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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSI*net*

Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

An Adaptive UKF Algorithm for Single Observer Passive Location in Non-Gaussian Environment

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Abstract: An adaptive Unscented Kalman Filter (UKF) for nonlinear stochastic systems is proposed and it is applied to the single observer passive location in Non-Gaussian environment. A Spherical Simplex Unscented Transformation (SSUT) is used to reduce the calculation requirement. In order to improve the filtering effect, an adaptive iterating estimation strategy is introduced to modify the gain of the algorithm update and the error covariance of the filtering is replaced by the square root of the error covariance to ensure numerical stability. The Monte Carlo simulation results show that, based on the glint noise statistical mode 1, the new algorithm has faster convergence, higher stability and accuracy.

Key words: Unscented Kalman filter, spherical simplex unscented transformation, adaptive iteration, single observer passive location, glint noise

INTRODUCTION

With the development of information war, the active radar is threatened strongly for its defects, such as bad abilities of anti-reconnaissance and anti-interference. By contrast, passive detection system has long ranging, high concealing and survival ability, due to not emitting electromagnetic wave (Sun and Guo, 2008). In fact, the key of single observer passive localization is the typical nonlinear filtering. Traditional EKF (Extended Kalman Filter) method and its derivative algorithms performed low calculation precision and significant ill-posed feature which lead to bad stability and divergence of filter in strong nonlinear conditions (Tawfeig *et al.*, 2011). However, UKF produces several sigma points which are gotten by the Unscented Transformation (UT) and deal them with nonlinear transformation (Chouraqui and Benyettou, 2009). It can avoid the issues which are introduced by the linearization process of extended Kalman filter, while its performance is superior to EKF (Juliers and Uhlmann, 2004; Hassanzadeh and Fallah, 2008). But in the system of single observer passive localization, classic UKF algorithm is effected by the rounding error of calculator, weak observability and large observational noise, which lead to the problem of poor stability, slow convergence speed and low precision. Therefore, SRUKF (square root unscented Kalman filtering) is put forward under this great background in some references and its performance is superior to the

ordinary UKF (Juliers and Uhlmann, 2004). However, the above algorithms can only be used in the environment with Gaussian noise (Kaawaase *et al.*, 2011). Due to scattering characteristic of target, Radar observation noise is not the only white Gaussian noise, but regularly glint noise with “the long tail” under the actual condition (Hu *et al.*, 2004; Zhu, 2007). To solve the problem, this study focuses on the method of moment matching, combined with SSUT (Yong *et al.*, 2010), principle of adaptive iteration (Zhan and Wan, 2007; Barzamini *et al.*, 2009; Xinchao *et al.*, 2011) and square root filter, a unite algorithm of SISRUUKF (Simplified Iteration Square Root Unscented Kalman filter) is proposed (Farivar *et al.*, 2009; Tong *et al.*, 2007), this new method is more effective in approximating the state estimation and evidently decreases calculational amount, finally provides an effective way to solve the filtering problem under Non-Gaussian situation.

PRINCIPLE AND PROCESS

Locating model: Locating and tracking of the target are always in certain coordinate system (Yedjour *et al.*, 2011), a two-dimensional model was built with observation point as the origin of coordinate, meanwhile, radiation signal reaching direction Angle, Angle variation, Doppler frequency variation and Doppler frequency were used as observational parameters. As shown in the first diagram $\mathbf{x}_k = [x_k \ y_k \ \dot{x}_k \ \dot{y}_k]$ is the state vectors of target at k point

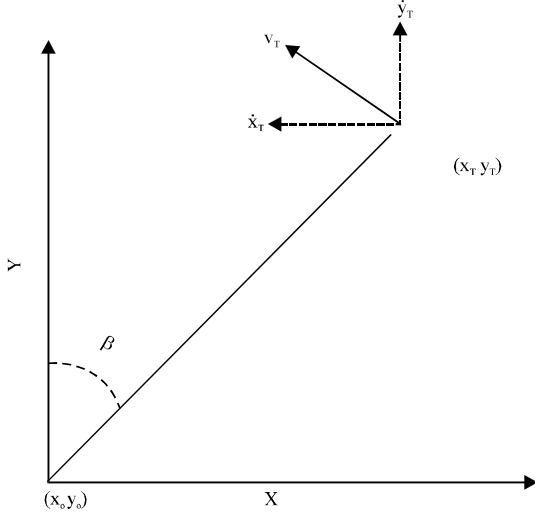


Fig. 1: Geometrical relation between observer and target in 2-D plane

in time and β is the azimuth. Figure 1 showed Geometrical relation between observer and target in 2-D plane.

Then, state equation and observed equation of positioning system can be established accordingly:

$$X_{k+1} = F_k X_k + B_k W_k = f(X_k, W_k) \quad (1)$$

$$Z_{mk} = h(X_k) + V_k = [\beta_k \quad \dot{\beta}_k \quad f_{dk} \quad \dot{f}_{dk}] + V_k \quad (2)$$

where:

$$F_k = \begin{bmatrix} I_2 & TI_2 \\ 0 & I_2 \end{bmatrix}$$

and:

$$B_k = \begin{bmatrix} T^2 I_2 / 2 \\ I_2 \end{bmatrix}$$

denote state and noise transition matrixes, I_3 is 3-D unit matrix. T is measurement period. W_k is the state noise. V_k is measurement noise. Given V_k and W_k irrelevantly. It means:

$$\begin{cases} E[W_k W_j^T] = \delta_{kj} Q_k \\ E[V_k V_j^T] = \delta_{kj} R_k \end{cases} \quad (3)$$

Based on the theory of kinematics, we get formulas as follows:

$$\beta_k = \arctan(x'_k / y'_k) \quad (4)$$

$$\dot{\beta}_k = \frac{(y'_k \dot{x}'_k - x'_k \dot{y}'_k)}{(x_k'^2 + y_k'^2)} \quad (5)$$

when observation point and target have relative radial velocity, Doppler frequency is obtained by observation station. Assuming target signal frequency is constant, there is:

$$f = f_T + f_d \quad (6)$$

where, f denotes the received signal frequency of observation station, f_T and f_d are frequency of target radiation and Doppler frequency (Gong, 2004). The expression is:

$$f_{dk} = -\frac{f_T}{c} (\dot{x}_k \sin \beta_k + \dot{y}_k \cos \beta_k) \quad (7)$$

Where, c is the speed of electromagnetic wave, the expression of Doppler frequency variation is:

$$\dot{f}_{dk} = -\frac{f_T}{c} [\ddot{x}_k \sin \beta_k + \ddot{y}_k \cos \beta_k + \dot{r}_k (\beta_k)^2] \quad (8)$$

Spherical simple unscented transformation (SSUT):

Computation efficiency of UKF algorithm depends on the number of sampling points in UT. For n-D random vector, the classic UT needs $2n+1$ sampling points and calculated amount is increased with the increase of the dimension of vector. SSUT has a good performance in approximating the probability distribution of the state by $n+1$ points with equal weight values. These points distribute in the hypersphere with the mean of random state as the centre. Then, $n+2$ sampling points of UT are composed of $n+1$ sampling points of hyperspheres distribution and the state mean-value point (Liu *et al.*, 2010). The selection procedure of SSUT is as follows:

Step 1: Given weight value w_0 and $0 \leq w_0 \leq 1$

Step 2: Set weight value w_i :

$$w_i = (1 - w_0) / (n + 1), i = 1, \dots, n+1 \quad (9)$$

Step 3: Initialization of vector sequences:

$$e_0^1 = [0], e_i^1 = [-1 / \sqrt{2w_i}], e_i^2 = [1 / \sqrt{2w_i}] \quad (10)$$

Step 4: Extend the vector sequences ($j = 2, \dots, n$):

$$e_i^j = \begin{cases} \begin{bmatrix} e_0^{j-1} \\ 0 \end{bmatrix}, & i = 0; \\ \begin{bmatrix} e_i^{j-1} \\ -1 / \sqrt{j(j+1)w_j} \end{bmatrix}, & i = 1, \dots, j; \\ \begin{bmatrix} 0^{j-1} \\ j / \sqrt{j(j+1)w_j} \end{bmatrix}, & i = j+1. \end{cases} \quad (11)$$

where, e_i^j denote the j dimension random variables at i sampling point. 0^j is zero vector of j dimensions.

For N dimensions random variables, with the mean \hat{x} and mean-square deviation P_{xx} , sampling points of hyperspheres distribution can be obtained by:

$$x_i^n = \hat{x} + \sqrt{P_{xx}} e_i^n, \quad i = 0, 1, \dots, n+1. \quad (12)$$

SSUT with $n+2$ sampling points takes the place of the classic UT with $2n+1$ sampling points. It can reduce nearly the half of the sampling points and greatly lessen the amount of calculation system.

SRUKF algorithm: Considering the robustness of the nonlinear filter, a square root version of the UKF was introduced, SSRUKF replaces the covariance matrix with the square root of the covariance matrix in recursive operation and it can avoid the trouble of negative definite covariance matrix.

The procedure for implementing the SSRUKF can be summarized as follows:

Step 1: Initialization:

$$\hat{x}_0 = E[x_0] \quad (13)$$

$$S_0 = \text{chol}\{E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T]\} \quad (14)$$

Step 2: Sampling points calculation:

$$x_i(k-1) = x(k-1) + S(k-1)e_i^n \quad i = 0, 1, \dots, n+1 \quad (15)$$

where, e_i^n denotes vector sequences of SSUT

Step 3: Time update:

$$x_i(k/k-1) = f(x(k-1)) \quad i = 0, 1, \dots, n+1 \quad (16)$$

$$\hat{X}(k) = \sum_{i=0}^{n+1} w_i x_i(k/k-1) \quad (17)$$

$$S(k/k-1) = \text{qr}\{\sqrt{w_i}(x_{i,n+1}(k/k-1) - \hat{X}(k)), \sqrt{Q(k)}\} \quad (18)$$

$$S(k/k-1) = \text{chol}\{S(k/k-1), x_0(k/k-1) - \hat{X}(k), w_0\} \quad (19)$$

$$y(k/k-1) = h(x(k/k-1)) \quad (20)$$

$$\hat{y}(k) = \sum_{i=0}^{n+1} w_i y_i(k/k-1) \quad (21)$$

Step 4: Measurement update:

$$S_y(k) = \text{qr}\{[\sqrt{w_i}(y_{i,n+1}(k/k-1) - \hat{y}(k)), \sqrt{R(k)}]\} \quad (22)$$

$$S_y(k) = \text{chol}\{S_y(k), y_0(k/k-1) - \hat{y}(k), w_0\} \quad (23)$$

$$P_{xy}(k) = \sum_{i=0}^{n+1} w_i [x_i(k/k-1) - \hat{X}(k)][y_i(k/k-1) - \hat{y}(k)]^T \quad (24)$$

$$\rho(k) = (P_{xy}(k) / S_y^T(k)) / S_y(k) \quad (25)$$

$$\hat{x}(k) = \hat{x}(k/k-1) + \rho(k)(y(k) - \hat{y}(k/k-1)) \quad (26)$$

$$U = \rho(k)S_y(k) \quad (27)$$

$$S(k) = \text{chol}\{S(k/k-1), U, -1\} \quad (28)$$

where, Q^w denotes the state noise variance of system R^v is the measurement noise variance of system qr means QR decomposition chol means Cholesky first-order update (Van der Merwe and Wan, 2001).

SISRUKF: In order to enhance the stability, convergence and precision of the algorithm, adaptive iterative method was introduced into SISRUKF algorithm. When observation information has been obtained, estimate value and prediction covariance are used to resample. Then, SSUT recalculate around the state estimation. Finally, the state estimation is updated by observed values and the performance of the filter is improved (Gui *et al.*, 2009; Gao *et al.*, 2008). The process of SISRUKF algorithm are expressed as follows:

Step 1: At k time, state estimation and covariance can be calculated via the formula 13~28.

Step 2: Resampling:

$$\hat{x}_0(k) = \hat{x}(k/k-1), S_0(k) = S(k/k-1) \quad (29)$$

$$\hat{x}_1(k) = \hat{x}(k/k-1), S_1(k) = S(k/k-1) \quad (30)$$

$$x_{i,d}(k-1) = x(k-1) + S(k-1)e_i^n \quad i = 0, 1, \dots, n+1 \quad (31)$$

where, d is the iteration time.

Step 3: Set the adaptive factor:

$$\eta(k) = (\hat{y}(k) - y(k))^T (\hat{y}(k) - y(k)) / \text{tr}[S_y(k)^T S_y(k)] \quad (32)$$

$$\mu(k) = \begin{cases} 1, & \eta(k) \leq \theta \\ \theta / \eta(k), & \eta(k) > \theta \end{cases} \quad (33)$$

where, θ is an empirical value, which is always 1~2.5.

Step 4: State estimation and variance update:

$$\rho(k) = \rho(k) / \mu(k) \quad (34)$$

$$\hat{x}(k) = \hat{x}(k/k-1) + \rho(k)(y(k) - \hat{y}(k/k-1)) \quad (35)$$

$$U = \rho(k) S_y(k) \quad (36)$$

$$S(k) = \text{chol}\{S(k/k-1), U, -1\} \quad (37)$$

Step 5: Given the following equation:

$$\hat{Z}_d(k) = h(\hat{X}_d(k)) \quad (38)$$

$$\tilde{Z}_d(k) = Z(k) - \hat{Z}_d(k) \quad (39)$$

$$\tilde{X}_d(k) = \hat{X}_d(k) - \hat{X}_{d-1}(k) \quad (40)$$

Then, set this inequality:

$$\begin{aligned} & \hat{X}_d^T(k) S_{y,d}^T(k) S_{y,d}(k) \hat{X}_d(k) + \hat{Z}_d^T(k) R^{-1}(k) \hat{Z}_d(k) \\ & < \tilde{Z}_d^T(k) R^{-1}(k) \tilde{Z}_d(k) \end{aligned} \quad (41)$$

If inequality (41) is workable, back to step 2 again;

Or else, return to the following values:

$$\begin{cases} \hat{X}(k) = \hat{X}_d(k) \\ S(k) = \hat{S}_d(k) \end{cases} \quad (42)$$

where, $\hat{x}(k)$ and $S(k)$ are state measure estimate and the square root of covariance after iteration updated respectively (Zhao *et al.*, 2011).

THE SIMULATION EXPERIMENT

Glnt noise environment: Glnt noise is a typical Non-Gaussian noise in actual application. Glnt noise distribution has a “long tail” which is similar to Gaussian

shape. The model creation method of Glnt noise is achieved through weighted sum of Gaussian noise and other noise. In this paper, the glnt noise is obtained by the weighted sum of two kinds of Gaussian noise with different variances. Probability density function of glnt noise can be expressed as:

$$p(\omega) = (1 - \epsilon)N(\omega; \mu_1, p_1) + \epsilon N(\omega; \mu_2, p_2) \quad (43)$$

where, $N(\omega; \mu_1, p_1)$ is a Gaussian probability density with the mean of μ_1 and the variance of p_1 , $N(\omega; \mu_2, p_2)$ is another Gaussian probability density with the mean of μ_2 and the variance of p_2 , ϵ denotes the strength of the glnt noise which values 0.05 in this study (Zhu, 2007).

Moments matching method is introduced to deal with the glnt noise in EKF and UKF algorithms. So, the first and second order moments can be obtained as:

$$\mu = E[\omega] = (1 - \epsilon)\mu_1 + \epsilon\mu_2 \quad (44)$$

$$P = E[(\omega - \mu)(\omega - \mu)^T] = (1 - \epsilon)P_1 + \epsilon P_2 + \tilde{P} \quad (45)$$

where, $\tilde{P} = (1 - \epsilon)\mu_1\mu_2 + \epsilon\mu_2\mu_1^T - \mu\mu^T$, then, the SISRUKEF algorithm can be applied in the non-Gaussian environment (Hu *et al.*, 2004).

SIMULATION

Assume the target is at constant velocity in 2-D plane, the initial position and velocity are $[150 \text{ km } 100 \text{ km } -250 \text{ m/s } 150 \text{ m/s}]^T$. Observation station is located in the origin of the coordinate. $W_x = w_y = 1 \text{ m/s}^2$ is the system error. Three groups of different observation accuracy are as follows:

- $\sigma_a = 1 \text{ mrad}$, $\sigma_{b_1} = 0.1 \text{ mrad/s}$, $\sigma_{b_2} = 1 \text{ mrad/s}$, $\sigma_{f_d} = 0.1 \text{ mrad/s}$, $\sigma_{f_d} = 0.5 \text{ Hz/s}$, $\sigma_{f_i} = 10 \text{ Hz}$
- $\sigma_a = 5 \text{ mrad}$, $\sigma_{b_1} = 0.2 \text{ mrad/s}$, $\sigma_{b_2} = 5 \text{ mrad/s}$, $\sigma_{f_d} = 0.5 \text{ mrad/s}$, $\sigma_{f_d} = 1 \text{ Hz/s}$, $\sigma_{f_i} = 20 \text{ Hz}$
- $\sigma_a = 8 \text{ mrad}$, $\sigma_{b_1} = 0.3 \text{ mrad/s}$, $\sigma_{b_2} = 0.01 \text{ rad/s}$, $\sigma_{f_d} = 1 \text{ mrad/s}$, $\sigma_{f_d} = 2 \text{ Hz/s}$, $\sigma_{f_i} = 20 \text{ Hz}$

where, σ_a , σ_{b_1} and σ_{b_2} denote standard deviation of azimuth and their variation in glnt noise environment. EKF, UKF, SRUKF and SISRUKEF are tested separately.

In this simulation, T is sampling cycle which values 1s, N denotes the number of time which values 100, f_t denotes target signal frequency which values 10 GHz. σ_f is observation accuracy which values 1 MHz, RRE (Relative Range Error) is used as evaluation index.

$$\text{RRE} = \sqrt{\frac{(x_{\text{True}} - \hat{x})^2 + (y_{\text{True}} - \hat{y})^2 + (z_{\text{True}} - \hat{z})^2}{(x_{\text{True}}^2 + y_{\text{True}}^2 + z_{\text{True}}^2)}} \times 100\% \quad (46)$$

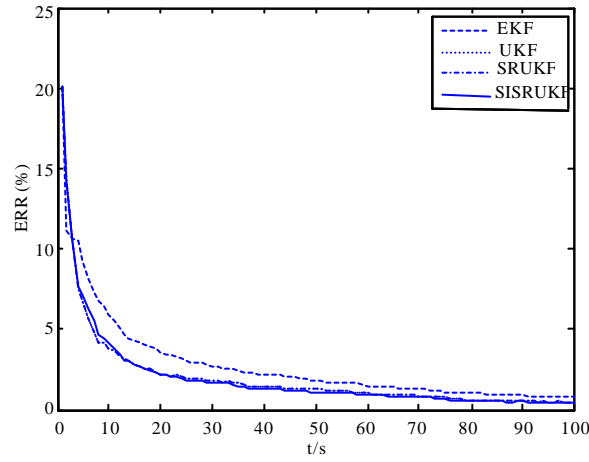


Fig. 2: Statistical average curve in observation accuracy, condition (a)

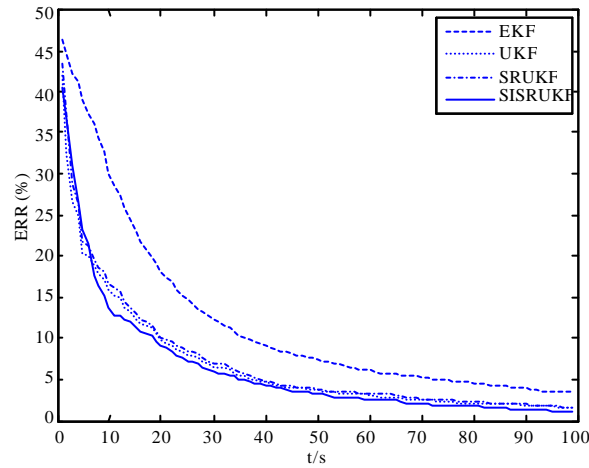


Fig. 3: Statistical average curve in observation accuracy, condition (b)

Table 1: Comparing robustness in different observation accuracy

Filtering algorithm	Single running time (msec)	Convergence times of 100 times experiments		
		In the (a) condition	In the (b) condition	In the (c) condition
EKF	8.02	100	76	57
UKF	37.93	100	87	74
SRUKF	25.85	100	88	78
SISRUKE	24.93	100	92	84

Each group do Monte Carlo experiment for 100 times, the relative error which is less than 15% is defined as convergence, positioning accuracy is the average of RRE at the tracking end time. The simulation results is showed in Table 1 and Fig. 2-4.

Table 1 gives convergence times under different observation accuracy of the four algorithms. First, in high

precision conditions, all of the algorithms have fairly good convergence. As the observation noise increases, the stability of various algorithms decreases accordingly, the stability of SISRUKE algorithm declines much more slowly than the other three. Then, in the condition of the same observation accuracy, the stability of the SISRUKE algorithm has the most convergence times than others. For reasons of SSUT and square root filtering, SISRUKE will decrease computation cost. The simulation results have proven that SISRUKE saved computing time through Table 1, compared with UKF and SRUKF.

Figure 2-4 reveal that, as the observation noise increases, the convergence speed of all filtering algorithms becomes slow, positioning accuracy and stability also decline, EKF falls the most, followed by UKF

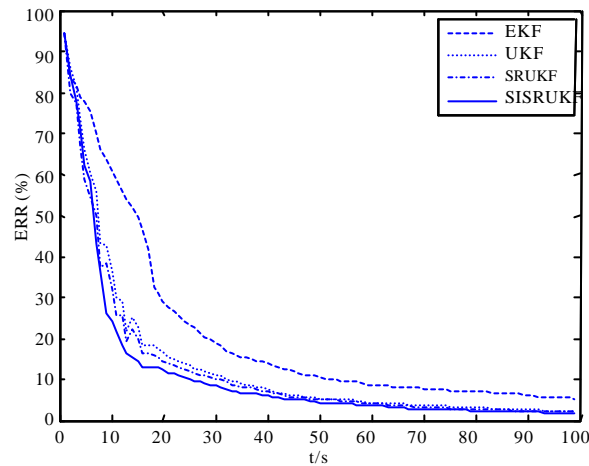


Fig. 4: Statistical average curve in observation accuracy, condition (c)

and SRUKF. However, SISRUKE algorithm has the highest positioning accuracy and the best stability. This is because SISRUKE is built based on SRUKF, the adaptive factor is used to adjust the effect of state information to SRUKF filter. Adaptive iteration method makes covariance of state parameter prediction more accurate. So, the performance of SISRUKE algorithm is superior to other algorithms.

CONCLUSION

In this study, a new adaptive simplified iterative algorithm was applied in single observer passive localization system. The method puts SSUT and adaptive iterative thought into square root filtering to improve the stability of the filter effectively. Simulation results showed that, in glint noise environment, the algorithm convergence, positioning accuracy and stability were improved compared with other similar algorithms. Therefore, the algorithm has certain directive significance in practical single observer location passive system.

REFERENCES

- Barzamini, R., A.R. Yazdizadeh, H.A. Talebi and H. Eliasi, 2009. Adaptive control of a double-electromagnet suspension system. *J. Applied Sci.*, 9: 1201-1214.
- Chouraqui, S. and M. Benyettou, 2009. Design and implementation for a non linear state filter for LEO Micro satellite. *J. Applied Sci.*, 9: 4195-4205.
- Farivar, F., M.A. Shoorehdeli, M.A. Nekoui and M. Teshnehlal, 2009. Gaussian radial basis adaptive backstepping control for a class of nonlinear systems. *J. Applied Sci.*, 9: 248-257.
- Gao, W.G., H.B. He and J.P. Chen, 2008. An adaptive UKF algorithm and its application for GPS-INS integrated navigation system. *Trans. Beijing Ins. Technol.*, 28: 505-509.
- Gong, X.Y., 2004. The study of challenge technology of single observer passive location and tracking using frequency rate and differential direction of arrival. National defense science and technology University, Changsha, pp: 10-15.
- Gui, Q.M., A.P. Xu and S.H. Han, 2009. A stepped robust and adaptive filtering and its applications in GPS kinematic navigation. *Geomatics Inf. Sci. Wu-han Uni.*, 34: 719-723.
- Hassanzadeh, I. and M.A. Fallah, 2008. Design of augmented extended and unscented Kalman filters for differential-drive mobile robots. *J. Applied Sci.*, 8: 2901-2906.
- Hu, H.T., Z.L. Jing, A.P. Li and S.Q. Hu, 2004. Particle filter based target tracking in non-Gaussian environment. *J. Shanghai Jiaotong Univ.*, 38: 1996-1999.
- Juliers, S.J. and J.K. Uhlmann, 2004. Unscented filtering and non-linear estimation. *Proceed. IEEE*, 92: 401-422.
- Kaawaase, K.S., F. Chi, J. Shuhong and Q.B. Ji, 2011. A review on selected target tracking algorithms. *Inform. Technol. J.*, 10: 691-702.
- Liu, D.P., X.C. Ma and Y. Zhu, 2010. Algorithm based on combined iterated UKF for SINS alignment. *J. Syst. Simulat.*, 22: 2404-2406.
- Sun, Z.K. and F.C. Guo, 2008. A passive location and tracking technology by single observe. *Nationan Defence Industry Press, ChangSha*, pp: 187-198.
- Tawfeig, H., S. Vijanth, Asirvadam and N. Saad, 2011. Predicting flow rate of V-shape custom tank using derivative free recursive algorithm. *J. Applied Sci.*, 11: 1279-1284.

- Tong, Z., H. Bing-Rong, S. Chao-Xia and P. Song-Hao, 2007. An improved method for multi-target tracking. *Inform. Technol. J.*, 6: 725-732.
- Van der Merwe, R. and E.A. Wan, 2001. The square root unscented Kalman filter for state and parameter estimation. *Proceed. IEEE Int. Confer. Acoust. Speech Signal Process.*, 6: 3461-3464.
- Xinchao, X.U., X.U. Aigong, S.U. Lijuan and X.U. Yantian, 2011. A new location method for LBS based on image. *Inform. Technol. J.*, 10: 2175-2181.
- Yedjour, H., B. Meftah, D. Yedjour and A. Benyettou, 2011. Combining spiking neural network with hausdorff distance matching for object tracking. *Asian J. Applied Sci.*, 4: 63-71.
- Yong, M., Y.L. Hao and W. Gao, 2010. A particle filter algorithm based on a spherical simplex unscented Kalman filter. *J. Harbin Engine. Univ.*, 13: 602-606.
- Zhan, R. and J. Wan, 2007. Iterated unscented Kalman filter for passive target tracking. *IEEE Transact. Aerospace, Elec. Syst.*, 43: 1155-1163.
- Zhao, L., X. Yan and Y. Hao, 2011. SLAM algorithm based on iterated square unscented Kalman filter. *J. Project.*, 31: 157-161.
- Zhu, Z.Y., 2007. Unscented Kalman filter for maneuver target tracking under glint noise. *Simulat. Compu.*, 11: 120-123.