Integration of INS and GPS system using Particle Filter based on Particle Swarm Optimization

Meriem JGOUTA, Benayad NSIRI

***Abstract*—** The localization performance of a navigation system can be enhanced by combining different types of sensors. This paper focuses on INS-GPS integration. INS and GPS measurements permit to identify a non-linear state area model suitable to particle filtering. The GPS/INS combination is carried out by a nonlinear filtering approach by which GPS measurements are used to put INS estimates right. Nevertheless, a conventional particle filter is bound to deviate due to the dynamics of the unknown parameters. Leading particles move to the most favorable position by using particle swarm optimization algorithm, therefore the number of active particles was augmented, the particle variety was enhanced, and the particle degradation was precluded. Simulation results show that the new algorithm enhanced the estimation precision considerably compare with the conventional particle filter.

***Keywords*—** GPS-INS, Navigation, Particle filter, Particle swarm optimization.

I. Introduction

Satellite navigation systems such as the Global Positioning System (GPS) or Galileo know an increasing popularity and find strategic as well as grand public applications. If the safety is committed, as in civil aviation, GPS accuracy is insufficient to be certified as a primary means of navigation. One solution consists in coupling it to other sensors. In this paper we focus on GPS hybridization with inertial navigation system (INS). These systems that were previously intended only for commercial and military navigation of high level are becoming more accessible to commercialization with the appearance on the inertial sensors market at low cost, based on Micro electromechanical System technology (MEMS) . The accuracy of an INS being independent of the external environment, it is thus possible to obtain a positioning when GPS signals are strongly attenuated or completely blocked. However, the rapid deterioration of the navigation solution caused by significant errors present on the measurements provided by the MEMS sensors greatly limits their use autonomously or semi-autonomously. It becomes pertinent to study possible methods to correct these errors of measurement, which would then allow continuous use of INS technology at low cost.

Conventionally, the coupling is achieved by taking advantage of the GPS data to estimate the estimation errors and sensor bias. They are indeed easier to estimate than the movement of the mobile because of slower dynamics. The estimation problem to solve is nonlinear, different hybridization filters were applied including the extended Kalman filter (EKF) [1], the particulate filter (PF) [2] or the unscented Kalman filter (UKF) [3] which offers a good compromise accuracy / computational cost.

This paper suggested a particle filter dependent on the algorithm of intelligence. The PSO algorithm is employed so as the particles can find the optimal position, lead particles to high probability area, prevent the particles degradation; then genetic algorithm is inserted in the particle filter to substitute the re-sampling, avert the particles degeneration phenomenon, make the particle more diverse, develop usage of particles by selection, crossover and transformation operations, thus preventing particle degradation and enhancing the filtering performance further.

The remainder of the paper is organized as follows. First, the GPS/INS integration concept is presented. Then we give a concise description of standard particle filter, particle swarm optimization algorithm and the combination of the two approaches applied for GPS/INS integration. Next, we illustrate some experimental results. Finally, we conclude the paper and point out future work.

II. The INS/GPS Integration Principle

A. The Global positioning system

GPS is a Global Positioning System founded on satellite technology. The basic technique of GPS is to measure the ranges between the receiver and perceived satellites. The positions of the satellites are predicted and transmitted alongside (along) with the GPS signal to the user. By divers known satellites positions and the measured distances between the receiver and the satellites, the position of the receiver can be located. The position transform, which can be also located, is the velocity of the receiver. The most important applications of the GPS are positioning and navigating [4]. GPS is composed of 3 segments: the Space Segment is composed of 24 satellites dispersed in six orbital planes, the Control Segment supervises the operation of satellite and sustains

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system performances, and the User Segment is composed of GPS receivers and user groups. Despite the fact that GPS is a high-tech system, errors exist yet by six main reasons (not comprising selective disposal error): satellite ephemeris, satellite clock, ionospheric delay, tropospheric delay, multi-path and receiver measurement errors [5].

B. Inertial Navigation System (INS)

INS is an independent system, integrating three orthogonal accelerometers and gyroscopes to quantify linear acceleration and angular rates in three directions respectively [6]. A set of mechanization equation is put in an application for the unprocessed measurements from the sensors to compute position, velocity and attitude detail. The INS inertial sensors have deep-rooted errors, which may lead to an important deterioration of INS performance through duration. Particularly for strap down INS (SINS), in which inertial sensors are put through the entire range of heading and attitude transforms and turn rates which the vehicle examines over its way. Consequently, GPS and INS are frequently combined together to surmount the disadvantages related to each system.

Strapdown mechanization (or INS mechanization) is the procedure of identifying the navigation states (position, velocity and attitude) from the crude inertial measurements by resolving the differential equations characterizing the system movement. Mechanization differential equations in the local level frame [7]:

$$\begin{pmatrix} \dot{r}^n \\ \dot{v}^n \\ \dot{C}_b^n \end{pmatrix} = \begin{pmatrix} D^{-1}v^n \\ C_b^n f^b - (2\Omega_{ie}^n + \Omega_{en}^n)v^n + g^n \\ C_b^n(\Omega_{ib}^b - \Omega_{in}^b) \end{pmatrix} \quad (1)$$

Where: $r^n = [\rho \quad \lambda \quad h]^T$, $v^n = [V_N \quad V_E \quad V_U]^T$, D^{-1} is a matrix whose non zero elements are functions of the user's latitude and height; C_b^n is transformation matrix from b-frame to n-frame; Ω_{ie}^n, Ω_{en}^n, Ω_{ib}^b, Ω_{in}^b are skew-symmetric matrix of corresponding respective angular velocity vector; f^b is special force vector in b-frame, g^n is gravity vector expressed in the n-frame.

C. The INS/GPS integration

GPS and INS are generally integrated with Kalman filter (KF) to surmount disadvantages associated with each system, and afford a vigorous navigation solution. GPS has reliable and long term precision; it is used to correct INS measurements and to avert the development of their faults. Alternatively, the precise short-term measurement gave by the INS is used to resolve problems allied to GPS like cycle slips and clock biases.

INS measures the linear acceleration and angular rates of moving vehicles through its accelerometers and gyroscopes sensors [8]. The principal aim is the position determination, which is realizable after a double integration of the accelerations and the angles of rotation, which is obtained by a single integration of the angular velocities. The INS error leap gets bigger with time, because of the unbounded placement errors caused by the uncompensated accelerometer faults influencing the INS measurements.

When the GPS positioning is mediocre or unavailable over short durations of time, INS gives high-precision three dimensional positioning. Moreover, it gives much higher update locating rates compared with the output rate classically available from GPS [9]. In any case in order to make effective use of the benefits of these two navigation sensors and acquire the data fusion advantages, we combine the data collected by each and use integrated system. There are numerous integration schemes employing a mixing filter such as particle filter to combine the GPS and INS data [10], [11]. So as to diminish the effect of accuracy reducing when GPS begins to be unavailable and attaining a high resolution compared with EKF as a conventional approach, a PF and PSO has been employed on a simplified navigation error model, constructed from stand-alone INS on one hand, and from the GPS on the other hand [12]. This fact has been exemplified in Fig. 1. For this reason, the GPS pseudo-ranges are very good external measurements for updating the INS, therefore improving its long-term precision.

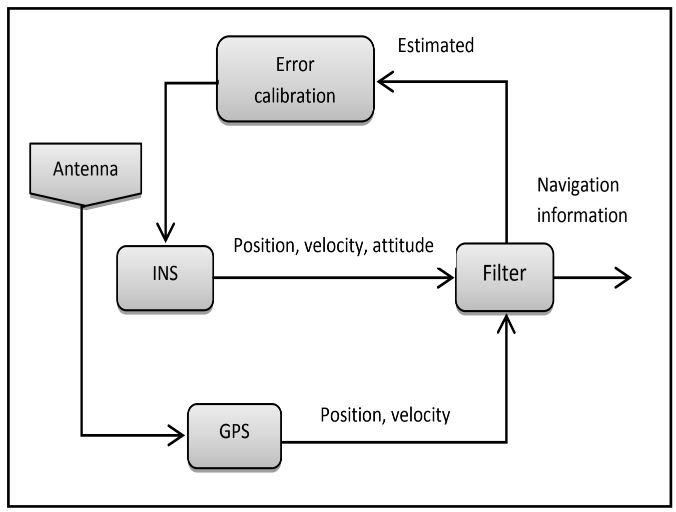

Fig. 1 Block diagram of loosely-coupled GPS/INS system.

III. PARTICLE FILTER ALGORITHM AIDED BY PARTICLE SWARM OPTIMISATION

A. The standard particle filtering

Though the EKF and UKF can process with some nonlinear filtering issues, nevertheless, they constantly approximate $p(x_t|y_t)$ to be Gaussian, where $p(x_t|y_t) = pdf$ of the state vector x_t conditioned on measurements $y_1, y_2, \dots, y_t$ at any time step t. The particle filter is a probability-based estimator. If the right density is non-Gaussian, particle filters may drive to better results in comparison to that of EKF or UKF. The recursive Bayesian state estimate, which is dependent on the Bayes' rule:

$$p(x_t|y_t) = \frac{p(z_t|x)p(x_t|y_{t-1})}{p(z_t|y_{t-1})} \quad (2)$$

To calculate $p(x_t|y_t)$, the equation $p(x_t|y_{t-1})$ must be gotten from the Chapman-Kolmogorov equation and the marginal density function:

$$p(x_t|y_{t-1}) = \int p(x_t|x_{t-1})p(x_{t-1}|y_{t-1})dx_{t-1} \quad (3)$$

The probability density function (pdf) $p(y_t|y_{t-1})$ can be obtained to be

$$p(y_t|y_{t-1}) = \int p(y_t|x_t)p(x_t|y_{t-1})dx_t \quad (4)$$

The basic PF fuse two principles that are the Monte Carlo (MC) and the Importance Sampling (IS) methods where the transition previous density $p(x_t|x_{t-1})$ is considered as the importance distribution:

$$q(x_t|x_{t-1}, y_t) = p(x_t|x_{t-1}) \quad (5)$$

The weights of these particles are assessed in accordance with:

$$w_t \infty\, w_{t-1}p(y_t|x_t) \quad (6)$$

And

$$w_k \infty\, \frac{p(x_t|y_t)}{q(x_t|y_t)} \quad (7)$$

Where $q(x_t|x_{t-1}, y_t)$the importance density function, w_{t-1} is are the importance weights of the last period particles and w_t are the importance weights of the current period. The parameter adjustment includes set P of N particle cases and set E of assessed values of all particles that vary temporarily.

Algorithm 1. A pseudo-code for PF algorithm.

```
Procedure Particle Filter ()
Var
    P[1 ... N]: Particle set;
    E[1 ... N]: Estimate set along time;
    t: time;
begin
    t = 0;
    Initialize (P);
    While (t < T) do begin
        Prediction (P);
        Estimate (P, E[t]);
        Resample (P, E[t]);
        t = t + 1 ;
    end
end
```

B. Particle Swarm Optimization

In the mid 1990s, Particle Swarm Optimization (PSO) was first introduced by Kennedy and Eberhart; it uses a population of possible solutions to recognize promising regions of the search area. This population is named swarm and the elements of the population are named particles. Every particle constitutes an acceptable solution to the imminent optimizing problem. During a PSO iteration, each particle speeds up separately in the direction of its proper best solution found up to now, as well as the direction of the overall best solution found out up to now by any other particle. Thus, if a particle comes up with a promising new solution, all other particles will move nearer to it, discovering the solution space more deeply [13].

A swarm is composed of a set of particles moving around the search area, each particle represents a potential solution (fitness) and has a velocity vector (v_i^{t+1}), a position vector (x_i^t), the position at which the best fitness (${p_{best}}_i^t$) met by the particle, and the index of the best particle (${g_{best}}_i^t$) in the swarm [14]. In every generation, each particle velocity is updated to their best-encountered position and the best position met by any particle using (7):

$$v_i^{t+1} = wv_i^t + C_1 \times rand_1 \times \left({p_{best}}_i^t - x_i^t\right) + C_2 \times rand_2 \times ({g_{best}}_i^t - x_i^t) \quad (8)$$

The parameters c1 and c2 are acceleration coefficients called self-cognitive and social parameter, respectively. $rand_1$ and $rand_2$ are random values, evenly distributed between zero and one. The values of $rand_1$ and $rand_2$ are not identical for each iteration. w is named inertia weight and is used to monitor the effect of the precedent velocities history on the current one. Shi and Eberhart [15] have come up with an important amelioration in the performance of PSO with the linearly diminishing inertia weight over the generations, time-varying inertia weight given in (8):

$$w = (w_1 - w_2)\left(\frac{\max iter - iter}{max\ iter}\right) + w_2 \quad (9)$$

Where w_1 and w_2 are the initial and final values of w, respectively, $max\ iter$ is the maximum number of optimization steps and $iter$ is the present iteration number. Every generation the location of each particle is updated by adding the velocity vector to the position vector, as in (9):

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (10)$$

The algorithms output is the best particle, which includes last formed weights and extents.

Algorithm 2. A pseudo-code for PSO algorithm.

```
Procedure Particle Swarm Optimization ()
Var
    P[1 ... N]: Particle set;
    V[1 ... N]: Velocity set along iteration;
    Ppbest [1 ... N]: The best particle set along iteration;
    Pgbest [1 ... N]: The best particle of all particles set
  along iteration;
    k: iteration;
begin
    k = 0;
    Initialize (P);
    While (k < K) do begin
        Compute Particle Best (P,Ppbest [k]);
        Compute Weight Best (Ppbest [k],Pgbest [k]);
        Compute Velocity (V[k]);
        Update (P);
        k = k + 1;
    end
end
```

V symbolizes the set of movement speeds of wholly particles in the k^{th} iteration. Set P_{pbest} is the set of recording the optimal position of every single particle, and set P_{gbest} symbolizes the set of weighted sum of P_{pbest} of the whole present particles or the set of optimal positions up to here.

C. An Optimized Particle Filter Algorithm based on particle swarm optimization in GPS/INS integration.

We notice from the introduction of the PSO and the PF above that there are many resemblances between the two methods. First, PSO meets the optimum value by updating the velocity and the particle position in the search area constantly. Although, the PF makes an approximation of the actual posterior probability distribution of the system by updating the location and weight of the particles. Then, in PSO algorithm, the particle with the maximum fitness constitutes the optimum value of the search zone; the one with the maximum weights constitutes the most probable system status. Next, PSO and the PF process have their proper motion process, the particles update their location and velocity by pursuing single optimum values and the overall optimum in PSO algorithm, though, every single particle in the PF algorithm updates their position by employing the motion model firstly, and after updates its proper weight value by measurement model. Consequently, the PSO algorithm can enhance the performance of normal PF dependent on the resemblances mentioned before.

Algorithm 3. A pseudo-code for PSO-PF algorithm.

```
Procedure PSO Algorithm-Particle Filter ()
Var
      P[1 ... N]: Particle set;
      E[1 ... N]: Estimate set along time;
      t: time;
begin                                   (Particle Filter)
      t = 0;
      Initialize (P);
      While (t < T) do begin
            Prediction (P);
            Estimate (P, E[t]);
            Resample (P, E[t]);
               k = 0;          (Particle Swarm Optimization)
               Initialize (P'= P);
               While (k < K) do begin
                  Compute Particle Best (P', Ppbest [k]);
                  Compute Weight Best (Ppbest [k],Pgbest [k]);
                  Compute Velocity (V[k]);
                  Update (P');
                  k = k + 1;
               end
            t = t + 1;
      end
end
```

The GPS and INS integration in this paper is based on PF-PSO method. The data of particle Filter is the combination of GPS and INS errors and the PSO is employed to filter the high frequency noise. After the filtering procedure, the arbitrary noises principally hailed from GPS are eliminated; the persisted INS errors are joined to INS output to obtain the right navigation value. One more preoccupation in commonly INS/GPS system is the dissimilarity in every single system's update rate. An INS system at all times has higher update rate than a GPS system that signifies from time to another, the system must perform without GPS information. In addition, GPS signal could undergo external environment and may gone, leading to an absence of GPS in corresponding long time. To cope with these situations, we use the arrangement with the capability to change back and forward between feed forward mode and feedback mode.

Feedback mode: Assume when GPS signal is gone, as there is no occurrence of GPS information, the PF chunk activate forecast mode which employ the final adjusted value to approximate the present situation using an active model. As the measurement signal is cut off, the whole measurement equation is outdated.

Feed-forward mode while GPS has its signal back, the feedback is eliminated, the PF chunk activate feed-forward mode, this latter employ INS and GPS information to perform ordinary.

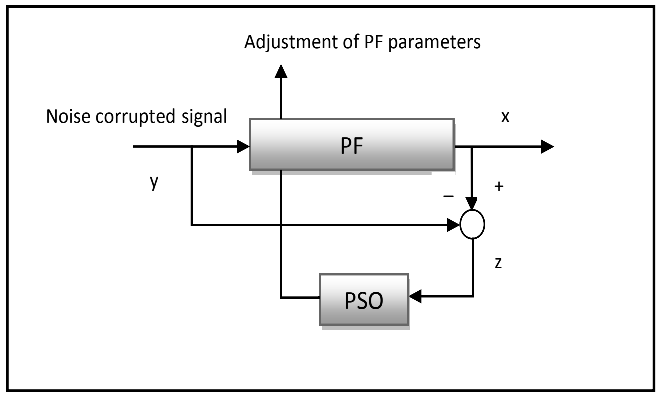

Fig. 2 PF-PSO functional block diagram.

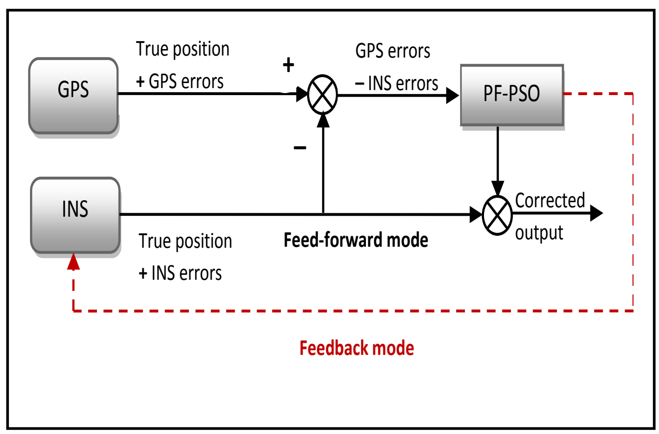

Fig. 3 Proposed approach in GPS/INS integration.

IV. SIMULATION RESULTS

This test assesses the precision and the strength of our fiducially detection and identification method. We suggest using PSO-PF algorithm by fusing the PF with the particle swarm optimization method. As the PSO method is an algorithm to obtain the best solution, it is employed to further refine the overall favorable output from all particle situations after the particle filter re-sampling for the sensor combination system on INS/GPS. PFs are sequent MC methods based on a point mass representation of likelihood densities, which can be applied to any state area model and which generalize the classical KF methods. We have experienced our algorithm to assess its performance and have compared the results with those given by a conventional PF.

First, the experimentations based on Matlab simulation soft, which is the language of technical counting. The original information of an aircraft tracking dependent on the inertia output information of the inertial measurement unit and real time GPS location and velocity. The outcome is taken on one-dimensional location above the error information study. Then, and respectively, used PSO and particle filter to data combination experiment.

According to the experimental data presented in the table I and under the same conditions of noise, PF-PSO prevents particle deterioration and it’s considered the most efficient in augmenting the variety of particles. RMSE values prove that it’s estimated the highest precision and the time of estimating is smaller as well. In the circumstance of an augmentation in noise, the RMSE value of the PF-PSO algorithm vary the minimum, which demonstrates PF-PSO anti-noise function, designates PF-PSO yet blocking particle deterioration in the circumstance of an augmentation in both noise and the particle variety, and maintain the algorithm extremely accurate and efficient.

At last, a recently developed technique increasing the powerful PF predictor with the PSO method for improving the INS/GPS integration system performance is presented. First test results show the importance of the proposed PF-PSO increase in reducing position and velocity movements during GPS outages as in fig. 4.

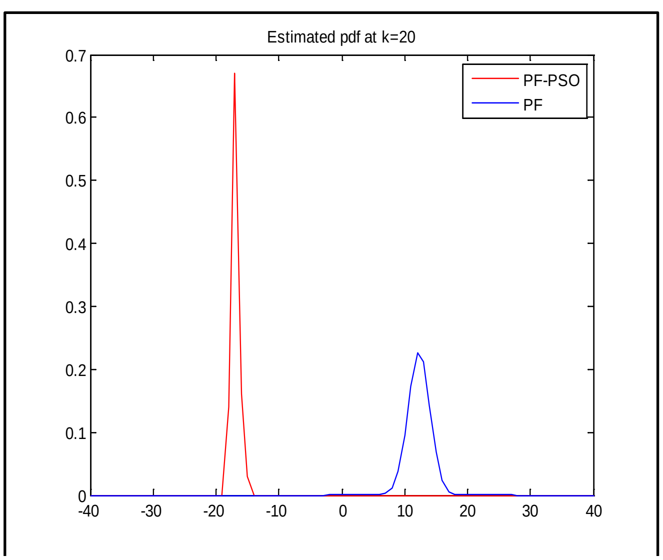

Fig. 2 The height and width of the pdf corresponding to the error attained by the PF-PSO filter reflect its better performance in comparison to the PF estimation techniques.

Fig. 2 illustrates the pdf of the absolute error in range estimation after applying PF and PF-PSO Fusion methods in order to compare their behavior.

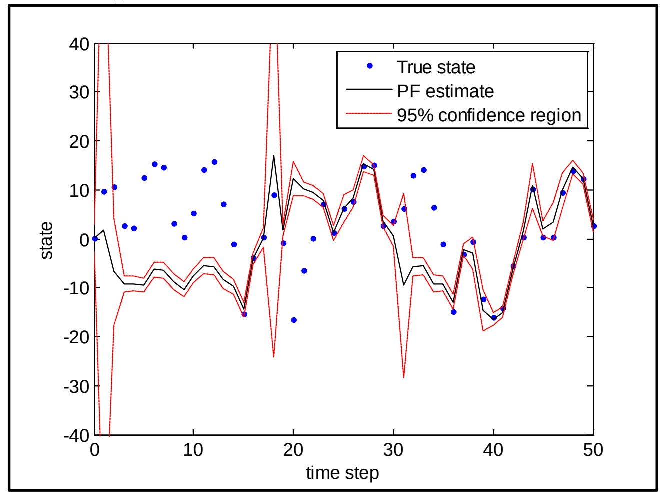

Fig. 3 PF estimates compared with true state

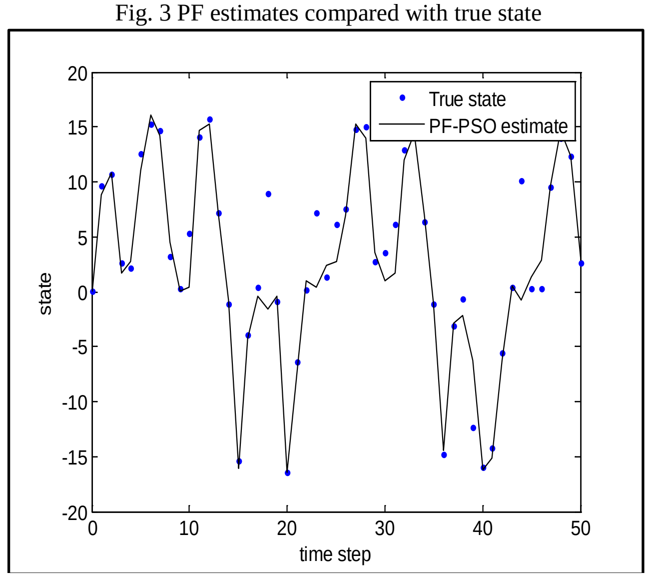

Fig. 4 PF-PSO estimates compared with true state.

	Particle number	RMSE	Running time
PF	100	5.6799	0.3068
PF-PSO	100	1.347	0.3705

Table. I The filtering performance statistics of the PF and PF-PSO.

V. Conclusion

Integration of Global Positioning System and Inertial Navigation System, has been lengthily used in aircraft appliances such autopilot, to supply better navigation, even in the nonexistence of GPS. Although Kalman Filter based GPS–INS integration offers a strong solution to the navigation, it necessitates prior information of the error model of INS, which augments the difficulty of the system. We presented in this paper a method which employs a particle filter and PSO to fuse GPS and inertial technologies in order to get better stability and accuracy of the positioning. A general view of the developed navigation system was characterized, and experiments revealed the feasibility and dependability of the system under different situations. , we have applied a PF and PSO to combine inertial and GPS data and, therefore, to approximate the aircraft poses. To illustrate the performances of the filter we have used the RMSE values. The results have been extremely satisfying compared to those of conventional PF techniques; they showed that the combination method using the PSO reaches high tracking precision, constancy and robustness. It is feasible to apply more than three distributions to the PF and there are more error areas to be examined in real positions. Therefore in the coming work we will develop a new intelligent method in order to investigate the filter performance.

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