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RBUKF Sensor Data Fusion for Localization of Unmanned Mobile Platform

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Abstract: Due to the limited localization precision of single sensor, a sensor data fusion is introduced based on Rao-Blackwellization Unscented Kalman Filter (RBUKF) that fuses the sensor data of a GPS receiver, one gyro and one compass. RBUKF algorithm is compared with that of Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) in this study. The experimental results show that the RBUKF algorithm can more effectively improve tracking accuracy and reduce computational complexity than the other algorithms and has practical significance.

Keywords: Data fusion, EKF, localization, RBUKF, sensor, UKF

INTRODUCTION

With the development of science and technology, the core weapon of the 21st century is unmanned combat systems. Unmanned mobile platform has attracted attention in search and rescue, monitoring, emergency, security and surveillance applications (Tomic *et al*., 2012). For this unmanned mobile platform, localization is a huge research field where lots of studies and experiments are performed to achieve maximum accuracy in the determination and tracking.

The state estimation of unmanned mobile platform in linear dynamical systems with nonlinear observations has been drawn a lot of attention in the signal processing community. The traditional solutions to this problem include linearization of the system and the use of Extended Kalman Filter (EKF) (Saha and Roy, 2009). However, EKF algorithm has its limitations. On the hand, linear approximations of nonlinear systems often introduce errors which may cause the algorithm to diverge. On the other hand, EKF makes use of Jacobian matrices which may be difficult to obtain for higher order systems. Due to the nonlinearities of unmanned mobile platform target motion model, nonlinear filtering techniques have to be used to estimate the unmanned mobile platform target state. Approaches based on Unscented Transform (UT) resulted in a technique called Unscented Kalman Filter (UKF) (Julier and Uhlmann, 1997). Recently UKF has widely used in nonlinear estimations (Wan and van der Merwe, 2000). The updating operation of UKF is realized by designing a few sigma points and calculating the propagation of these sigma points via nonlinear functions and is accurate up to the second order in estimating mean and covariance (Kandepu *et al*., 2008; Julier and Uhlmann, 2004). Moreover, the UKF can be further simplified by using the Rao-Blackwellization technique, leading to the so-called Rao-Blackwellized UKF (RBUKF) (Briers *et al*., 2003).

Due to the limited localization precision of single sensor, multi-sensors fusion is utilized. When these sensors are attached to a mobile platform then the whole system is called a strapdown system (Titterton and Weston, 2005). Complimentary sensor types like an Inertial Navigation System (INS) and the Global Positioning System (GPS) are fused to yield a system which combines the positive characteristics of the complimentary sensors. The positive effects of this combination are well known and documented (Kim *et al*., 2011). GPS is widely used in the field of navigation, positioning, velocity measuring and orientation. Because its signal could be blocked by objects on terrain or the terrain itself, GPS downgrade its precision or even not be functional. To overcome this problem, compass can feed the system to verify GPS signals. So even if the GPS connection with the satellite fails, orientation is still functional. In this study, we consider applications of the RBUKF to the unmanned mobile platform. This RBUKF fuses the sensor data of a GPS receiver, one gyro and one compass.

UNMANNED MOBILE PLATFORM

This section introduces the unmanned mobile platform. The mobile platform is used as a test platform for the implementation of the sensor fusion and the localization is especially adapted to this mobile platform.

The dimensions of the unmanned mobile platform are 820×430×450 mm (length × width × high). Its

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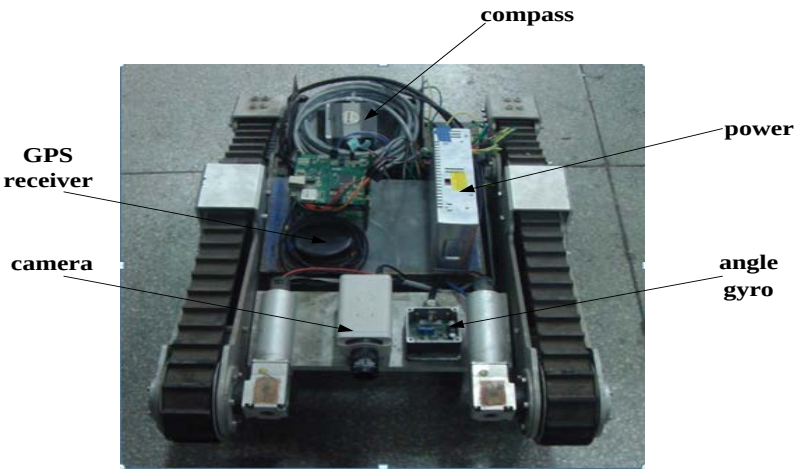

Fig. 1: The unmanned mobile platform

Fig. 2: Remote monitoring interface

weight is 38 kg, including a payload of 50 kg. The two track drive mobile platform can reach velocities up to 25 m/min. The maximum climbing angle that unmanned mobile platform can reach 40°. The picture of the unmanned mobile platform is shown in Fig. 1.

A battery provides 24 volt for platform. DC/DC converters offer stabilized 5, 24 and 3.3V, respectively for different modules of the platform. For the onboard data processing the microcontroller LPC2378 is used. A self designed PCB offers with a variety of microcontroller interfaces, e.g., four UARTs, six PWM outputs, I2C, CAN, GPIO and ADC. The platform is equipped with different sensors: angle gyro, compass and GPS receiver. The angle gyro is mounted in the front of the mobile platform. A front camera is integrated on the mobile platform for monitoring. The picture of the remote monitoring interface is shown in Fig. 2. The communication link to the control station is realized with a standard WLAN connection.

A modular is running on the LPC2378 and all sensor interfaces and functions are encapsulated in modules. The modules are ordered in different layers, according to their application. Basic functions, like steering or acceleration are low level modules. Modules with more sophisticated capabilities are in higher levels and can combine low level functionalities into their application. The implementation of the introduced localization algorithm is encapsulated in a module. It includes some low level modules as interface to the sensors. Hence, in future the localization can be used by a path planning and a path following module to control the unmanned mobile platform more accurate.

SENSOR DATA FUSION

The sensor data fusion is achieved with the use of Rao-Blackwellization Unscented Kalman Filter (RBUKF). The first subsection presents the RBUKF localization system and afterwards the theory of RBUKF will be described.

RBUKF localization system: Practically, the unmanned mobile platform usually does not move at a steady rate or at a constant acceleration, thus a reasonable and exact motion model needs to be established. In this study, Current Statistical (CS) model is adopted as the unmanned mobile platform's moving model (Zhou, 1984; Zhang *et al*., 2012). When a mobile platform moves at a rate of acceleration, the value of its acceleration at next time will be limited and be in the neighborhood of the current acceleration.

State equation of the system: In order to estimate unmanned mobile platform's location and velocity for its tracking system, the discrete state equation of the CS model is described as follows:

$$X(k+1) = F(k+1,k)X(k) + G(k)\bar{a}(k) + w(k) \quad (1)$$

where,

$$X(k) = [x(k)\ v_x(k)\ a_x(k)\ y(k)\ v_y(k)\ a_y(k)\ \theta(k)\ v_\theta(k)\ a_\theta(k)]^T$$

denotes the state vectors. x (k) and y (k) are the unmanned mobile platform's location along x and y direction, v_x (k) and v_y (k) are the unmanned mobile platform's velocity along x and y direction, a_x (k) and a_y (k) are the unmanned mobile platform's acceleration along x and y direction, θ (k) is unmanned mobile platform's azimuth, v_θ (k) is unmanned mobile platform's azimuth velocity, a_θ (k) is unmanned mobile platform's azimuth acceleration. F (k + 1, k) is the state transition matrix. $\bar{a}(k)$ is the mean value of maneuvering acceleration and G (k) is the control input matrix. The process noise w (k) is considered as zero mean white Gaussian noise sequence with covariance matrix Q (k). Matrices F (k + 1, k), G (k), $\bar{a}(k)$ are specified as follows:

$$F(k+1,k) = \begin{bmatrix} F_x(k+1,k) & 0_{3\times3} & 0_{3\times3} \\ 0_{3\times3} & F_y(k+1,k) & 0_{3\times3} \\ 0_{3\times3} & 0_{3\times3} & F_\theta(k+1,k) \end{bmatrix}$$

$$\bar{\alpha}(k) = \begin{bmatrix} \bar{\alpha}_{a_x}(k) \\ \bar{\alpha}_{a_y}(k) \\ \bar{\alpha}_{a_\theta}(k) \end{bmatrix} \quad G(k) = \begin{bmatrix} G_x(k) & 0_{3\times1} & 0_{3\times1} \\ 0_{3\times1} & G_y(k) & 0_{3\times1} \\ 0_{3\times1} & 0_{3\times1} & G_\theta(k) \end{bmatrix}$$

where,

$$F_x(k+1,k) = \begin{bmatrix} 1 & T & (-1+\alpha_x T + e^{-\alpha_x T})\alpha_x^{-2} \\ 0 & 1 & (1-e^{-\alpha_x T})\alpha_x^{-1} \\ 0 & 0 & e^{-\alpha_x T} \end{bmatrix}$$

$$F_y(k+1,k) = \begin{bmatrix} 1 & T & (-1+\alpha_y T + e^{-\alpha_y T})\alpha_y^{-2} \\ 0 & 1 & (1-e^{-\alpha_y T})\alpha_y^{-1} \\ 0 & 0 & e^{-\alpha_y T} \end{bmatrix}$$

$$F_\theta(k+1,k) = \begin{bmatrix} 1 & T & (-1+\alpha_\theta T + e^{-\alpha_\theta T})\alpha_\theta^{-2} \\ 0 & 1 & (1-e^{-\alpha_\theta T})\alpha_\theta^{-1} \\ 0 & 0 & e^{-\alpha_\theta T} \end{bmatrix}$$

$$G_x(k) = \begin{bmatrix} (-T + \alpha_x T^2/2 + (1-e^{-\alpha_x T})\alpha_x^{-1})\alpha_x^{-1} \\ T - (1-e^{-\alpha_x T})\alpha_x^{-1} \\ 1 - e^{-\alpha_x T} \end{bmatrix}$$

$$G_y(k) = \begin{bmatrix} (-T + \alpha_y T^2/2 + (1-e^{-\alpha_y T})\alpha_y^{-1})\alpha_y^{-1} \\ T - (1-e^{-\alpha_y T})\alpha_y^{-1} \\ 1 - e^{-\alpha_y T} \end{bmatrix}$$

$$G_\theta(k) = \begin{bmatrix} (-T + \alpha_\theta T^2/2 + (1-e^{-\alpha_\theta T})\alpha_\theta^{-1})\alpha_\theta^{-1} \\ T - (1-e^{-\alpha_\theta T})\alpha_\theta^{-1} \\ 1 - e^{-\alpha_\theta T} \end{bmatrix}$$

where, a_x, a_y, a_θ are the reciprocal of the maneuver time constant and T is the sampling interval.

Measurement equation of the system: In the localization of unmanned mobile platform system, measurement vector is:

$$Z = [x_{GPS}, y_{GPS}, \omega, \theta_m]^T$$

where,

x_{GPS} & y_{GPS} : Unmanned mobile platform's localizations measured by GPS receiver

ω : Unmanned mobile platform's angle velocity output from angle gyro

θ_m : Unmanned mobile platform's azimuth output from compass

The theory of the sensor data fusion is shown in Fig. 3. The measurement equation of the mobile platform is as follows:

$$Z(k) = h(X(k)) = \begin{bmatrix} x_{GPS}(k) \\ y_{GPS}(k) \\ \omega(k) \\ \theta_m(k) \end{bmatrix} = \begin{bmatrix} x(k) \\ y(k) \\ \dfrac{v_x(k)a_y(k) + v_y(k)a_x(k)}{v_x^2(k) + v_y^2(k)} \\ \theta(k) \end{bmatrix} + n(k) \quad (2)$$

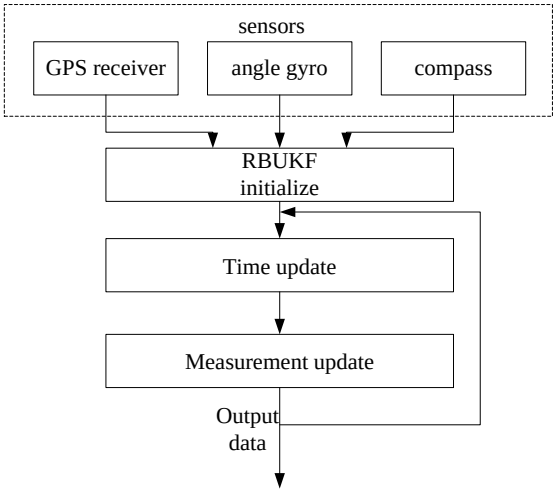

Fig. 3: Date fusion

where,

$$n(k) = [n_x(k)\ n_y(k)\ n_\omega(k)\ n_\theta(k)]^T$$

the measurement noise n (k) is considered as zero mean white Gaussian noise sequence with covariance matrix R (k).

The theory of RBUKF: Rao-Blackwellization Unscented Kalman Filter (RBUKF) is essentially a combined filter of Unscented Kalman Filter (UKF) and Kalman Filter (KF). It utilizes characteristics of the model to increase localizing precision and reduce computation complexity.
The RBUKF algorithm can be derived as follows:

- **Parameters initialize:**

$$\hat{x}(0) = E(X(0)) \tag{3}$$

$$\hat{P}(0) = \mathrm{E}[(\hat{x}(0) - X(0))(x(0) - X(0))^{\mathrm{T}}] \tag{4}$$

- Calculation singular value and Selection of sigma points:

$$W_0^{(m)} = \frac{\lambda}{L+\lambda} \tag{5}$$

$$W_0^{(c)} = \frac{\lambda}{L+\lambda} + (1 - \partial^2 + \beta) \tag{6}$$

$$W_i^{(m)} = W_i^{(c)} = \frac{1}{2(L+\lambda)}, i = 1, 2 \cdots\cdots 2L \tag{7}$$

$$\chi(k-1) = \left[\hat{x}(k-1)\ \ x(k-1) + \sqrt{(L+\lambda)P(k-1)}\ \ x(k-1) - \sqrt{(L+\lambda)P(k-1)}\right] \tag{8}$$

- **Time update equations:**

$$\chi_i(k/k-1) = F(k/k-1)\chi(k-1) \tag{9}$$

$$\hat{x}(k/k-1) = \sum_{i=0}^{2L} W_i^m \chi_i(k/k-1) \tag{10}$$

$$P(k/k-1) = F(k/k-1)P(k-1)F^T(k/k-1) + Q \tag{11}$$

$$Z(k/k-1) = h(\chi_i(k/k-1)) \tag{12}$$

$$\hat{Z}(k/k-1) = \sum_{i=0}^{2L} W_i^{(m)} Z(k/k-1) \tag{13}$$

- **Measurement update equations:**

$$P_{zz}(k/k-1) = \sum_{i=0}^{2L} W_i^{(c)} (Z(k/k-1) - \hat{\hat{Z}}(k/k-1))\,(Z(k/k-1) - Z(k/k-1))^T \tag{14}$$

$$P_{xz}(k) = \sum_{i=0}^{2L} W_i^{(c)} (\chi_i(k/k-1) - \hat{x}(k/k-1))(Z(k/k-1) - \hat{Z}(k/k-1))^T \tag{15}$$

$$K(k) = P_{xz}(k) P_{zz}(k/k-1)^{-1} \tag{16}$$

$$\hat{x}(k) = x(k/k-1) + K(k)(Z(k/k-1) - \hat{Z}(k/k-1))^T \tag{17}$$

$$P(k) = P_{zz}(k/k-1) - K(k)P_{zz}(k/k-1)K^T(k) \tag{18}$$

where,
L : System's dimension
W_i : A set of scalar weights
α : Constant determines the spread of the sigma points around X and is usually set to 1e - 4≤α≤1
κ : A secondary scaling parameter
β : Used to incorporate prior knowledge of the distribution of x (for Gaussian distributions, β = 2 is optimal)
$\lambda = \alpha^2 (L + \kappa) - L$: Scaling parameter

SIMULATION RESULTS

The simulation is accomplished with a computer named Lenovo IdeaPad Y570 which configures an intel CORE i5-2400M @2.30GHz dual CPU and a 4GB memory. In this section, the performance of the RBUKF algorithm is evaluated and compared with EKF and UKF algorithm. The initial value of the state vector is X (0) = [0 1 0 0 1 0 π/4 0 0]$^{\mathrm{T}}$. The measurement error $\sigma_{a_x} = \sigma_{a_y} = 0.1\, m/s^2$, $\sigma_{a_\theta} = 0.1\, rad/s^2$, $\sigma_\omega = 0.1\, rad/s$, $\sigma_s = 0.5\, m$:

$\alpha_x = \alpha_\theta = \alpha_y = 1s$

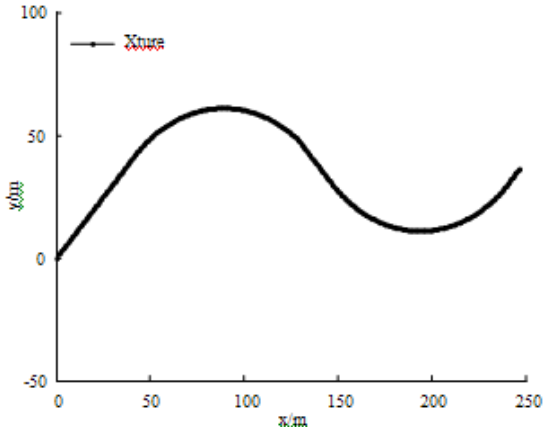

Fig. 4: The mobile platform target trajectory

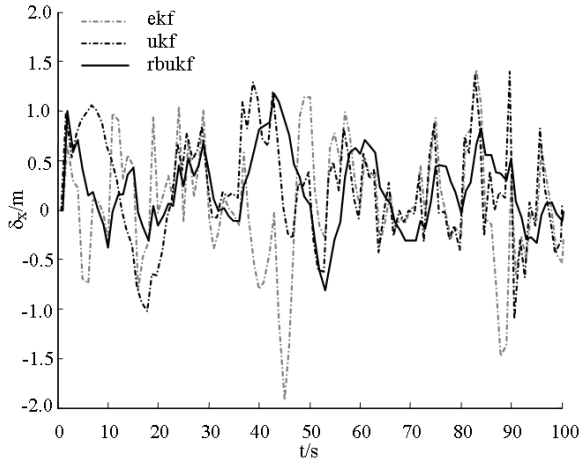

Fig. 5: Position estimation error in x direction

The sampling interval T = 1s. The initial state estimation error covariance is:

$$\tilde{\boldsymbol{P}}(0)=\begin{bmatrix}\tilde{\boldsymbol{P}}_{\boldsymbol{x}}(0) & 0_{3\times3} & 0_{3\times3}\\ 0_{3\times3} & \tilde{\boldsymbol{P}}_{\boldsymbol{y}}(0) & 0_{3\times3}\\ 0_{3\times3} & 0_{3\times3} & \tilde{\boldsymbol{P}}_{\theta}(0)\end{bmatrix}$$

$$\tilde{\boldsymbol{P}}_x(0)=\tilde{\boldsymbol{P}}_y(0)=\begin{bmatrix}\sigma_x^2 & \sigma_x^2/T & \sigma_x^2/T^2\\ \sigma_x^2/T & 2\sigma_x^2/T^2 & 3\sigma_x^2/T^3\\ \sigma_x^2/T^2 & 3\sigma_x^2/T^3 & 6\sigma_x^2/T^4\end{bmatrix}$$

$$\tilde{\boldsymbol{P}}_{\theta}(0)=\begin{bmatrix}\sigma_{\theta}^2 & \sigma_{\theta}^2/T & \sigma_{\theta}^2/T^2\\ \sigma_{\theta}^2/T & 2\sigma_{\theta}^2/T^2 & 3\sigma_{\theta}^2/T^3\\ \sigma_{\theta}^2/T^2 & 3\sigma_{\theta}^2/T^3 & 6\sigma_{\theta}^2/T^4\end{bmatrix}$$

Figure 4 shows the unmanned mobile platform's target trajectory. Figure 5 and 6 show the position estimation error of third algorithms along x and y

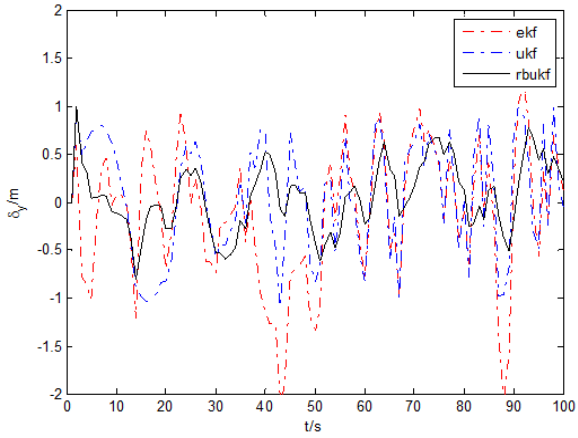

Fig. 6: Position estimation error in y direction

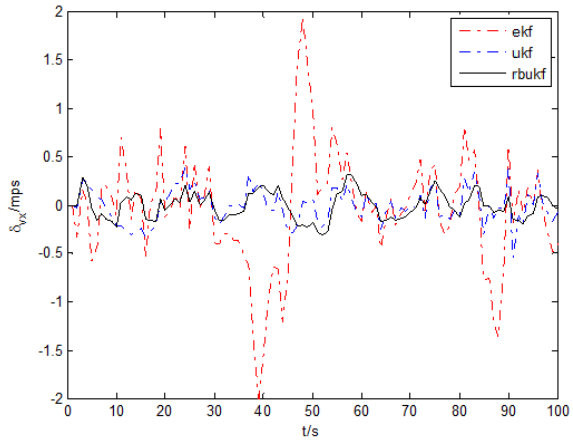

Fig. 7: Velocity estimation error in x direction

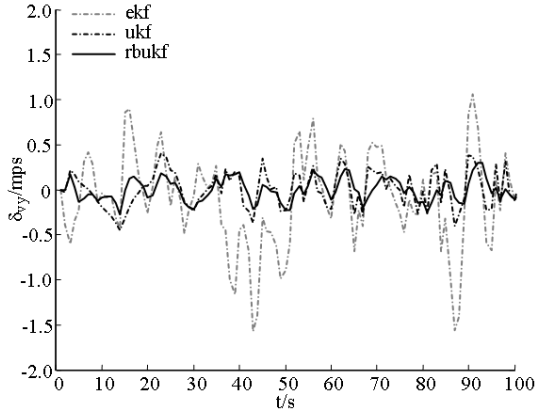

Fig. 8: Velocity estimation error in y direction

direction respectively. Figure 7 and 8 show the velocity estimation error of third algorithms along x and y direction, respectively. Figure 9 shows the angle estimation error of third algorithms. Table 1 is the comparison of the average estimation error and the time consuming by the third algorithms. The total position

Table 1: Comparison of the average estimation error and the time consuming

Algorithms	δ_x (m)	δ_y (m)	δv_x (m/s)	δv_y (m/s)	Time (s)
EKF	0.5077	0.4621	0.3991	0.3437	0.0485
UKF	0.5631	0.4809	0.3159	0.2585	0.2685
RBUKF	0.3498	0.2825	0.1218	0.0964	0.2499

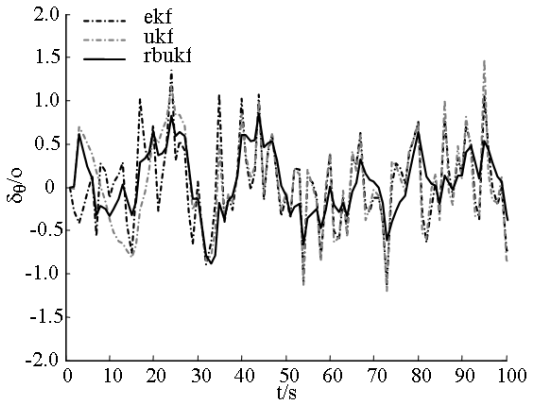

Fig. 9: Angle estimation

tracking error of RBUKF is reduced by 39.28% and 34.51% than UKF and EKF, respectively. The velocity tracking error is also reduced by 61.95% and 70.51% than UKF and EKF, respectively. Also, the computing time of RBUKF is less than that of UKF.

Due to the fact that the sate model is linear, the measurement model is nonlinear, a RBUKF instead of an UKF can be used. RBUKF is essentially a combined filter of Kalman Filter for the linear part (time update) and Unscented Kalman Filter for the nonlinear part (measurement update). As a result, the quasi Monte Carlo variance and computational complexity is reduced (Fritsche and Klein, 2009). In order to compare the computational complexity between the RBUKF and UKF, for their measure-update algorithms are the same (Li *et al*., 2008). In the RBUKF algorithm:

$$P(k/k-1) = F(k/k-1)P(k-1)F^T(k/k-1) + Q$$

we only need to do L dimensional matrix multiplication, but in the UKF algorithm:

$$P(k/k-1) = \sum_{i=0}^{2L} W_i^c(\chi_i(k/k-1) - \hat{x}(k/k-1))(\chi_i(k/k-1) - x(k/k-1))^T$$

we need to do 2L+1 dimensional matrix multiplication. Obviously, RBUKF can reduce much computation work which contributes efficiency improvement compare with original UKF. So the computational complexity has been greatly decreased.

From the simulation results, we can see that the RBUKF algorithm has the highest tracking precision and the less computational complexity than other algorithms.

CONCLUSION

In this study a new RBUKF variant is described to fuse a GPS receiver, one gyro and one compass yielding the global position of unmanned mobile platform. Compared to UKF and EKF, RBUKF is not less computational cost, but also higher accuracies. The filtering performance comparison of the UKF, EKF and RBUKF are analyzed through simulation. The simulation results show that the RBUKF algorithm is an effective algorithm for unmanned mobile platform tracking.

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REFERENCES

Briers, M., S.R. Maskell and R. Wright, 2003. A rao-blackwellised unscented Kalman filter. Proceeding of the 6th International Conference, July 8-11, pp: 55-61.

Fritsche, C. and A. Klein, 2009. On the performance of Hybrid GPS/GSM mobile terminal tracking. Proceeding of the International Conference of Communications, International Workshop on Synergies in Communications and Localization. Dresden, June, Germany,

Julier, S.J. and J.K. Uhlmann, 1997. A new extension of the Kalman filter to nonlinear systems. Proceedings of the SPIE Aero Sense International Symposium on Aerospace/Defense Sensing, Simulation and Controls. Orlando, Florida, April 20-25, 3068: 182-193.

Julier, S.J. and J.K. Uhlmann, 2004. Unscented filtering and nonlinear estimation. Proc. IEEE, 92(3): 401-422.

Kandepu, R., B. Foss and L. Imsland, 2008. Applying the unscented Kalman filter for nonlinear state estimation. J. Process Contr., 18: 753-768.

Kim, S.B., J.C. Bazin and H.K. Lee, 2011. Ground vehicle navigation in harsh urban conditions by integrating inertial navigation system, global positioning system, odometer and vision data. IET Radar, Sonar Nav., 5(8): 814-824.

Li, H.P., D.M. Xu, L.J. Jiang and De-min, 2008. Sequence unscented Kalman filtering algorithm. Proceedind of 3rd IEEE Conference on Industrial Electronics and Applications. Singapore, pp: 1374-1378.

Saha, N. and D. Roy, 2009. Extended Kalman filters using explicit and derivative-free local linearizations. Appl. Math. Model., 33: 2545-2563.

Titterton, D. and J. Weston, 2005. Strapdown Inertial Navigation Technology. The Institution of Electrical Engineers, Michael Faraday House, United Kingdom.

Tomic, T., K. Schmid and P. Lutz, 2012. Toward a fully autonomous UAV: Research platform for indoor and outdoor urban search and rescue. Robot. Autoation Mag., 9(3): 46-56.

Wan, E.A. and R. van der Merwe, 2000. The Unscented Kalman filter for nonlinear estimation. Proceeding of IEEE Adaptive Systems for Signal Processing, Communications and Control Symposium, pp: 153-158.

Zhang, F., P.L. Wu and L.M. Zhao, 2012. Improved SR-UKF algorithm for mobile robot tracking. J. Comput. Inform. Syst., 8(15): 6499-6506.

Zhou, H.R., 1984. A current statistical model and adaptive algorithm for estimating maneuvering targets. AIAA J. Guidance Control Dynam., 7(5): 596-602.