this issue, we do not have tutorials on particle filtering, and instead, we refer the reader to some recent references [3, 4, 5, 6].

General theory

In the first paper, "Global sampling for sequential filtering over discrete state space," Cheung-Mon-Chan and Moulines study conditionally Gaussian linear state-space models, which, when conditioned on a set of indicator variables taking values in a finite set, become linear and Gaussian. In this paper, the authors propose a global sampling algorithm for such filters and compare them with other state-of-the-art implementations.

Guo et al. in "Multilevel mixture Kalman filter" propose a new Monte Carlo sampling scheme for implementing the mixture Kalman filter. The authors use a multilevel structure of the space for the indicator variables and draw samples in a multilevel fashion. They begin with sampling from the highest-level space and follow up by drawing samples from associate subspaces from lower-level spaces. They demonstrate the method on examples from wireless communication.

In the third paper, "Resampling algorithms for particle filters: A computational complexity perspective," Bolić et al. propose and analyze new resampling algorithms for particle filters that are suitable for real-time implementation. By decreasing the number of operations and memory access, the algorithms reduce the complexity of both hardware and DSP realization. The performance of the algorithms is evaluated on particle filters applied to bearings-only tracking and joint detection and estimation in wireless communications.

In "A new class of particle filters for random dynamic systems with unknown statistics," Míguez et al. propose a new class of particle filtering methods that do not assume explicit mathematical forms of the probability distributions of the noise in the system. This implies simpler, more robust, and more flexible particle filters than the standard particle filters. The performance of these filters is shown on autonomous positioning of a vehicle in a 2-dimensional space.

Finally, in "A particle filtering approach to change detection for nonlinear systems," Azimi-Sadjadi and Krishnaprasad present a particle filtering method for change detection in stochastic systems with nonlinear dynamics based on a statistic that allows for recursive computation of likelihood ratios. They use the method in an Inertial Navigation System/Global Positioning System application.

Applications in communications

In "Particle filtering for joint symbol and code delay estimation in DS spread spectrum systems in multipath environment," Punskaya et al. develop receivers based on several algorithms that involve both deterministic and randomized schemes. They test their method against other deterministic and stochastic procedures by means of extensive simulations.

In the second paper, "Particle filtering equalization method for a satellite communication channel," Sénécal et al. propose a particle filtering method for inline and blind equalization of satellite communication channels and restoration of the transmitted messages. The performance of the algorithms is presented by bit error rates as functions of signal-to-noise ratio.

Bertozzi et al. in "Channel tracking using particle filtering in unresolvable multipath environments," propose a new timing error detector for timing tracking loops of Rake receivers in spread spectrum systems. In their scheme, the delays of each path of the frequency-selective channels are estimated jointly. Their simulation results demonstrate that the proposed scheme has better performance than the one based on conventional early-late gate detectors in indoor scenarios.

Applications to target tracking

In "Joint tracking of manoeuvring targets and classification of their manoeuvrability," by Maskell, semi-Markov models are used to describe the behavior of maneuvering targets. The author proposes an architecture that allows particle filters to be robust and efficient when they jointly track and classify targets. He also shows that with his approach, one can classify targets on the basis of their maneuverability.

In the other paper, "Bearings-only tracking of manoeuvring targets using particle filters," Arulampalam et al. investigate the problem of bearings-only tracking of maneuvering targets. They formulate the problem in the framework of a multiple-model tracking problem in jump Markov systems and propose three different particle filters. They conduct extensive simulations and show that their filters outperform the trackers based on standard interacting multiple models.

Applications to speech and music

In "Time-varying noise estimation for speech enhancement and recognition using sequential Monte Carlo method," Yao and Lee develop particle filters for sequential estimation of time-varying mean vectors of noise power in the log-spectral domain, where the noise parameters evolve according to a random walk model. The authors demonstrate the performance of the proposed filters in automated speech recognition and speech enhancement, respectively.

Hainsworth and Macleod in "Particle filtering applied to musical tempo tracking" aim at estimating the time-varying tempo process in musical audio analysis. They present two algorithms for generic beat tracking that can be used across a variety of musical styles. The authors have tested the algorithms on a large database and have discussed existing problems and directions for further improvement of the current methods.

In summary, this special issue provides some interesting theoretical developments in particle filtering theory and novel applications in communications, tracking, and speech/music signal processing. We hope that these papers will not only be of immediate use to practitioners and theoreticians but will also instigate further development in the field. Lastly, we thank the authors for their contributions and the reviewers for their valuable comments and criticism.

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Petar M. Djurić received his B.S. and M.S. degrees in electrical engineering from the University of Belgrade in 1981 and 1986, respectively, and his Ph.D. degree in electrical engineering from the University of Rhode Island in 1990. From 1981 to 1986, he was a Research Associate with the Institute of Nuclear Sciences, Vinca, Belgrade. Since 1990, he has been with Stony Brook University, where he is a Professor in the Department of Electrical and Computer Engineering. He works in the area of statistical signal processing, and his primary interests are in the theory of modeling, detection, estimation, and time series analysis and its application to a wide variety of disciplines including wireless communications and biomedicine.

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Arnaud Doucet was born in France on the 2nd of November 1970. He graduated from Institut National des Telecommunications in June 1993 and obtained his Ph.D. degree from Université Paris-Sud Orsay in December 1997. From January 1998 to February 2001 he was a research associate in Cambridge University. From March 2001 to August 2002, he was a Senior Lecturer in the Department of Electrical Engineering, Melbourne University, Australia. Since September 2002, he has been a University Lecturer in information engineering at Cambridge University. His research interests include simulation-based methods and their applications to Bayesian statistics and control.