The Precise Positioning Algorithm Optimization Base on PSO-PF for Agricultural Machinery Navigation System

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Abstract. A Modified Weight Particle Swarm Optimization-Particle Filter is proposed for the integrated navigation nonlinear system in agricultural machinery operation. The algorithm combines the advantages of particle filter and the global and local searching ability of particle swarm optimization, which modifies the particle weight and accelerates the particle convergence on optimizing particle update mode by adding advantage and disadvantage. It reduces the probability of falling into local optimum, and the global accurate positioning is achieved in a short time. The feasibility and superiority of modified weight particle swarm optimization particle filter are verified by simulation and experiment.

1. Introduction

Precision Agriculture is a new direction of the high efficiency and sustainable agriculture development [1]. In recent years, research work has been carried out on path planning, tracking control, automatic obstacle avoidance and agricultural machinery control system[2]. Agricultural machinery automatic navigation control technology is one of the key technologies of precision agriculture and an important part of agricultural machinery intellectualization. The design of agricultural machinery automatic navigation system is focused on precise positioning based on navigation system, and at the same time agricultural machinery realizes self-walking operation according to the predefined path. In order to achieve precise positioning of navigation, it is necessary to filter out the interference error signals in satellite signals and navigation data, and obtain effective navigation parameters with ideal accuracy.

Among the current filtering technologies, Kalman Filter and Extended Kalman Filter linearize the non-linear problems firstly, so there are some errors. There are certain limitations since the application must strictly meet the preconditions. Unscented Kalman Filter improves the filtering accuracy and computing speed of non-linear problems and reduces the computational complexity. Particle Filtering algorithm effectively solves the problem of non-linear filtering, but there are also some problems such as particle exhaustion and excessive computation. In this paper, the Particle Swarm Optimization-Particle Filter (PSO-PF) algorithm is studied. It combines system identification with filter estimation organically. It optimizes the updating mode of particles by adding superior and inferior velocities so as to modify and change the weight of particles, which reduces the probability of falling into local optimum and search time in particle filter. Global precision positioning is achieved at the fastest speed.
2. Modified Weight Particle Swarm Optimization-Particle Filter (MWPSO-PF)

2.1 Particle Filter algorithm

Particle Filter (PF) extracts several samples from a subset of a posteriori probability density function that satisfies the condition[3]. The weight of the particle is the probability density of the particle in the sample, which is updated by the state measurement, so that the distribution probability of the particles conforms to the true posterior probability density of the system. The essence of particle filter is that the integral operation in Bayesian estimation is solved by Monte Carlo method. Particles are generated by discrete sampling methods, which are more convenient to transfer between nonlinear transformations. Therefore, particle filter can be widely applied to nonlinear stochastic system with non-Gaussian distribution.

Set the nonlinear system state equation be:

\[
\begin{align*}
  x_k &= f(x_{k-1}) + \omega_{k-1} \\
  z_k &= h(x_k) + v_k
\end{align*}
\]

(1)

Where \( f(x) \) is the transfer state function, \( \omega_{k-1} \) is process noise, \( h(x) \) is the measurement matrix, and \( v_k \) is measuring noise. \( x_k \) is set to be only relevant to \( x_{k-1} \), which is the first-order Markov process. The system observation variables \( z_k \) are not related to each other and are only concern to the measurement data for the time period \( t \). \( p(x_0) \) is the state prior condition for a nonlinear system.

\[
p(x_{0,n}) = p(x_0) \prod_{k=1}^{n} p(x_k | x_{k-1})
\]

(2)

Posterior probability:

\[
p(z_{0,n} | x_{0:n}) = \prod_{k=0}^{n} p(z_k | x_k)
\]

(3)

The observations are known, then:

\[
p(z_k | x_{0:k}) = \frac{p(z_k | x_{0:k}) p(x_k | z_{0:k-1})}{p(z_k | z_{0:k-1})}
\]

(4)

\( p(x_{0:k} | z_{1:k}) \) is the posterior probability distribution of state \( x_k \) at \( k \) moment, and the sampled particle set is \( \{ x_{0:k}^{j}, \omega_k^j \}_{j=1}^{N} \) . The minimum mean square error of state \( x_k \) at \( k \) moment is

\[
\hat{x}_k = \sum_{j=1}^{N} \omega_k^j x_k^j
\]

2.2 Particle Swarm Optimization

In 1995, Particle Swarm Optimization (PSO) is proposed by Jim Kennedy. The algorithm simulates the migration and accumulation of the bird's foraging process, which searches for the global optimal solution by simulating the interaction between simple individual communities and individuals[4]. The particle swarm optimization algorithm adopts the velocity position search model. There aren’t the processes of selection, mutation and crossover, that is different from the genetic algorithm.

The particle swarm is constituted of \( m \) particles. In the \( n \) dimension search space, the potential solution of the optimization problem is represented by the particle position. There are three principles for updating the state: (1) keeping inertia of itself; (2) changing the state according to its optimal position; (3) changing the state according to the optimal position of the group. In the dimension \( n \) search space, the \( m \) particles constitutes a population \( x = (x_0, x_1, \cdots, x_m)^T \). The \( i \) -th particle is \( x_i = (x_{i,0}, x_{i,1}, \cdots, x_{i,n})^T \). The velocity is \( v_i = (v_{i,0}, v_{i,1}, \cdots, v_{i,n})^T \). The individual extremum is
After the global extremum of individual and population is found, the particle updates its speed and position.

\[ v_{i,d}^{k+1} = v_{i,d}^k + c_1 \text{rand}(p_{i,d}^k - x_{i,d}^k) + c_2 \text{rand}(p_{g,d}^k - x_{i,d}^k) \]  
\[ x_{i,d}^{k+1} = x_{i,d}^k + v_{i,d}^{k+1} \]  

where \( c_1, c_2 \) is the learning factor (acceleration constant); \( \text{rand}() \) is the random number in \((0, 1)\) interval; \( v_{i,d}^k \) and \( x_{i,d}^k \) are respectively the \(d\)-dimensional velocity and position of \(i\) particle in the \(k\)-th iteration; \( p_{i,d}^k \) is the individual extreme position; \( p_{g,d}^k \) is the global extreme position. The step to the best position of particles is adjusted by \( c_1 \) and the step to the best position in the whole world is adjusted by \( c_2 \).

In order to reduce restrictions in the evolutionary process, the probability of particles leaving the search space is reduced in the \([v^\text{min}, v^\text{max}]\) range.

### 2.3 Modified Weight Particle Swarm Optimization-Particle Filter

Particle Filter adopts the importance density function which leads to the result is suboptimal, so the importance sampling process of PF algorithm is suboptimal. The sampling step of PF algorithm is optimized by PSO algorithm, which is called Particle Swarm Optimization - Particle Filter[5].

Fitness function is defined by particle swarm optimization particle filter algorithm as follows:

\[ \text{fitness} = \exp \left( -\frac{1}{2R_k}(z_{\text{new}} - z_{\text{pred}})^2 \right) \]  

where, \( z_{\text{pred}} \) is the predicted measurements, \( z_{\text{new}} \) is the latest measurements, and \( R_k \) is the measurement noise variance.

The formula (5) and (6) of particle swarm optimization are used to update the particle search to the best position step by step, so that all particles are close to the best position to search for the best solution. In PSO-PF algorithm, the velocity and position of particles are updated continuously by Gaussian distribution. It solves the weakness of particle swarm optimization algorithm that it is difficult to determine the maximum velocity parameter, which is helpful to the convergence of the optimization algorithm.

The problems of particle degeneration and exhaustion in PF algorithm are solved effectivly by PSO-PF algorithm, and which needs few adjusting parameters. However, PSO-PF algorithm is easy to fall into local optimum in later algorithm search, and the unstable operation results easily lead to search loss or mistake. Aiming at the above phenomena, a modified weighted particle swarm optimization particle filter algorithm is proposed. It optimizes the updating mode of particles by adding superior and inferior speeds to modify and change the weight of particles. It integrates the global and local search ability of PSO algorithm, speeds up the convergence of particles, reduces the probability of falling into local optimum in particle filter, and reduces the search time. Global precision positioning is achieved at the fastest speed.

### 3. Simulation and verification

Extended Kalman Filter (EKF) is an efficient autoregressive recursive filter. The robust adaptive Kalman filter (AKF) utilizes the measured data to filter, and at the same time the filter itself is constantly to judge whether the dynamic of the system has changed. The model parameters and the statistical characteristics of noise are estimated and modified to improve performance and reduce the actual error. The MWPSO-PF algorithm is an organic combination of system identification and filtering estimation. In order to verify the performance of each algorithm, this paper chooses a non-
linear function to simulate and analyze which is the typical analysis object in large number of references.

The process state equation and measurement equation of the nonlinear function model are respectively:

\[
x(t) = \frac{1}{2} x(t-1) + \frac{25x(t-1)}{1+[x(t-1)]} + 8\cos\left\{\frac{1}{2}(t-1)\right\} + \sqrt{Q} \times \text{randn}
\]

\[
y(t) = \frac{x^2(t)}{20} + \sqrt{Q} \times \text{randn}
\]

The initial state is zero, \(\text{randn}\) is the random function in \((0, 1)\) interval, the measured noise covariance \(R\) is 1, the process noise covariance \(Q\) is 10, and the simulation time step is 50. The estimations of EKF, AKF and PSO-PF are showed in figure 1. The estimation errors of EKF, AKF and PSO-PF are showed in figure 2. The real value and the PSO-PF estimation are showed in figure 3.

Kalman filtering method needs to acquire exactly the noise statistical characteristics of the system. In practice, the characteristics of the system are changing and the system model itself is uncertain. Although EKF and AKF can deal with some non-linear problems, the state and noise of the system still need to satisfy the Gauss distribution. The simulation results show that PSO-PF is superior to the other two algorithms in estimation accuracy, and the mean square of estimation error is better estimation effect than the former two algorithms in the non-linear system, which embodies the superiority of PSO-PF algorithm. Therefore, the PSO-PF algorithm improves the accuracy, and the filtering performance is obviously superior to other traditional algorithms, which improves the efficiency of the algorithm.

**Figure 1.** Estimates of EKF, AKF and PSO-PF.

**Figure 2.** Estimation Errors of EKF, AKF and PSO-PF.
Agricultural machinery generally follows a straight line path when it works in the field. When it reaches the edge of a field, it needs to switch from a straight line to a curve path. After the turn, it will continue to work in a straight line path. Therefore, the main paths are straight line path tracking and curve path tracking. The positioning experiments of agricultural machinery are carried out along straight lines and curves with a speed of 2 m/s based on Beidou navigation controller. The positioning errors are as follows Figure 4 and Figure 5. According to the experimental data, the standard deviation of straight line and curve path is less than 0.25m.

Figure 3. True Value and PSO-PF Estimate.

Figure 4. Linear Driving Positioning Error (2m/s).

Figure 5. Curve Driving Positioning Error (2m/s).
4. Conclusion

In this paper, a modified weighted particle swarm optimization particle filter algorithm is used to improve the positioning accuracy in integrated navigation non-linear system, which is applied to agricultural machinery navigation. By comparing the estimated value and errors of EKF, UKF and PSO-PF through simulation experiments, PSO-PF can achieve global accurate positioning in a relatively short time. In the positioning and path tracking experiment of agricultural machinery based on Beidou navigation system, the better performance parameters are achieved. The superiority and feasibility of modified weighted particle swarm optimization particle filter algorithm are verified.

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