Outdoor position estimation based on a combination system of GPS-INS by using UPF

Yunki Kim, Jaehyun Park, Jangmyung Lee

(*Dept. of Electrical Engineering*, *Pusan National University*, *Pusan 609-735*, *Korea*)

Abstract: This paper proposes a technique that global positioning system (GPS) combines inertial navigation system (INS) by using unscented particle filter (UPF) to estimate the exact outdoor position. This system can make up for the weak point on position estimation by the merits of GPS and INS. In general, extended Kalman filter (EKF) has been widely used in order to combine GPS with INS. However, UPF can get the position more accurately and correctly than EKF when it is applied to real-system included non-linear, irregular distribution errors. In this paper, the accuracy of UPF is proved through the simulation experiment, using the virtual-data needed for the test.

Key words: global positioning system (GPS); unscented particle filter (UPF); navigation; inertial navigation system (INS); strapdown inertial navigation system (SDINS)

The position estimation of the moving objects is of great interest to be studied, especially for global positioning system(GPS) and inertial navigation system (INS), a lot of researches are in progress[1].

INS is navigation system that assumes position, posture and the direction by calculating according to the initial location and direction of the acceleration of the fuselage with inertial measurement unit (IMU)[2]. IMU consists of inertial sensors gyroscope, accelerometer, etc, and it can provide small and accurate information with the development of micro electro mechanical systems (MEMS). Especially, it has been used in aviation and marine fields. IMU can provide precise location information during short time. However, if it is used for a long time, due to errors and disturbances, the final estimated value is very different from the original value. To compensate for this kind of absolute value, the sensor fusion is used[3,4]. GPS is used mainly outdoors. which can provide accurate and absolute position based on satellite radio navigation system.

Extended Kalman filter (EKF) is mainly used to amalgamate both INS and GPS data. EKF transfers nonlinear system to linear system by using Taylor series expansion. Therefore, there is disadvantage that according to change of time, tolerance can be greater. To solve these limitations, unscented Kalman filter (UKF) or Hybrid type filter, toting both particle filter (PF) and other filters[5], are used.

This paper introduces unscented particle filter (UPF), which consists of particle filter and UKF for combination of INS and GPS, into outdoor location estimation system.

The paper is organized as follows: Section 1 introduces INS; Section 2 describes the characteristics of various probability-based filters; Section 3 gives the simulation experiments to verify the validity of UPF; and finally, a conclusion is drawn.

1 INS

1.1 Strapdown INS (SDINS)

SDINS is the system in which inertial sensors are directly attached to an antibody. Here, sensor's output angular velocity and acceleration value are expressed as variations on body frame.

So, the process changing measurement value to navigation frame is needed[6]. First, measured angular velocity is cumulative to estimate position. transformation matrix is calculated to change from body frame to navigation frame, which transfers the measured value from body frame's acceleration to navigation frame. Then, gravity included in acceleration is removed and a value is got. By accumulating acceleration to the initial values of velocity, current speed and position can be obtained.

Fig. 1 shows strapdown inertial navigation algorithm. What primarily used in strapdown system for coordinate transformation are direction cosine, Eul-

er angle and a way of quaternions. Comparison of features, advantages and disadvantages of each method is shown in Table 1[7].
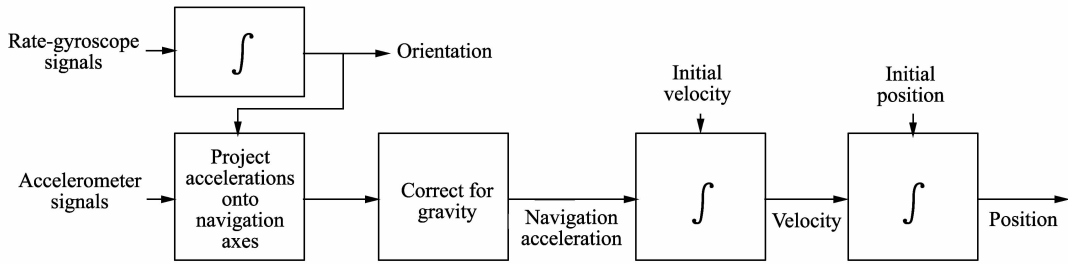

Fig. 1   Strapdown inertial navigation algorithm

Table 1   Pros and cons of the various coordinate transformation method

Coordinate transformation	advantages	disadvantages
Euler Angles	·Calculated with minimum parameters (roll, pitch, yaw) ·Easy to understand physically	·Nonlinear differential equations ·Singularity problem of trigonometric functions may occur ·Rotation sequence is important
Direction Cosines	·Singularity does not exist ·Transformation matrix can be calculated directly	·There is burden for the amount of computation because of having 9 kinds of differential equations
Quaternions	·Calculatin is relatively simple since it is done by 4 linear differential equations ·Singularity does not exist, so Gimbal-Lock phenomenon can be avoided	·Difficult to understand physically ·An initial value must be obtained using Euler angles

This paper is oriented for fast and accurate system. Thus, 3-D position of the antibody is determined using the quaternion method.

1.2   Aided inertial navigation

Aided INS amalgamated sensor with the absolute value in order to overcome the shortcomings that cumulate errors of the inertial sensor to get the value of the position by INS[8]. Fig. 2 shows a block diagram of aided SDINS which corrects position and location using information obtained from the inertial sensors and GPS[2,9].
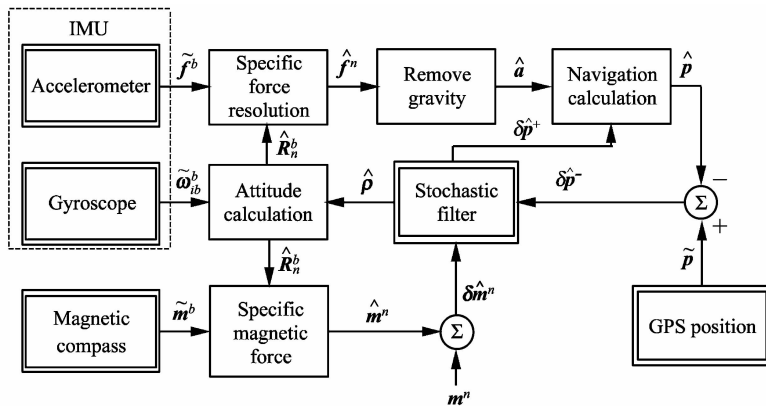

Fig. 2   Block diagram of aided inertial navigation

A formula is updated from position equation expressed in quaternion attitude ($\hat{q}$) using the information obtained from angular rate ($\tilde{\omega}_{ib}^{b}$) gyroscope.

$$\hat{q} = \frac{1}{2} \begin{bmatrix} -\hat{q}_1 & -\hat{q}_2 & -\hat{q}_3 \\ \hat{q}_0 & \hat{q}_3 & -\hat{q}_2 \\ -\hat{q}_3 & \hat{q}_0 & \hat{q}_1 \\ \hat{q}_2 & -\hat{q}_1 & -\hat{q}_0 \end{bmatrix} (\tilde{\omega}_{ib}^{b} - \hat{b}_{gyro}). \qquad (1)$$

The attitude expressed with quaternion can obtain transformation matrix by converting antibodies in the coordinate system to coordinate navigation

$$\hat{R}_n^b =$$

$$\begin{bmatrix} \hat{q}_0^2 + \hat{q}_1^2 - \hat{q}_2^2 - \hat{q}_3^2 & 2(\hat{q}_1\hat{q}_2 - \hat{q}_0\hat{q}_3) & 2(\hat{q}_0\hat{q}_2 + \hat{q}_1\hat{q}_3) \\ 2(\hat{q}_1\hat{q}_2 + \hat{q}_0\hat{q}_3) & \hat{q}_0^2 - \hat{q}_1^2 + \hat{q}_2^2 - \hat{q}_3^2 & 2(\hat{q}_2\hat{q}_3 - \hat{q}_0\hat{q}_1) \\ 2(\hat{q}_1\hat{q}_3 - \hat{q}_0\hat{q}_2) & 2(\hat{q}_0\hat{q}_1 + \hat{q}_2\hat{q}_3) & \hat{q}_0^2 - \hat{q}_1^2 - \hat{q}_2^2 + \hat{q}_3^2 \end{bmatrix},$$

$$(2)$$

$\delta \hat{p} \equiv \tilde{p} - \hat{p}$ is defined with the difference obtained the position ($\hat{p}$) that is cumulative acceleration of navigation coordinate twice and the position ($\tilde{p}$) that is got from GPS. Measured value ($\tilde{m}^b$) from the geomagnetic sensor is changed using transformation matrix to navigation coordinate values ($\tilde{m}^n \equiv \hat{R}_n^b \tilde{m}^b$). By doing so, the value of the Earth's magnetic field is measured. The difference between the actual Earth's magnetic field (m^n) and the calculated value of the Earth's magnetic field is defined as $\delta \hat{m}^n \equiv m^n - \hat{m}^n$. State-space equation of the probability-based filter which is as the measure of $\delta \hat{p}^-$ and $\delta \hat{m}^n$ is designed as follows. Then, the attitude error ($\hat{\rho}$) and the position error ($\delta \hat{p}^+$) are estimated. Using error information, corrected information is obtained by updating the position and location[10]. At this point, $\hat{k}$ is defined as the estimated value of k, and $\bar{k}$ is as k.

$$\delta x_k = f_k(\delta x_{k-1}) + \omega_k,$$
$$\delta y_k = h_k(\delta x_k) + v_k, \qquad (3)$$

where f_k is state wave function (system equation), h_k is measurement equation (measurement Eq.), ω_k is the system error, v_k is the measurement error and δy_k is the measured value.

State which is used in esuimation filter shown Fig. 2 has respective 3-D position error (δp), the speed error (δv), the attitude error ($\delta \rho$), and the acceleration sensor and the gyro sensor bias errors ($\delta b_{acc}, \delta b_{gyro}$) as random variables. The variables have a total of 15 dimensions as $\delta x = [\delta p^T \quad \delta v^T \quad \delta \rho^T \quad \delta b_{acc}^T \quad \delta b_{gyro}^T]$. At this point, $\delta k \equiv k - \hat{k}$ is defined, and each element of random variable is defined as

$$- p \equiv [x \quad y \quad z]^T,$$
$$- v \equiv [v_x \quad v_y \quad v_z]^T,$$
$$- \rho \equiv [\varepsilon_N \quad \varepsilon_E \quad \varepsilon_D]^T, \qquad (4)$$

where $-\varepsilon_N$ and ε_E are tilt errors; $-\varepsilon_D$ is heading error.

2 Probability based filters

Various fields have tried actively to solve the problem about the estimation of the state variables for dynamic systems. Of them, methods based on stochastic constitute probability space consisting of state variables. Using system's dynamic characteristics and measurement, when the initial probability density ($p(x_0)$), the state transition density ($p(x_k | x_{k-1})$), and likelihood in the measurement model ($p(y_k | x_k)$) are given, the optimal current state value which is based on input and measures, and essentially posterior probabilities ($p(x_k | y_{0:k})$ or $p(x_{0:k} | y_{0:k})$) are estimated. This method is generally based on Bayesian estimation. In the field of localization, EKF, which is the extended one of Kalman filter, UKF and the particle filter are notably being studied[3]. Filters are applied differently depending on how to define the system model and the characteristics of the noise distribution. Table 2 summarizes the characteristics of typical filters.

In the case of KF, it can be only used for linear systems, and it leads the result that many fields can not apply to using it. For this reason, EKF was developed right after KF had been developed. EKF is the probability-based filter which is largely used in various fields. For every estimation, the nonlinear system is estimated as the value of the state, and develops Taylor series for linearization[11]. This method has an advantage that it is fast and simply. On the other hand, it is a disadvantage that the error may become bigger when nonlinear is severe or the noise strays from the normal distribution a lot. Thus, the proposed method is UKF. The filter, like EKF, can be used in nonlinear and models having normal distribution noise. However, unlike EKF which linearizes, UKF generates expected value of sample points (sigma points) by calculating dispersion. It is the method that obtains more correct state of the expected value and dispersion[12,13].

Table 2 Mean of the error of attitude and position

T Filter	System Model	Noise Distribution
KF	Linear	Normal Distribution
EKF	Nonlinear	Normal Distribution
UPF	Nonlinear	Normal Distribution
PF	Nonlinear	Irregular Distribution

Fig. 3 (a) is got by actual mean and variance through passing all sampling points to f, nonlinear system. Fig. 3 (b) is got by unscented transform (UT) of UKF, and Fig. 3 (c) predicts the following conditions and variance through EKF's linearization method.

As you can see in Fig. 3, UPF than EKF in nonlinear systems can predict the next state more accurately.

Therefore, UKF is more suitable than EKF in nonlinear systems[14]. However, the UKF also assumes that the errors follow a normal distribution, and thus there are some differences from the actual system model. PF repeatedly performs the Monte Carlo integration, unlike the other filters to minimize non-linear system assumption, irregular distribution of the error model takes advantage of high accuracy can be estimation. For outdoor mobile robot, because of environmental factors, disturbance and tolerance, using PF increases the accuracy. PF algorithm, as shown in Fig. 3, using the state transi-

tion function, can predict the following state and the weight, and using measurement value, particle weight update and normalize is the weighted effective bias reduction in the number of particles to prevent the re-sampling of particles will be sequenced[15,16].
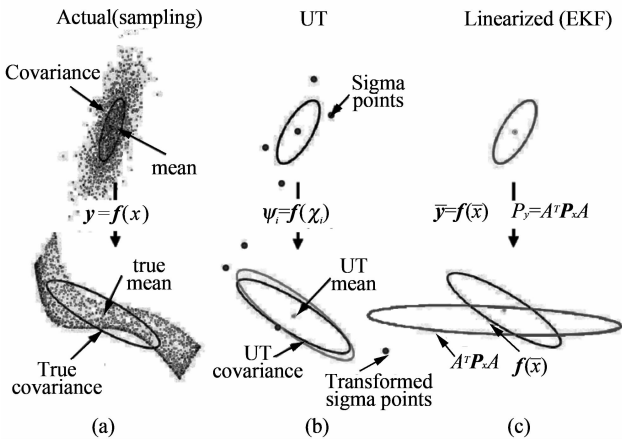

Fig. 3   Estimation comparison of UKF and EKF

At this point in the EKF or UKF prediction step of the way, the more accurate the next state and the weight of the particle can be predicted[5,17]. In this paper, using UPF, combining PF and UKF, more precise positioning estimation can be got.

3   Experiment

This paper compares performance according to the kind of filter for system estimating outdoor location using UPF. To compare performance of filter, driving information of arbitrary circle path is generated. The generated driving information (posture, position) are compared. To prove excellence of UPF, comparison is made in case applying no filter, applying EKF and UPK, respectirely. Particle number of UPF is experimented by setting 250.
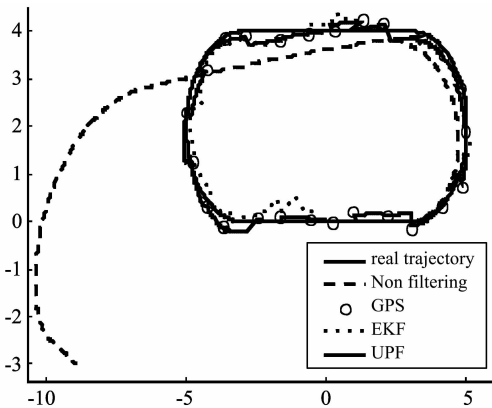

Fig. 4   Estimated position (particle number = 250)

Fig. 4 is the estimated position of antibodies. The

actual path starts at (0,0) →3 m straight to the right →2 m radius semicircle path rotation →6 m straight →→2 m radius semicircle path rotation →3 m straight(Initial position). Non filtering is in case if do not apply, and GPS is local information got from GPS.

To quantitatively compare performance of each filter, appear average value of posture error and local error are got through 10 times experiment. Table 3 shows posture error and local error.

Table 3   Mean of the error of attitude and position

Filter	Attitude error	Position error
Non filtering	0.001 7	4.152 7
EKF	0.001 5	0.229 9
UPF	0.002 9	0.196 1

4   Conclusion

EKF is the quick and simple method to estimate indoor local error by combining GPS and INS, which has been used recently and will be used for a long time and be verified. But it is difficulty to use in non-linear system. To apply model in close actual system, another method is needed. The UPF is kind of PF, being non-linear and using the model similar to the actual system. And it is the filters that has more enhanced estimation accuracy by using method of UPF. The usefulness of UPF is proved through experiments. From now, leave fusion methods that be used in real time position estimation through combining various filters more quickly estimated as a next project.

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