

application considered basically provides an illustration of how the above-mentioned nonlinear filtering techniques work in the temporal case. It would be very interesting to illustrate their performance with a more complex model involving spatial-temporal interaction. For example, in the context (C2) considered, the incorporation of the spatial-temporal interaction between weapons to the state model for the definition of the damage potential and the danger field would be of interest. In the definition of the observation model, an interesting extension would be to consider the optimum design of the placement of observation devices, possibly moving over time, jointly with the time sampling frequency.

In our opinion, some interpretations derived from the application, which are used to establish the conclusion in the paper on the outperformance of UPF, are not strongly supported by the results obtained. For instance, one can see that UPF-based estimates of position (see Figure 4) and danger (see Figures 7 and 8) are sometimes better, sometimes worse than EKF-based or UKF-based estimates. Furthermore, we cannot agree with the appreciation on the UPF-based estimates being advantageous for ‘showing evidence of danger earlier’, since by the same way of thinking one would be led to say that 1 minute sampling gives better results than 1/4 minute sampling (see Figure 9), which would be paradoxical. Further clarifications on these aspects would be appreciated.

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We congratulate the authors for an excellent review of some Sequential Monte Carlo (SMC) algorithms for nonlinear filtering and a very interesting application using SMC. It has been shown that SMC is a powerful tool in handling nonlinear and non-Gaussian dynamic systems. This paper provides another evidence in this regard. Here we would like to make one general comment and discuss two issues, one general and one specific.

SIS versus MCMC: It is commonly believed that SMC and its variations are just cheap (and inferior) alternatives to the more computationally demanding MCMC procedures. This is true to a certain extent, especially

for a class of the state-space models. However, the extreme flexibility of SMC methods sometimes make them the primary choices for certain problems, with efficiencies far exceeding that of the standard MCMC procedure. Two dramatic examples in this direction are the counting and inference of zero-one tables with fixed margins (Liu (2001, §3.4.2 and §4.3)) and the simulation of long-chain polymers (Zhang and Liu (2002)). These examples demonstrate that innovative SIS designs can outperform most MCMC schemes in certain difficult problems where the involved variables (or part of which) are highly correlated (or interlocked). It has also been shown that using MCMC steps in SMC and, conversely, using SMC in MCMC can be beneficial (Liu (2001)).

The use of the current observation Z_t : The authors advocate the use of information in the current observation Z_t to construct the sampling distribution, first proposed by Liu and Chen (1998). In UPF, significant amount of computational resources are devoted to achieve this, using the scaled unscented transformation. It should be noted that the efficiency of SMC is not solely measured by the variance of the weights. The amount of computation is also an important issue. A good measure should be the accuracy of the final estimate given the same amount of computational time. For example, if UPF uses 10 times of computation as a simple particle filter (SPF) that uses only the state equation, then one should compare the accuracy of the final estimate between a UPF using m samples and a SPF using $10m$ samples. The key here is actually how much information the current observation Z_t brings in. Let us examine two extreme situations: (1) If the observation noise is very large, then there is virtually no benefit to include Z_t in the sampling. In this case, a SPF with 10 times more samples would probably work better. (2) If the observation noise is very small, or the state equation is not adequate (e.g. one sample per 3 minutes for the battle field example), then Z_t becomes very important. In fact, in this case one can do the complete opposite of the SPF – using only the observation equation for sampling and the state equation for updating the weight. One way of doing this is to generate $Z_t^{(j)} = Z_t + e_t^{(j)}$ and construct $X_t^{(j)}$ by inverting the observation equation using $Z_t^{(j)}$, if it is not too difficult. Procedures such as UPF may show significant benefit when the information from both the observation equation and the state equation are comparable.

The Movement Model: The movement model used in the example does not have a maneuvering component. A very simple multilevel model (e.g. Bar-Shalom and Fortmann (1988, p. 125–127), Chen and Liu (2000)) can be very useful in cases like this. Figure 3 in the paper shows that the current system has some difficulties tracking the target after a maneuvering at the pathway. It may be partially due to the fact that the filter “trusts” the movement model more than the observation model (due to the relatively large observation measurement error), even at the time the movement model is not true. With a multilevel model which assumes several levels of uncertainty in the movement model, the filter may be able to detect persistent one-sided deviations between the estimated states and the observations, hence engage a maneuvering mode to increase the uncertainty in the movement model. Then the filter will weight more on the observations and allows to track the maneuvering better.

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Irwin, Cressie and Johannesson (ICJ) have provided an interesting review of several generalizations of the Kalman-filter algorithm for nonlinear problems. ICJ compare the performance of two recent methods of filtering, Unscented Particle filter (UPF) and Unscented Kalman filter (UKF) to the traditional Extended Kalman filter (EKF) in a Command and Control (C2) setting. This article is Bayesian in the sense that the main focus is on currently updated posterior distributions.

I certainly agree that the Bayesian perspective on the Kalman filter is the most natural way of viewing this sequential estimation procedure that predicts the dynamically changing configuration of objects in a C2 setting. My specific comments are of two types: First, regarding the movement model in the C2 setting presented by the authors, and secondly regarding the estimation of relevant parameters. I present here an alternative model of the the movement and suggest a different danger potential. In the illustration to the C2 setting that ICJ present, the state parameters are fixed and treated as known. I suggest here a procedure to estimate parameters and take into account the uncertainty about these parameters in the subsequent prediction.