ONLINE PARAMETER IDENTIFICATION OF RICE TRANSPLANTER MODEL BASED ON IPSO-EKF ALGORITHM
/
基于 IPSO-EKF 算法的插秧机模型参数在线辨识

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DOI: *https://doi.org/10.35633/inmateh-61-03*

Keywords: *dynamic model, online parameter identification, improved particle swarm optimization, extended Kalman filter*

ABSTRACT

In order to improve the accuracy of rice transplanter model parameters, an online parameter identification algorithm for the rice transplanter model based on improved particle swarm optimization (IPSO) algorithm and extended Kalman filter (EKF) algorithm was proposed. The dynamic model of the rice transplanter was established to determine the model parameters of the rice transplanter. Aiming at the problem that the noise matrices in EKF algorithm were difficult to select and affected the best filtering effect, the proposed algorithm used the IPSO algorithm to optimize the noise matrices of the EKF algorithm in offline state. According to the actual vehicle tests, the IPSO-EKF was used to identify the cornering stiffness of the front and rear tires online, and the identified cornering stiffness value was substituted into the model to calculate the output data and was compared with the measured data. The simulation results showed that the accuracy of parameter identification for the rice transplanter model based on the IPSO-EKF algorithm was improved, and established an accurate rice transplanter model.

摘要

为了提高插秧机模型参数辨识精度，提出了一种基于改进的粒子群算法(IPSO)和扩展卡尔曼滤波算法(EKF)的插秧机模型参数在线辨识方法。建立了插秧机动力学模型，用于确定插秧机模型参数。针对 EKF 算法中噪声矩阵难以选取而影响最佳滤波效果的问题，该算法在离线状态下应用 IPSO 算法对 EKF 算法的噪声矩阵进行优化。根据实车试验，采用 IPSO-EKF 对前后轮胎的侧偏刚度进行在线辨识，将辨识的侧偏刚度值代入模型中计算得到输出数据与测量数据进行对比。试验和仿真结果表明,基于 IPSO-EKF 算法提高了插秧机模型参数的辨识精度，建立了准确的插秧机模型。

INTRODUCTION

With the intelligent and modernized development of agricultural machinery, a rice transplanter with autonomous navigation has played a key role in rice planting. However, an accurate dynamic model must be established before the model-based rice transplanter control algorithm is designed. The accuracy and real-time of parameters for the dynamic model directly affect the path tracking control of the rice transplanter (*Kayacan E., et al., 2019*). The cornering stiffness of the front and rear tires for a rice transplanter is an important parameter of the dynamic model, it needs to be accurately identified online. At present, it is difficult for sensors to directly measure the cornering stiffness of tires in real time, so the system identification method is particularly important to identify the parameter of vehicle models.

The least square algorithm is widely used in parameter identification. The non-linear least squares algorithm is used to identify the vehicle parameter, namely, the cornering stiffness of the front and rear tires (*Kayacan E., et al., 2015*). The offline least squares algorithm is used to identify tire cornering stiffness by real vehicle tests (*Li L., et al., 2016*). They don't consider that the cornering stiffness is a time-varying parameter. The variable forgetting factor recursive least squares algorithm is used to identify online parameters such as the vehicle mass and the rotational inertia (*Khaknejad M B., et al., 2011*). Although the algorithm meets the requirements of online identification, it is only suitable for simple linear models and can't be directly used for nonlinear models. The modern intelligent optimization algorithms are also applied to parameter identification.

The eight unknown parameters of the semi-trailer train model are identified by genetic algorithm and L-M optimization algorithm (*Liang Q.Z., 2016*). The improved genetic algorithm is presented to optimize the parameters of the inertia for three coordinate axes (*Zhang Q.C.,2007*). The genetic algorithm can identify multiple parameters at the same time and can reach the global optimal solution, but the calculation is large and complicated, and the identification of time-varying parameters can't be well applied. Considering the real-time nature of the algorithm, the EKF algorithm is used to identify the vehicle's mass and the cornering stiffness of front and rear tires online (*Wang J., 2019*). The EKF is used to identify the cornering stiffness of the front and rear tires of vehicle (Reina et al., 2019). As the noise matrices are selected according to experience, the filtering didn't reach the expected effect. A method is presented for identifying parameters of a vehicle dynamic model (*Best., et al., 2007*). They used an adaptive EKF with variable fading factor to identify vehicle's mass, the rotational inertia and wheelbase parameters online, but this algorithm was more complicated and adjusted more parameters.

Considering the above-mentioned problems, this paper proposes an online parameter identification algorithm based on IPSO-EKF. As the selection of the process noise matrix Q and the measurement noise matrix R determines the convergence for EKF algorithm, and the true value of the Q and R can't be obtained directly, combined with PSO algorithm, Q and R matrices are identified offline to determine the optimal noise matrices. This algorithm not only solves the difficult problem of determining the noise matrices in traditional EKF, but also doesn't need to change the original EKF algorithm. Therefore, the IPSO-EKF algorithm is used to identify the cornering stiffness of the front and rear tires for the rice transplanter online.

MATERIALS AND METHODS

Dynamic model of the rice transplanter

According to motion characteristics of rice transplanter, the two degrees of freedom of the bicycle model with only lateral and yaw motion are established. In the range of small angles, the lateral tire forces are assumed to be proportional to the slip angles. The front wheel of the rice transplanter is steered and the front wheel has a small angle. The bicycle model is shown in Fig.1.

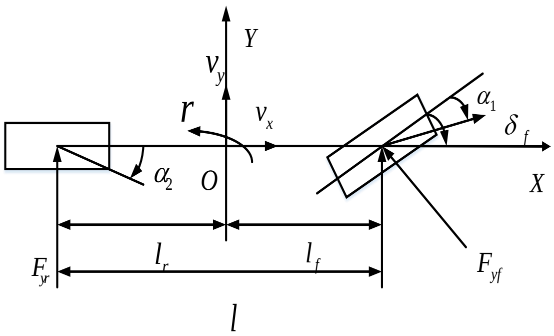

Fig. 1 - Two degrees of freedom of the bicycle dynamic model

According to Newton's second law of motion, the lateral and yaw motion of the rice transplanter is written as follows (Xu Y., et al., 2019):

$$\begin{cases} \sum F_Y = (m\dot{v}_y + mrv_x) = 2F_{yf}cos\delta_f + 2F_{yr} \\ \sum M_Z = I_z\dot{r} = 2F_{yf}l_f - 2F_{yr}l_r \end{cases} \tag{1}$$

Where m - is the mass of the rice transplanter, kg; v_x - the longitudinal velocity, m/s; $\dot{v}_y$ - the lateral acceleration, m/s²; v_y - the lateral velocity, m/s; $\dot{r}$ - the yaw acceleration, rad/s²; r - the yaw rate, rad/s; F_{yf} - the lateral force on the front wheels, N; F_{yr} - the lateral force on the rear wheels, N; δ_f - the steering angle of the front wheels, rad; I_z - the moment of inertia around the vertical axis, Kg·m²; l_f - the distance between the front axle and the centre of gravity, m; l_r - the distance between the rear axle and the centre of gravity, m.

The lateral tire forces are calculated in a linear model in which they are assumed to be proportional to the slip angles, and they are written as follows:

$$\begin{cases} F_{yf} = C_f \alpha_1 \\ F_{yr} = C_r \alpha_2 \end{cases} \tag{2}$$

$$\begin{cases} \alpha_1 = \delta_f - \dfrac{v_y + l_f r}{v_x} \\ \alpha_2 = \dfrac{l_r r - v_y}{v_x} \end{cases} \tag{3}$$

Where C_f - is the cornering stiffness of the front tires, N/rad; C_r - the cornering stiffness of the rear tires, N/rad; α_1 - the side slip angles of the front tires, rad; α_2 - the side slip angles of the rear tires, rad. By combining equations (1), (2) and (3), the state-space model of the rice transplanter can be written as follows:

$$\begin{bmatrix} \dot{v}_y \\ \dot{r} \end{bmatrix} = \begin{bmatrix} -\dfrac{2C_f + 2C_r}{mv_x} & -v_x - \dfrac{2C_f l_f - 2C_r l_r}{mv_x} \\ \dfrac{2C_r l_r - 2C_f l_f}{I_z v_x} & -\dfrac{2l_f^2 C_f + 2l_r^2 C_r}{I_z v_x} \end{bmatrix} \begin{bmatrix} v_y \\ r \end{bmatrix} + \begin{bmatrix} \dfrac{2C_f}{m} \\ \dfrac{2C_f l_f}{I_z} \end{bmatrix} \delta_f \tag{4}$$

An approximate value for the rotational inertial can be calculated as follows:

$$I_z = ml_f l_r \tag{5}$$

In equation (4), m , l_f , l_r and I_z are invariant parameters of the rice transplanter, I_z can be approximated by (5), δ_f is steering angle of the front wheel as input variable, v_x can be approximately equal to the speed of the rice transplanter on the ground, C_f and C_r are the cornering stiffness to be identified. In this paper, the cornering stiffness of tires for the rice transplanter will be changed for the complexity of the road surface. Therefore, the cornering stiffness is regarded as a time-varying parameter for online identification. Equation (4) can be equivalently expressed as:

$$\dot{x}(t) = f(x(t), \delta(t)) \tag{6}$$

In order to collect the data, the steering angle of the front wheel is set to 20 degrees step, and the rice transplanter is driven counter clockwise on the asphalt ground at a low speed, as shown in Fig. 2. The rice transplanter uses RTK system for precise positioning. The speed and heading angle of the rice transplanter are obtained by the M600 receiver, and the data collection frequency is 5 Hz. The lateral velocity v_y and yaw rate r of the rice transplanter are obtained by coordinate transformation.

The measurement vector $z = [v_y, r]^T$ is introduced as the measurement equation of the system, which is equivalently expressed as:

$$z(t) = h(x(t)) \tag{7}$$

Fig. 2 - The actual vehicle test of the rice transplanter

EKF algorithm for online identification parameters

The EKF algorithm can be used as a parameter online identification algorithm of nonlinear systems which can be transformed into a linear problem by Taylor decomposition, and be the same as linear Kalman filtering (*Battistelli G., 2016*). In the process of parameter identification, the state vector $x=[v_y,r]^T$ and the cornering stiffness of the front and rear tires to be identified are combined into a joint state vector, and the EKF algorithm is used to make the optimal estimation of the parameters by combining the joint state vector. When the value of the parameter to be identified converges, the convergent value is used as the value of the optimal parameter. EKF is widely used for online identification of model parameters due to its small amount of calculation and high real-time performances.

In this paper, EKF is applied to the online identification of the parameters for the rice transplanter's dynamic model, C_f and C_r are added to the state vector x. The equations (6) and (7) can be expressed as a nonlinear system.

$$\begin{cases} \dot{x}(t) = f(x(t),\delta(t)) + w(t) \\ z(t) = h(x(t)) + v(t) \end{cases} \tag{8}$$

Where $w(t)$, $v(t)$ - the process noise and the measurement white Gaussian noise with zero mean, respectively. First, the above continuous-time nonlinear equations need to be converted in a discrete-time state-space representation.

$$\begin{cases} x_{k+1} = f(x_k,\delta_k) + w \\ z_k = h(x_k) + v \end{cases} \tag{9}$$

Where $f(.)$ - the state evolution function represents the rice transplanter dynamics, $h(.)$ - the relationship between the state vector and measurement, $x_k = \left[v_{y_k}, r_k, C_{f_k}, C_{r_k}\right]^T$ - the joint state vector at time k, δ_{f_k} - the steering angle of the front wheel, and $z_k = [v_{y_k}, r_k]^T$ - the measurement vector at time k. If the sampling period is dt, the discrete system is represented by a first-order difference quotient, $f(.)$ is expressed as follows:

$$\begin{aligned} & f_1: v_{y_{k+1}} = \left(1-\frac{2C_{f_k}+2C_{r_k}}{mv_x}dt\right)v_{y_k} + \left(-v_x - \frac{2C_{f_k}l_f - 2C_{r_k}l_r}{mv_x}\right)dtr_k + \frac{2C_{f_k}}{m}dt\delta_k \\ & f_2: r_{k+1} = \frac{2C_{r_k}l_r - 2C_{f_k}l_f}{I_z v_x}dtv_{y_k} + \left(1-\frac{2l_f^2C_{f_k}+2l_r^2C_{r_k}}{I_z v_x}dt\right)r_k + \frac{2C_{f_k}l_f}{I_z}dt\delta_k \\ & f_3: C_{f_{k+1}} = C_{f_k} \\ & f_4: C_{r_{k+1}} = C_{r_k} \end{aligned} \tag{10}$$

Similarly, $h(.)$ can be obtained as:

$$\begin{aligned} & h_1: v_{y_{k+1}} = v_{y_k} \\ & h_2: r_{k+1} = r_k \end{aligned} \tag{11}$$

The EKF algorithm can be given by the following recursive equations:

$$\begin{cases} \bar{x}_{k+1} = f(\hat{x}_k,\delta_k) \\ \bar{P}_{k+1} = A_k P_k A_k^T + Q \\ K_{k+1} = \bar{P}_{k+1}H_k^T(H_k\bar{P}_{k+1}H_k^T + R)^{-1} \\ \hat{x}_{k+1} = \bar{x}_{k+1} + K_{k+1}(z_{k+1} - H_{k+1}\bar{x}_{k+1}) \\ P_{k+1} = (I - K_{k+1}H_{k+1})\bar{P}_{k+1} \end{cases} \tag{12}$$

Where $\bar{x}_{k+1}$ - the priori state vector prediction; $\bar{P}_{k+1}$ - the posteriori error covariance matrix prediction; Q - the process noise matrix; R - the measurement noise matrix; K_{k+1} - the Kalman gain; $\hat{x}_{k+1}$ - the posteriori state vector prediction; z_{k+1} - the measurement vector; I - the identity matrix; P_{k+1} - the posteriori error covariance matrix prediction; In these equations, A_k , H_k - the Jacobian matrix of the state vector and the Jacobian matrix of the measurement vector, respectively.

$$A_K = \left[\frac{\partial f(x_k, u_k)}{\partial x_k}(\hat{x}_k)\right] = \begin{bmatrix} A_{11} & A_{12} & A_{13} & A_{14} \\ A_{21} & A_{22} & A_{23} & A_{24} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{13}$$

$$H_k = \left[\frac{\partial h(x_k)}{\partial x_k} | (\bar{x}_{k+1})\right] = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{14}$$

Where:

$$A_{11} = 1 - \frac{2\hat{C}_{f_k} + 2\hat{C}_{r_k}}{mv_x}dt \text{ , } A_{12} = (-v_x - \frac{2\hat{C}_{f_k} l_f - 2\hat{C}_{r_k} l_r}{mv_x})dt$$

$$A_{13} = -\frac{2v_{y_k} dt + 2r_k l_f dt}{mv_x} + \frac{2\delta_k dt}{m} \text{ , } A_{14} = \frac{2l_r r_k dt - 2v_{y_k} dt}{mv_x}$$

$$A_{21} = \frac{2\hat{C}_{r_k} l_r - 2\hat{C}_{f_k} l_f}{I_z v_x}dt \text{ , } A_{22} = 1 - \frac{2l_f^2 \hat{C}_{f_k} + 2l_r^2 \hat{C}_{r_k}}{I_z v_x}dt$$

$$A_{23} = -\frac{2l_f v_{y_k} dt + 2l_f^2 r_k dt}{I_z v_x} + \frac{2l_f \delta_k dt}{I_z} \text{ , } A_{24} = \frac{2l_r v_{y_k} dt - 2l_r^2 r_k dt}{I_z v_x}$$

The initial values $P(0)$ and $x(0)$ are selected by experience, and the measurements of the vehicle's response (v_y, r) are input into the extended Kalman filter that recursively outputs the vector (C_f, C_r) according to equation (12). Then the optimal state estimate is obtained, and model parameters of the rice transplanter are obtained in real time.

Parameter identification algorithm of IPSO-EKF

The Q and R matrices corresponding to the statistical characteristics of noise w and v have a greater impact on the convergence of EKF. In this paper, IPSO combined with the EKF algorithm is used to optimize Q and R offline. Particle swarm optimization (PSO) is a population-based stochastic search algorithm inspired by the social behaviour of bird flocking. It was first introduced by Kennedy and Eberhart in 1995. Each particle in the PSO algorithm represents a feasible solution, and the particle has two properties: velocity and position. In the search space, individual particles compare the optimal positions they pass with the optimal position of all the particles and adjust their speed continuously so that they can move closer to the global optimal position. The velocity and position of each particle are updated according to the following equations (Liu W.X., et al., 2011):

$$v_{i,d}(k+1) = wv_{i,d}(k) + c_1 r_1 (p_{i,d} - x_{i,d}(k)) + c_2 r_2 (g_d - x_{i,d}(k)) \tag{15}$$

$$x_{i,d}(k+1) = x_{i,d}(k) + v_{i,d}(k) \tag{16}$$

Where i - the number of the particle; d - the dimension of the particle; k - the number of iterations; c_1, c_2 - the acceleration coefficient; r_1, r_2 - two random numbers uniformly distributed in the interval [0,1]; $p_{i,d}$ - the historically optimal position of particle i; g - the optimal position experienced by all particles in the population; w - the inertia decreasing weight. In order to increase the new space solution for more extensive search, an adaptive detection radius is proposed (Zhang Q., et al.,2019).

$$R(k) = \frac{(x_{\max}^d + x_{\min}^d)}{2} + \frac{(x_{\max}^d - x_{\min}^d)}{2} \bullet e^{-\lambda t} \bullet \cos(2\pi u) \tag{17}$$

Where λ is a variable parameter ($\lambda > 2$), u represents the random numbers uniformly distributed in the interval [0,1]. $x_{\max}^d$ and $x_{\min}^d$ are the upper and lower bounds of the variables, respectively. The IPSO velocity equation is updated according to the following equation:

$$v_{i,d}(k+1) = wv_{i,d}(k) + c_1 r_1 (p_{i,d} - x_{i,d}(k)) + c_2 r_2 (g_d - x_{i,d}(k)) + c_3 r_3 (R(k) - x_{i,d}(k)) \tag{18}$$

Because the standard PSO algorithm is easy to fall into the local optimal value, chaotic search is introduced into the PSO algorithm. After updating the velocity and position of each particle according to equations (15) and (16), the fitness function f of each particle is updated accordingly. When the particle i satisfies $|f(x_i)-f(p_i)|<\delta$ for N consecutive times, it is judged that the particle has a stagnation state. So, the chaotic sequence generated by Logistic is used to search again; it is expressed as follows:

$$y_{k+1,d}=4y_{k,d}(1-y_{k,d}) \tag{19}$$

Each component of the initial value y_0 is randomly generated in a uniform distribution in the interval [0,1]. In a carrier-like manner, the particles expanded to an area with R_d radius centred on the current position.

$$x_{i,d}^{k}=x_{i,d}+R_d(2y_{k,d}-1) \tag{20}$$

When $f(x_{i,d}^{k})<f(x_{i,d})$ is satisfied, the current particle position is updated. When $k>N_{\max}$ is satisfied, chaotic iteration ends. By increasing the adaptive detectable radius and chaotic sequences generated by stagnation, the IPSO algorithm solves the problem which falls into a local optimal solution, and greatly improves the reliability of global optimization.

IPSO optimizes the noise matrices

The parameters optimized by the IPSO algorithm are Q and R noise matrices in EKF. The sequence of lateral speed, the yaw rate and the steering angle of the front wheel collected by the above M600 receiver were input into a discrete rice transplanter model. IPSO randomly generates $F\times D$ dimensional matrices, and uses equations (15) and (16) to update the position and velocity of particles and chaotic search for stagnant particles. The random Q and R noise matrices are input into EKF, and the optimal Q and R matrices are obtained according to the objective function until the maximum number of iterations is met. The selection of fitness function is a core part of the PSO algorithm. If it is not adopted properly, it will affect the global optimization performance of the algorithm. The optimized noise matrices Q and R in EKF are designed to minimize the cumulative absolute error between the sampled measurement data y_{k+1} and the filtered output $H\overline{x}_{k+1}$. The objective function is defined as follows (Xiang Y., et al., 2016):

$$f=\frac{1}{N}\sum_{k=1}^{N}\left|y_{k+1}-H\overline{x}_{k+1}\right| \tag{21}$$

Where N - the number of the measurement data. The two degree of freedom dynamic model of the rice transplanter established in this paper has four state variables and two output variables, where the matrices corresponding to the Q and R are as follows:

$$\begin{aligned}&Q=diag(q_{11},q_{22},q_{33},q_{44})\\&R=diag(r_{11},r_{22})\end{aligned} \tag{22}$$

The structure of the noise matrices for the EKF algorithm identified by the IPSO algorithm is shown in Fig.3.

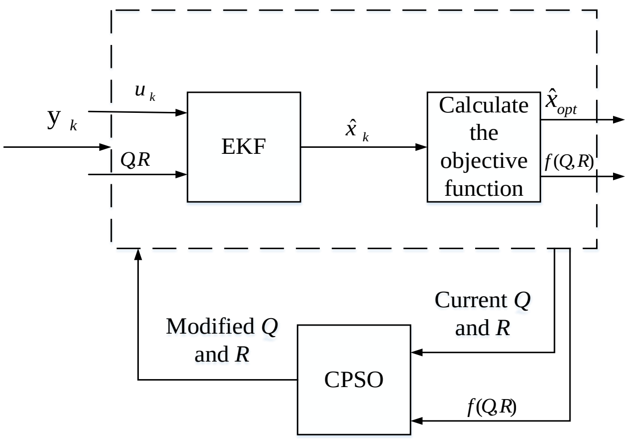

Fig. 3 - Structure diagram of IPSO optimized noise matrices

The parameters of the identification algorithm are set as: $F=20$, $D=6$, N_c=20, $c_1=1$, $c_2=1.5$, $c_3=2$, $k_{max}=40$, $N_{max}=10$, $N=5$, $R_d=10$, $\lambda=4$, $\delta=10^{-6}$, w decreases linearly at [0.9,0.4]. When the IPSO algorithm is run, the change curve of the global optimal objective function value for population is shown in Fig.4. It can be known that about 13 iterations tend to stabilize in the search process. Chaotic search and adaptive detection radius are introduced to solve the problem that the PSO algorithm is easy to fall into the local optimal value, and the global optimal solution can be searched. The identified Q and R noise matrices will be used in the online identification algorithm based on IPSO-EKF in the next chapter.

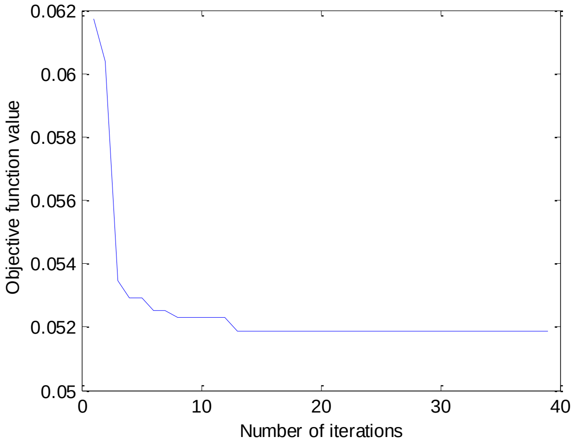

Fig. 4 - Evolution of the objective function

RESULTS

Simulation of parameters setting

This simulation uses MATLAB to verify the accuracy of the IPSO-EKF algorithm. The model parameters of the rice transplanter PZ60-DT are shown in Table 1. The ground speed and course angle of the rice transplanter come from the M600 receiver, and the yaw rate and lateral acceleration are calculated by coordinate transformation.

Table 1

Simulation model parameters of the rice transplanter

Parameters	m	l_f	l_r	I_z	δ_f
	[Kg]	[m]	[m]	[Kg·m^2]	[°]
Values	720	0.7	0.4	201.6	20

Online identification of cornering stiffness based on IPSO-EKF

The data collected by the above M600 receiver and the Q and R noise matrices identified by IPSO-EKF are input into dynamic simulation model of the rice transplanter. The initial value of the cornering stiffness is set to $C_f=C_r$=1000N/rad, the simulation results of the cornering stiffness of the front and rear tires for the rice transplanter are shown in Fig.5, which shows the evolution in the cornering stiffness of the front and rear tires at each sampling time. Considering the unevenness of the test field and the serious side slip of the front wheels during driving, the change in the cornering stiffness of tires is obvious. In order to more intuitively verify the accuracy of the identification results, the identified cornering stiffness of the front and rear tires are substituted into the dynamic model of the rice transplanter, and the model output obtained is compared with the measurement data collected by M600 receiver as shown in Fig.6. It can be seen from Fig.6 that the cornering stiffness and yaw rate response curves of the model output after IPSO-EKF identification are basically consistent with the collected data. In what follows and for comparison purposes, our proposed method will be compared with trial-error method for standard EKF. As shown in Fig.7, it can be known that model output identified based on EKF algorithm doesn't match the measured value. There is a large error between the model output calculated from the identified model parameters and the measured data in Table 2. The simulation results show that the noise matrices optimized by IPSO have a better optimization effect on the online identification algorithm of EKF, and can accurately identify the model parameters.

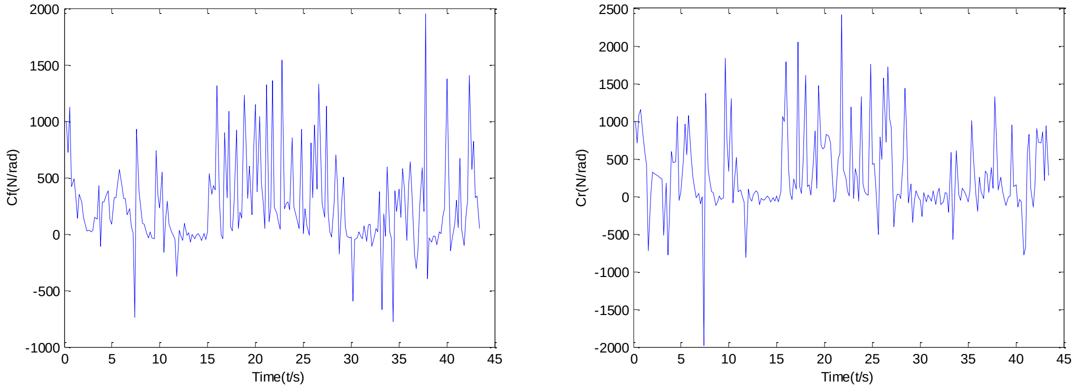

Fig. 5 - The cornering stiffness of the front and rear tires under 20-degree step condition

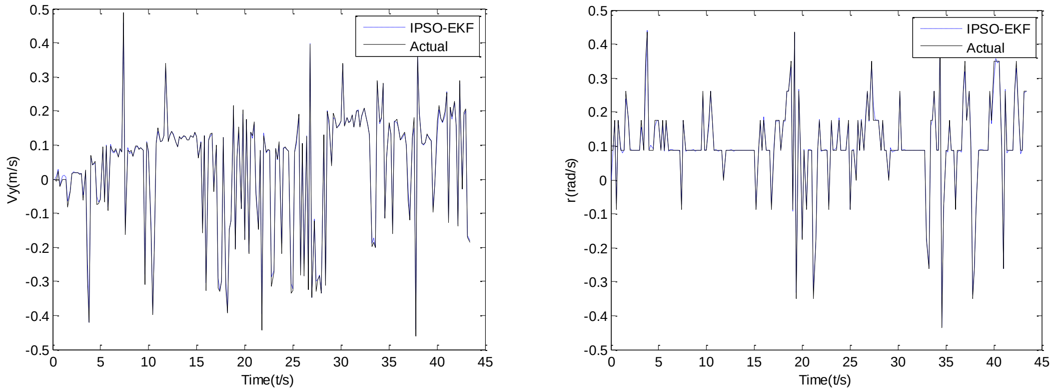

Fig. 6 - The value of model output and measured value obtained by IPSO-EKF algorithm under 20-degree step condition

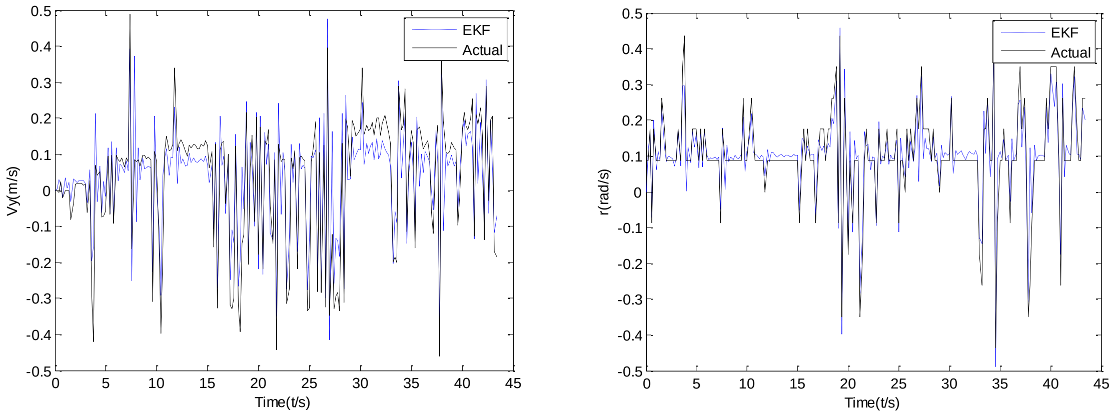

Fig. 7 - The value of model output and measured value obtained by EKF algorithm under 20-degree step condition

Table 2

The statistics of lateral velocity and yaw rate for errors under 20-degree step condition

Identification algorithm	Maximum error v_y [m/s]	Maximum error r [rad/s]	Average error v_y [m/s]	Average error r [rad/s]
IPSO-EKF	0.0672	0.0873	0.0064	0.0050
EKF	0.3050	0.3841	0.0595	0.0316

Simulation verification under different operating conditions

In order to verify the consistency of the algorithm, the data under different working conditions are used to simulate the IPSO-EKF algorithm. The steering angle of the front wheels for the rice transplanter is set to

30 degrees, and it is driven clockwise at low speed along the field. Similarly, the collected longitudinal velocity, lateral velocity and yaw rate are input into the dynamic model of the rice transplanter. The cornering stiffness of the front and rear tires are identified by the EKF algorithm, as shown in Fig.8. The comparison between the output data calculated by the model and the data measured by M600 receiver is shown in Fig.9. Fig.9 shows that the data calculated by the model are basically consistent with the measured data, although there are some errors which are small and can better match the measured data, and the overall curve trend is consistent.

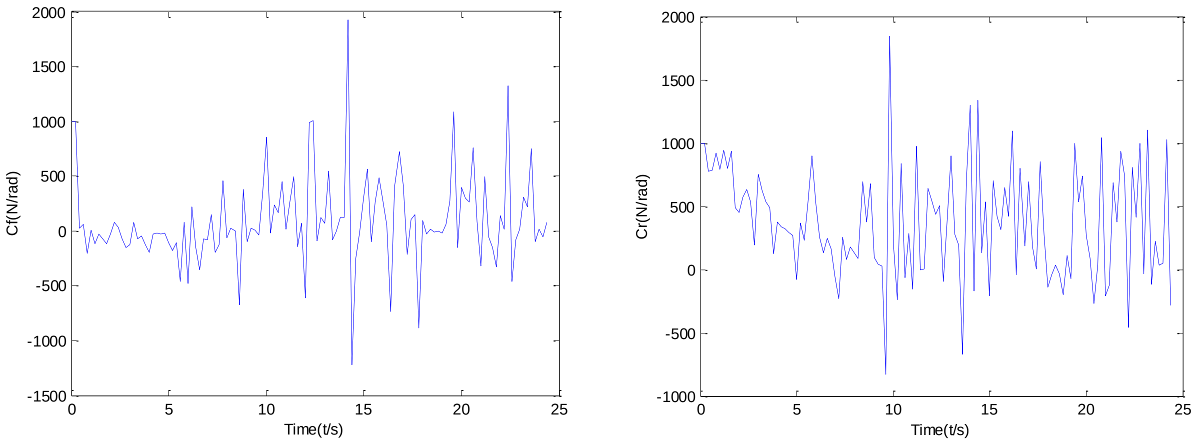

Fig. 8 - The cornering stiffness of the front and rear tires under 30-degree step condition

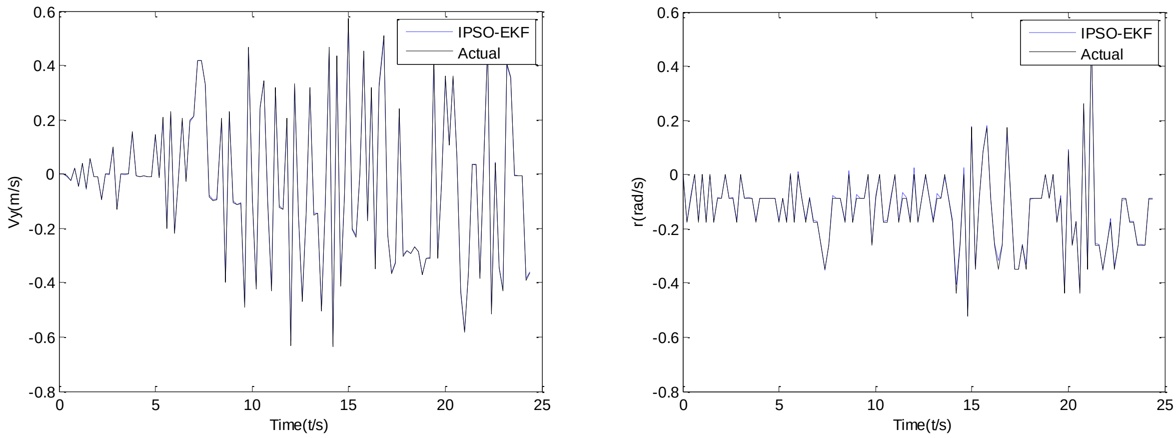

Fig. 9 - The value of model output and measured value obtained by IPSO-EKF algorithm under 30-degree step condition

CONCLUSIONS

In this paper, through the dynamic analysis of the rice transplanter, a lateral dynamic model of the rice transplanter was established. In order to accurately identify the parameters of the rice transplanter dynamic model, the IPSO-EKF algorithm was proposed. In the offline state, combined with data collected by M600 receiver, the noise matrices in EKF were optimized by IPSO algorithm. The optimized noise matrices are selected as the best matrices, and the cornering stiffness of the front and rear tires for the rice transplanter model was identified online based on the IPSO-EKF algorithm. The simulation results showed that the output data calculated by the model was basically consistent with the data collected by M600 receiver. Compared with the EKF algorithm, the IPSO-EKF algorithm greatly improved the accuracy of the identification. In order to verify the consistency of the algorithm proposed in this paper, the data collected under different operating conditions of the rice transplanter were used to verify the algorithm. The simulation results showed that the algorithm can better describe the dynamic characteristics of the rice transplanter and accurately realize the online identification of the parameters for the rice transplanter model. This algorithm lays the foundation for the design of a rice transplanter based on a dynamic model control algorithm.

ACKNOWLEDGEMENT

This work was supported in part by the Transformation of Scientific and Technological Achievements of Shenyang (Grant no. Z17-5-032), and the name of the work is The Transformation of Technological Achievements for Automatic Agricultural Machinery.

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