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Comparative Study of Several Nonlinear Identification Algorithms for PMSM Rotor Flux Linkage

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Abstract:

Accurate identification of rotor flux linkage is an effective method to realize working status monitoring of permanent magnet and high-performance control of permanent magnet synchronous motor (PMSM) drive system. The current rotor flux linkage identification methods and their technical characteristics are reviewed firstly, and then, the identification method based on Unscented Kalman Filter (UKF), Particle Filter (PF), Unscented Particle Filter (UPF) and algebraic identification algorithm are also proposed to identify rotor flux linkage. The identification performance of UKF, PF, UPF and algebraic identification algorithm is studied and compared in gaussian distribution noise and non-gaussian distribution noise by means of simulation, and the identification performance of algebraic identification algorithm is verified by experiment. Research achievements provide some effective references for achieving high performance control and reliable permanent magnet demagnetization fault diagnosis of PMSM drive system.

Keywords: *PMSM, Rotor flux linkage, Nonlinear identification algorithm, Comparative study.*

I. INTRODUCTION

PMSM has been widely used in electric vehicles, new energy power generation and other applications due to its advantages of low maintenance rate, high power density and good control performance[1]. However, most of abovementioned applications are limited by installation space, the heat dissipation condition is poor and the operating conditions are complex, all of which easily lead to high working temperature and strong armature reaction, and then resulting in permanent magnet demagnetization fault and rotor flux linkage loss, which will inevitably reduce the control performance and operation reliability of the PMSM drive system.

In order to achieve high performance control and reliable operation of PMSM drive system, luenberger observer[2], least square method[3], model reference adaptive algorithm[4], genetic algorithm[5], immune clonal selection differential[6], adaptive mutation dynamic differential evolution[7] and dynamic particle swarm optimization algorithm with learning strategy[8] have been successively used in online identification of PMSM rotor flux. However, the identification results of luenberger observer, least square

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method and model reference adaptive algorithm are susceptible to measurement noise, the identification accuracy is easy to decrease under strong measurement noise. While, the genetic algorithm, differential evolution algorithm and particle swarm optimization algorithm usually need a large amount of data for algorithm training and target optimization, which easily result in a large amount of computation, moreover, these model-free parameter identification algorithm abovementioned lack theoretical support with strict mathematical significance.

Bayesian filter theory provides a consistent solution for the state estimation of dynamic stochastic systems, it can provide a strict mathematical framework for PMSM rotor flux linkage identification to realize its optimal estimation or suboptimal estimation. Research on PMSM rotor flux linkage identification based on EKF algorithm [9]and the method combining EKF with wavelet transform[10] has been already proposed. EKF is a suboptimal filtering algorithm under the minimum variance criterion and it is sensitive to the initial value of state vector[11], although many improved algorithms have been proposed on the basis of EKF algorithm, such as iterative EKF[12] and high-order truncation EKF[13], the abovementioned deficiency is still difficult to overcome completely.

Therefore, based on the principle analysis of UKF, PF, UPF and algebraic identification algorithm, the rotor flux linkage identification methods based on abovementioned four algorithms are proposed in this paper, their identification performances are simulated and analyzed respectively in gaussian distribution noise and non-gaussian distribution noise, the time consuming, accuracy and discreteness of the identification results are also compared for the first time, and the correctness and feasibility of the algebraic identification method are verified by experiments.

II. STATE EQUATION FOR PMSM ROTOR FLUX LINKAGE IDENTIFICATION

The dynamic current equation of PMSM in dq coordinate system is

$$\begin{cases} \dfrac{di_d}{dt} = \dfrac{u_d}{L_d} - \dfrac{R_s}{L_d} i_d + \dfrac{\omega_e L_q}{L_d} i_q \\ \dfrac{di_q}{dt} = \dfrac{u_q}{L_q} - \dfrac{R_s}{L_q} i_q - \dfrac{\omega_e L_d}{L_q} i_d - \dfrac{\omega_e \psi_f}{L_q} \end{cases} \tag{1}$$

where, $u_{d,q}$ represent d axis and q axis stator voltage; $i_{d,q}$ represent d axis and q axis stator current; $L_{d,q}$ represent d axis and q axis stator inductance; R_s is stator resistance; ψ_f is rotor flux linkage; ω_e represents the rotor electrical angular velocity and N_p represents the number of pole pairs.

Due to its slow changing characteristic, the rotor flux linkage variation in a control cycle of PMSM drive system is set to zero, the state equation for rotor flux linkage identification can be obtained by combining equation(1) and shown in equation (2).

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$$\begin{cases} \dfrac{di_d}{dt} = \dfrac{u_d}{L_d} - \dfrac{R_s}{L_d} i_d + \dfrac{\omega_e L_q}{L_d} i_q \\ \dfrac{di_q}{dt} = \dfrac{u_q}{L_q} - \dfrac{R_s}{L_q} i_q - \dfrac{\omega_e L_d}{L_q} i_d - \dfrac{\omega_e \psi_f}{L_q} \\ \dfrac{d\psi_f}{dt} = 0 \end{cases} \tag{2}$$

According to the state equation shown in equation (2), the state vector x, input vector u and output vector y can be given as

$$\begin{cases} x = \begin{bmatrix} i_d & i_q & \psi_f \end{bmatrix}^T \\ u = \begin{bmatrix} u_d / L_d & u_q / L_q \end{bmatrix}^T \\ y = \begin{bmatrix} i_d & i_q \end{bmatrix}^T \end{cases} \tag{3}$$

Because the rotor flux linkage is in the state vector, the online identification of rotor flux linkage can be achieved by state vector estimation based on nonlinear identification algorithm.

III. THE PRINCIPLE OF UKF, PF, UPF AND ALGEBRAIC IDENTIFICATION ALGORITHM

The state equation and discrete measurement equation of the general nonlinear system are usually expressed as

$$\begin{cases} \dot{x}(t) = f[x(t)] + Bu(t) + \sigma(t) \\ y(t_k) = h[x(t_k)] + \mu(t_k) \end{cases} \tag{4}$$

Where, $x(t)$ is state vector, $y(t_k)$ is measurement vector, $f(\cdot)$ and $h(\cdot)$ represent state transition function and measurement function of the nonlinear system respectively, $\sigma(t)$ and $\mu(t_k)$ represent system noise and measurement noise considering model uncertainty and measurement uncertainty, $Q(t)$ and $R(t)$ are variance matrix of abovementioned system noise and measurement noise, $u(t)$ is deterministic system input vector.

3.1 UKF Algorithm

UKF is a nonlinear filtering algorithm based on unscented transformation proposed in 1995[14], this algorithm does not require approximate linearization of the state equation and the measurement equation of the nonlinear system, but uses the nonlinear system actual model to directly approximate the posterior probability density function of the state vector by definite samples and unscented transformation, and then, the statistical information such as mean value and covariance value of the state vector can be obtained. Therefore, this algorithm can effectively solve the non-convergence or divergence problem of EKF

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algorithm caused by strong nonlinearity of controlled system, at the same time, the linearization error is avoided and the estimation accuracy is improved, and there is no need to calculate jacobian matrix, which obviously reduces the computation and implementation difficulty of the UKF algorithm.

UKF algorithm and its improved algorithm have been widely used in navigation and positioning[15], autonomous robot positioning[16], nonlinear system state estimation[17] and other application fields. In this paper, the algorithm is applied to PMSM rotor flux linkage identification, for the nonlinear system shown in equation (4), the rotor flux linkage identification based on UKF algorithm has four steps, that is, state vector initialization, Sigma point calculation, time update and measurement update.

Step 1. state vector initialization

The system noise covariance matrix Q and the measurement noise covariance matrix R are set firstly according to prior knowledge, and then, the state vector x and its state covariance matrix P are initialized as shown in equation (5).

$$\hat{x}_0 = E[x_0] \qquad P_0 = E[(x_0 - \hat{x}_0)(x_0 - \hat{x}_0)^T] \tag{5}$$

Step 2. Sigma point calculation

In each sampling period (k=1,2,···,∞), sigma points are calculated according to equation (6) to obtain sigma point matrix.

$$\chi_{k-1} = \left[\hat{x}_{k-1} \quad \hat{x}_{k-1} + \sqrt{(n+\lambda)P_{k-1}} \quad \hat{x}_{k-1} - \sqrt{(n+\lambda)P_{k-1}} \right] \tag{6}$$

Where, n is the dimension of the stator vector, $\lambda = \alpha^2(n+b) - n$ is a proportionality coefficient, α determines the sigma points distribution, that is, it determines the dispersion of the sigma points near the mean value of the state vector, which is usually taken as a small positive number in the interval$[10^{-4},1]$. b is a scale coefficient, which is usually taken as 0 or $3-n$.

Step 3. Time updata

The sigma point transfer is realized by discretized state equation expressed as equation(7), and the predicted mean value and covariance value of the state vector are calculated by equation (8). Where, $W_i^{(c)}$ and $W_i^{(m)}$ represent the mean value weight and covariance value weight of the state vector respectively, and can be expressed as equation (9).

$$\chi^*_{i,k|k-1} = f(\chi_{i,k-1}) + Bu(k-1) \tag{7}$$

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$$\begin{cases} \hat{x}_k^- = \sum_{i=0}^{2n} W_i^{(m)} \chi_{i,k|k-1}^* \\ P_k^- = \sum_{i=0}^{2n} W_i^{(c)} [\chi_{i,k|k-1}^* - \hat{x}_k^-][\chi_{i,k|k-1}^* - \hat{x}_k^-]^T + Q \end{cases} \tag{8}$$

$$\begin{cases} W_0^{(m)} = \lambda / n+\lambda \\ W_0^{(c)} = \lambda / n+\lambda + (1-\alpha^2+\beta) \qquad (i=1,2,\cdots,2n) \\ W_i^{(m)} = W_i^{(c)} = 1 / 2(n+\lambda) \end{cases} \tag{9}$$

Step 4. Measurement updata

According to the measurements, the one-step prediction and kalman gain update can be achieved ,and the optimal estimation of the state vector and its variance matrix are also obtained by equation(10).

$$\begin{cases} \hat{y}_k^- = H\hat{x}_k^- \\ P_{x_k y_k} = P_k^- H^T \\ K_k = P_{x_k y_k} P_{x_k y_k}^- , P_{y_k y_k}^- = HP_k^- H^T + R \\ \hat{x}_k = \hat{x}_k^- + K_k [y_k - \hat{y}_k^-] \\ P_k = P_k^- - K_k P_{y_k y_k}^- K_k^T \end{cases} \tag{10}$$

Set k=k+1 and repeat setp2 to step 4, the iterative output of state vector can be achieved. By substituting the state equation , state vector, input vector and output vector of PMSM described in equations (2) and (3) into the UKF algorithm expressed by equation(5) to equation(10), the recursive estimation of the state vector is obtained, and the online identification of PMSM rotor flux linkage is also achieved.

3.2 PF Algorithm

UKF algorithm approximate the posterior probability density of system state based on gaussian distribution, when it does not meet the requirement of gaussian distribution, there may have a certain of errors in identification results. The main idea of PF algorithm is to express the posterior probability density of the state vector by the weighted sum of some random samples, because of the good applicability of Monte Carlo method for generating random particles, the PF algorithm is more suitable for nonlinear and non-gaussian systems.

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The discretization form of nonlinear system described in equation (4) can be described as

$$\begin{cases} x_{k+1} = f(x_k, u_k, \sigma(t_k)) \\ y_k = h(x_k, \mu(t_k)) \end{cases} \tag{11}$$

Where, x_k is state vector, y_k is measurement vector, $\sigma(t_k)$ and $\mu(t_k)$ represent system noise and measurement noise respectively, $f(\cdot)$ and $h(\cdot)$ represent state transition function and measurement function of the nonlinear system respectively.

Using all of the observations $y_{0:k}$ to estimate state vector $x_{0:k}$, then the estimation of state vector posteriori probability distribution function can be achieved, which is described as equation (12) .

$$\hat{p}\left(x_{0:k} \mid y_{0:k}\right) = \frac{1}{N}\sum_{i=1}^{N} \delta_{x_{0:k}^{(i)}}(dx_{0:k}) \tag{12}$$

Where, $\left\{x_{0:k}^{(i)} \mid i = 1, \cdots N\right\}$ is random sample, which are extracted from the posterior probability distribution, $\delta(d\cdot)$ represents the Dirac sampling function.

For nonlinear systems, important sampling is often used to extract samples from a known and easily sampled function, which is called important density function, and its distribution is called recommended distribution. Supposing the recommended distribution function is described as $q(x_{0:k}|y_{0:k})$, the posteriori probability distribution function can be described as

$$\hat{p}\left(x_{0:k} \mid y_{0:k}\right) = \frac{1}{N}\sum_{i=1}^{N} \frac{p\left(x_{0:k}^{(i)} \mid y_{0:k}\right)}{q\left(x_{0:k}^{(i)} \mid y_{0:k}\right)} \delta_{x_{0:k}^{(i)}}(dx_{0:k}) = \frac{1}{N}\sum_{i=1}^{N} \omega_k^{(i)} \delta_{x_{0:k}^{(i)}}(dx_{0:k}) \tag{13}$$

Where, $\omega_k^{(i)} = \frac{p\left(x_{0:k}^{(i)} \mid y_{0:k}\right)}{q\left(x_{0:k}^{(i)} \mid y_{0:k}\right)}$ are initial weights, in order to ensure the weight sum of all samples is 1, the sample weights need to be normalized.

The sampling process abovementioned is called importance sampling, the difference between sampling from the posterior probability density and sampling from the suggested distribution function can be compensated by determining appropriate weight, and the accuracy of state estimation is then improved. If there is no correlation between the system initial state and the observed information, and the system is a Markov process, the following equation can be obtained:

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$$\begin{cases} p(x_{0:k}) = p(x_0)\prod_{j=1}^{k} p(x_j \mid x_{j-1}) \\ p(y_{0:k}) = \prod_{j=1}^{k} p(y_j \mid x_{j-1}) \end{cases} \tag{14}$$

The weight calculation formula is achieved and described as

$$\omega_k^{(i)} = \frac{p(y_{0:k} \mid x_{0:k}^{(i)})\,p(x_{0:k}^{(i)})}{q\left(x_{0:k-1}^{(i)} \mid y_{0:k-1}\right)q(x_k^{(i)} \mid x_{0:k-1}^{(i)}, y_{0:k})} = \omega_{k-1}^{(i)} \frac{p(y_k \mid x_k^{(i)})\,p(x_k^{(i)} \mid x_{k-1}^{(i)})}{q(x_k^{(i)} \mid x_{0:k-1}^{(i)}, y_{0:k-1})} \tag{15}$$

For the PF algorithm, the prior probability density function is usually taken as importance density function, that is

$$q(x_k^{(i)} \mid x_{0:k-1}^{(i)}, y_{0:k-1}) = p(x_k^{(i)} \mid x_{k-1}^{(i)}) \tag{16}$$

Substituting equation (16) into equation (15), the equation (17) is obtained

$$\omega_k^{(i)} = \omega_{k-1}^{(i)} p(y_k \mid x_k^{(i)}) \tag{17}$$

Substituting equation (17) into equation (13), the correctness of approximating the true posterior probability density by equation (13) can be guaranteed by large numbers law.

Numerous studies have now found that the variance of samples weight increases rapidly over time. After several iterations, except for a few particles, the weight of the remaining particles decreases sharply, which are no longer plays a role in posterior probability estimation, this phenomenon is called particle degradation. In order to solve the problem of particle degradation, an effective solution is to introduce resampling algorithm. The importance sampling introduced resampling algorithm is called sequential importance resampling, also known as PF algorithm, the complete description of PF algorithm is shown in TABLE I.

TABLE I. The particle filter algorithm

Step 1. Algorithm initialization, Setting k=0, extracting N particles from the prior probability distribution $p(x_0)$, that is, $\{x_0^{(i)}\}_{i=1}^{N} \sim p(x_0)$, meantime, set $\omega_0^{(i)} = 1/N$.
Step 2. Calculating the new weight of each sample according to equation (18) and Normalize it.
Step 3. resampling particle set according to resampling algorithm.
Step 4. Outputting the estimation results of state vector, that is $\hat{x}_k = \sum_{i=1}^{N} \tilde{\omega}_k^{(i)} x_k^{(i)}$ and

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$P_k = \sum_{i=1}^{N} \tilde{\omega}_k^{(i)} (x_k^{(i)} - \hat{x})(x_k^{(i)} - \hat{x})^T$

Step 5. Time updata, generating new particles according to the state transition function, that is, $\{x_{k+1}^{(i)}\}_{i=1}^{N} \sim p(x_{k+1} \mid x_k^{(i)})$

Step 6. Set k=k+1, return to step2 and repeat the algorithm

3.3 UPF Algorithm

In order to ensure that the generation of random particles can be integrated into the latest measurements of the system, UPF algorithm has been proposed based on the idea that UKF algorithm generates particle filtering importance density function [18]. Due to the larger overlap between the importance density function generated by UKF and the posterior probability density function of the system real state, the UPF algorithm can achieve higher estimation accuracy than standard PF algorithm, and can overcome the constraint of gaussian distribution on UKF algorithm, the complete description of UPF algorithm is shown in TABLE II.

TABLE II. The unscented particle filter algorithm

Step 1. Algorithm initialization, Setting k=0, extracting N particles from the prior probability distribution $p(x_0)$, that is, $\{x_0^{(i)}\}_{i=1}^{N} \sim p(x_0)$, meantime, set $\omega_0^{(i)} = 1/N$.

Step 2. Importance density sampling. obtaining each random sampling point $x_k^{(i)}$ and the recommended distribution function $N(\bar{x}_k^i, P_k^i)$ based on UKF algorithm, extracting particles from recommended distribution function, calculating and normalizing the particle weights.

Step 3. Resampling. Resampling particle set $\{\hat{x}_k^{(i)}, \omega_k^{(i)}\}$ according to the resampling algorithm, obtaining the new particle set $\{x_k^{(i)}, \tilde{\omega}_k^{(i)}\}$ and setting $\tilde{\omega}_k^{(i)} = 1/N$.

Step 4. Outputting the estimation results of state vector, that is $\hat{x}_k = \sum_{i=1}^{N} \tilde{\omega}_k^{(i)} x_k^{(i)}$ and $P_k = \sum_{i=1}^{N} \tilde{\omega}_k^{(i)} (x_k^{(i)} - \hat{x})(x_k^{(i)} - \hat{x})^T$

Step 5. Set k=k+1, return to step2 and repeat the algorithm

3.4 Algebraic Identification Algorithm

The detailed theoretical derivation and proof of algebraic identification algorithm has been carried out [19], and this algorithm has been successfully applied to identify brushless DC motor parameters [20]. Based on the current state equation of PMSM described in equation (1), this algorithm is applied to identify PMSM parameters for the first time, and the specific derivation is described as follows:

The q axis voltage equation in equation (1) is rewritten as follows

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$$u_q = R_s i_q + L_q \frac{di_q}{dt} + \omega_r L_d i_d + \omega_e \Psi_f \tag{18}$$

Multiply both sides of equation (18) by t and integrate it in [0, t], equation (19) can be obtained.

$$\int tu_q = R_s \int ti_q + L_q \int t\frac{di_q}{dt} + L_d \int t\omega_e i_d + \psi_f \int t\omega_e \tag{19}$$

Rewriting equation (19) as follows

$$\int tu_q = R_s \int ti_q + L_q (ti_q - \int i_q) + L_d \int t\omega_e i_d + \psi_f \int t\omega_e \tag{20}$$

Setting $\gamma = \begin{bmatrix} L_q & L_d & R_s & \psi_f \end{bmatrix}, P_t = \begin{bmatrix} ti_q - \int i_q & \int t\omega_e i_d & \int ti_q & \int t\omega_e \end{bmatrix}, q_t = \int tu_q$

There is

$$P_t * \gamma = q_t \tag{21}$$

Since matrix P_t is a singular matrix, the equation (21) can be transformed into an optimization problem to solve. Define the squared error criterion function, as shown in equation (22).

$$J_{(\gamma,t)} = \frac{1}{2}\int_0^t \varepsilon^2_{(\gamma,\sigma)} d\sigma \tag{22}$$

Define the error vector $\varepsilon(t)=P_t * \gamma - q_t$ and Substitute it into equation (22), there is

$$J_{(\gamma,t)} = \frac{1}{2}\int_0^t (P_t\gamma - q_t)^2 d\sigma \tag{23}$$

Differentiating the equation (23) with identified vector γ, there is

$$\nabla_\gamma J_{(\gamma,t)} = \int_0^t P_t^T (P_t\gamma - q_t) d\sigma \tag{24}$$

Where, PtT is transposed matrix of Pt. Setting $\nabla_\gamma J_{(\gamma,t)} = 0$, there is

$$\int_0^t P_t^T (P_t\gamma - q_t) d\sigma = \tag{25}$$

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According to equation (25), the parameters to be identified can be expressed as

$$\hat{\gamma} = \left[\int_0^t P_t^T P_t d\sigma \right]^{-1} \int_0^t P_t^T q_t d\sigma \tag{26}$$

It can be seen from equation (16) to equation (26) that the algebraic identification algorithm can realize the online identification of PMSM parameters including rotor flux linkage without injecting disturbance current and without setting the initial value of identified parameters.

IV. SIMULATION STUDY AND PERFORMANCE COMPARISON OF THE PROPOSED ALGORITHM

The simulation research and identification performance comparison of the proposed four rotor flux linkage algorithms in this paper are implemented by using PMSM vector control system. PMSM parameters are shown as follows: rated power is 50KW, rated speed is 900rpm, stator resistance is 0.0154Ω, *d* axis inductance is 2.517mH, *q* axis inductance is 5.99mH, rotor flux linkage is 0.1732 Wb, moment of inertia is 0.00625 kg.m^2 and pole pairs is 4. In the simulation, the sampling period of speed, current and voltage, the control period of identification algorithm and the simulation step size are all set as 0.1ms. In order to give consideration to the stability, identification speed and identification accuracy of UKF, PF and UPF algorithms, the state vector initial value, the state sector variance matrix initial value, the system noise variance matrix and the measurement noise variance matrix are uniformly taken as

$$x(0) = \begin{bmatrix} 3 & 3 & 0.01 \end{bmatrix}^T ; P(0) = \begin{bmatrix} 0.5 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.1 \end{bmatrix}; \quad Q = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1e-5 \end{bmatrix}; \quad R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

The reference speed and load torque are set and shown in Fig.1 and Fig.2 respectively. Fig.3 shows the *d* axis and *q* axis stator current of PMSM under abovementioned working condition. In the simulation, gaussian noise described as $X \sim N(0,5)$ was injected into the measurements and the particle number of PF and UPF algorithm are all set as 100. The independent simulation results of the proposed four algorithms are shown in fig.4, and the quantitative evaluation of time-consuming, mean value of steady-state identification results and variance of steady-state identification results is achieved based on 10 independent simulation results, the detailed evaluation results are shown in TABLE III

It can be seen from the Fig.4 and TABLE III that the identification mean value of the four algorithms proposed in this paper can well approximate the actual rotor flux linkage, but the identification results of PF algorithm has a certain extent fluctuation and the identification variance is relatively large. In terms of a time-consuming, UKF, PF and UPF algorithms all have a relatively poor real time performance, while the algebraic identification method takes the least time with the same data length, which is conducive to

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online identification of PMSM rotor flux linkage. Therefore, algebraic algorithm has an excellent overall performance on PMSM rotor flux linkage identification with gaussian distribution measurement noise.

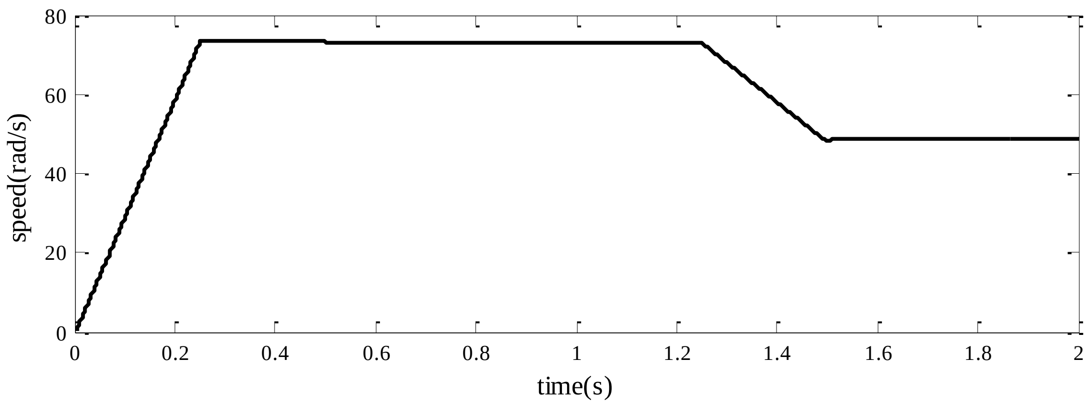


Fig.1 The reference speed

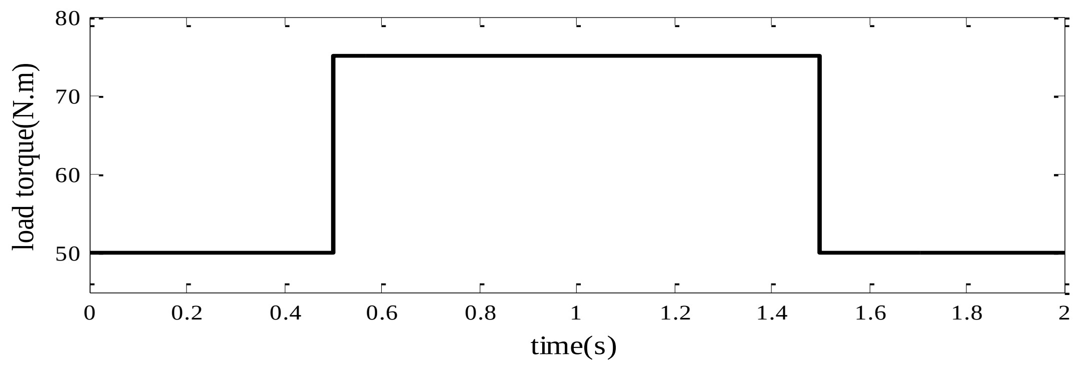
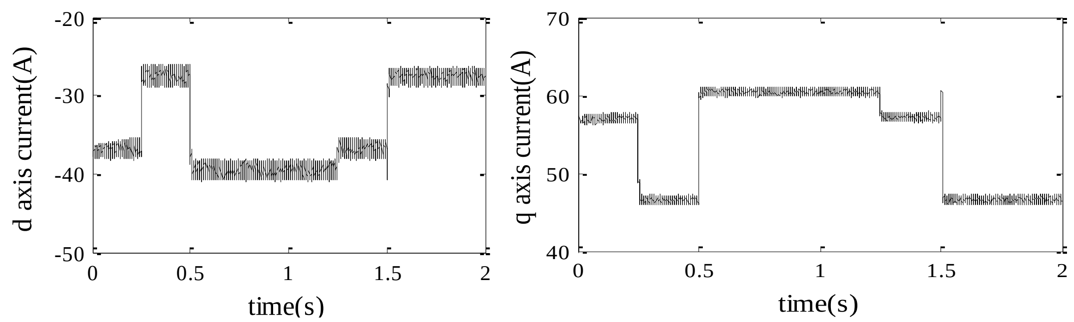


Fig.2 The load torque



(a) *d* axis current (b) *q* axis current

Fig.3 The *dq* axis stator current

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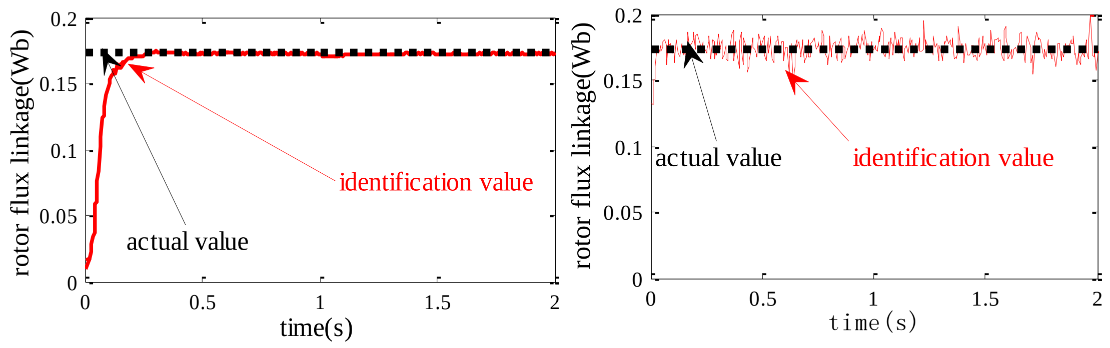
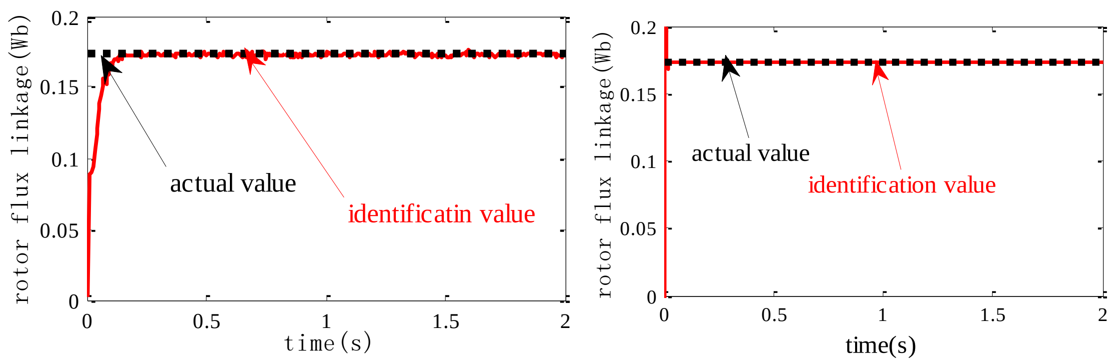


(a) The identification value of UKF algorithm (b) The identification value of PF algorithm



(c) The identification value of UPF algorithm (d) the identification value of algebraic algorithm

Fig.4 The rotor flux linkage identification results based on UKF, PF, UPF and algebraic identification algorithm with gaussian measurement noise

TABLE III. The evaluation of UKF, PF, UPF and algebraic algorithm under gaussian noise

algorithm	Average time consuming(μs)	Mean value (Wb)	variance
UKF algorithm	80	0.1730	0.000281
PF algorithm	261	0.1727	0.14
UPF algorithm	826	0.1729	0.0011
Algebraic algorithm	23	0.1731	0.000293

In order to study the identification performance of the proposed four algorithms with non-gaussian distribution noise, the gamma distribution random noise shown in Fig.5 is injected into the measurements and its probability density distribution is shown in Fig.6.

The independent simulation results of the four algorithms proposed in this paper with gamma distribution measurement noise are shown in Fig.7, and the quantitative evaluation of time-consuming, mean value of steady-state identification results and variance of steady-state identification results based on

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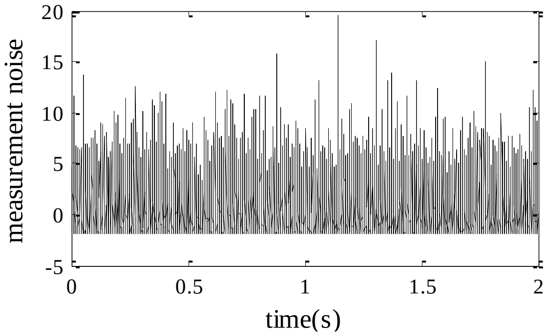
10 independent simulation results is detailed shown in TABLE IV. It can be seen from Fig.7 and TABLE IV that the gamma distribution measurement noise has a certain negative effects on the identification accuracy of UKF algorithm, while the other three identification algorithms all can achieve relative accurate rotor flux linkage identification, the variance of PF algorithm identification results is relatively large, and the algebraic identification algorithm has the fastest convergence speed and minimum time-consuming among the four algorithm, which can realize online identification of rotor flux linkage without additional hardware system. Therefore, the algebraic identification algorithm still shows obvious advantages over the other three algorithms on rotor flux linkage identification with non-gaussian distribution measurement noise.



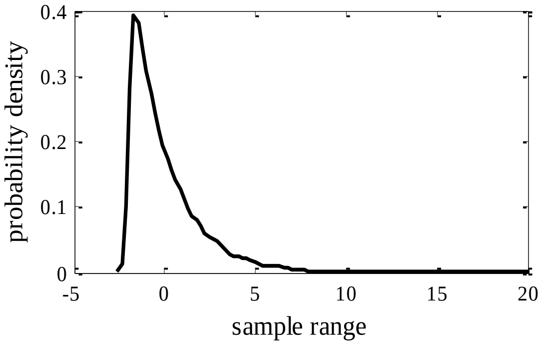
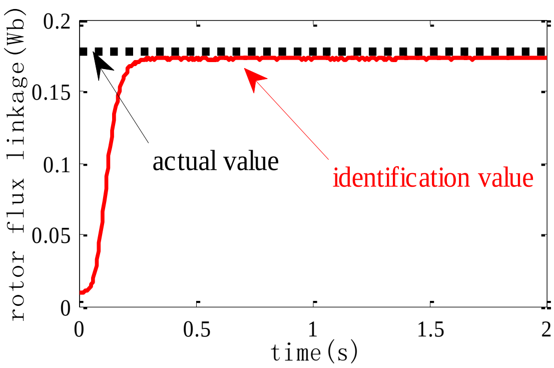
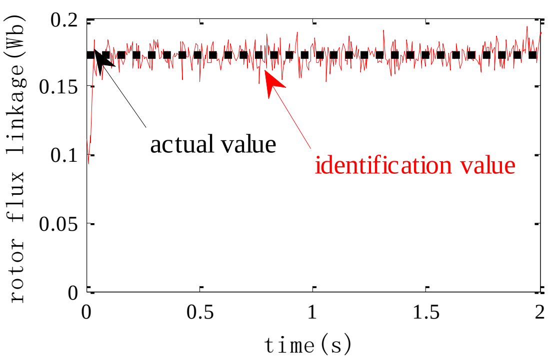
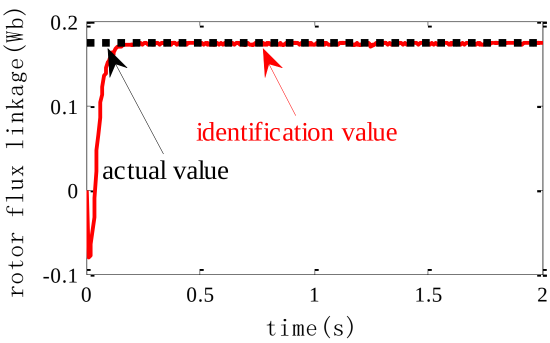


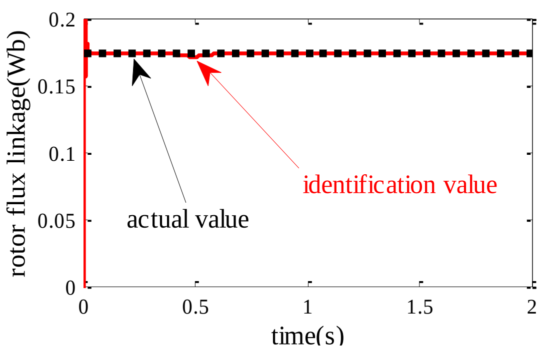
Fig.5 The gamma distribution measurement noise Fig.6 The probability density distribution curve





(a) The identification value of UKF algorithm (b) The identification value of PF algorithm





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(c) The identification value of UPF algorithm (d) the identification value of algebraic algorithm
Fig.7 The identification results of rotor flux linkage based on UKF, PF, UPF and algebraic identification algorithm under Gamma measurement noise

TABLE IV. The evaluation of UKF, PF, UPF and algebraic algorithm under non-gaussian noise

algorithm	Average time consuming(μs)	Mean value (Wb)	variance
UKF algorithm	78	0.1657	0.000683
PF algorithm	266	0.1726	0.189
UPF algorithm	839	0.1727	0.000764
Algebraic algorithm	21	0.1730	0.000433

V. EXPERIMENTAL VERIFICATION OF ALGEBRAIC IDENTIFICATION ALGORITHM

The experimental platform of PMSM drive system is designed based on AC dynamometer and dSPACE component system, and the experimental verification of the proposed algebraic identification algorithm is implemented. Experimental motor parameters are as follows: rated voltage is 380V, rated power is 2.6KW, rotor flux linkage is 0.128Wb, stator resistance is 0.28Ω, d axis and q axis inductance all are 1.273mH and pole pairs is 4. In the experimental study, the load torque is set as 3$N·m$ and the motor speed dynamic is taken as 900 *rpm*~450 *rpm*, the measured speed waveform is shown in Fig.8, and the stator current is shown in Fig.9 with the motor speed drops to 450 *rpm*.

The rotor flux linkage identification result based on algebraic identification algorithm under the set PMSM drive system working conditions is shown in Fig.10. Compared with the actual value, it is found that the algebraic identification algorithm can accurately identify PMSM rotor flux linkage with both dynamic and steady working conditions, and the variance of identification result is relatively small. The experimental results are in agreement with that of simulation, the feasibility and correctness of the proposed algebraic identification algorithm in PMSM rotor flux linkage identification are verified, which provides a foundation for high performance control and reliable permanent magnet demagnetization fault diagnosis of PMSM drive system.

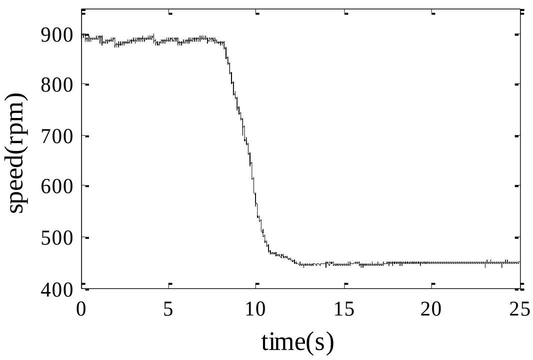

Fig 8 Speed dynamic of PMSM

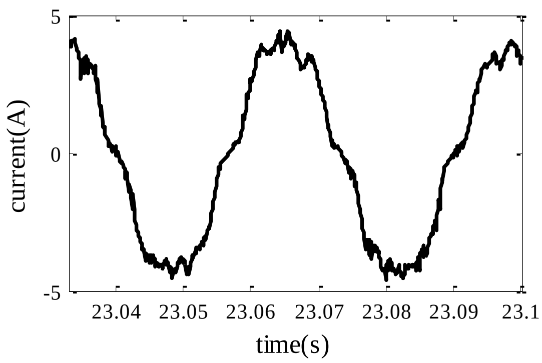

Fig 9 Stator current of PMSM

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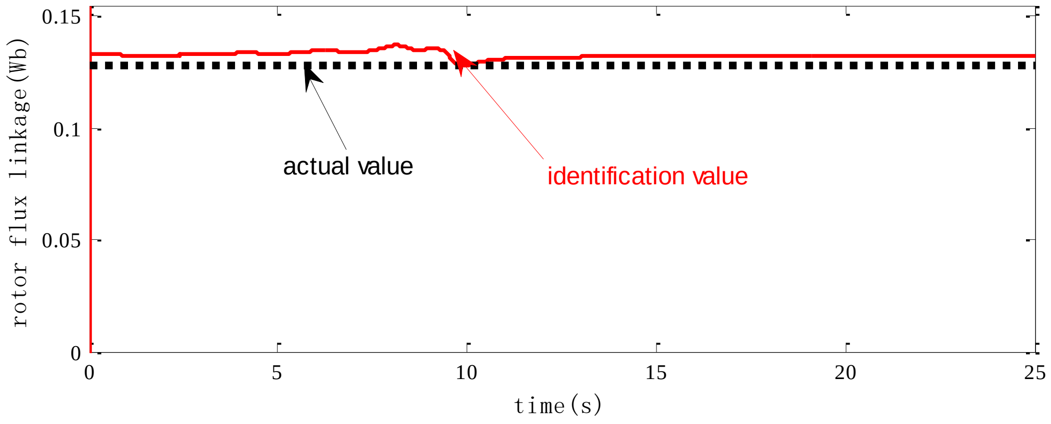

Fig 10 The identification results of rotor flux linkage based on algebraic algorithm

VI. CONCLUSIONS

In this paper, PMSM rotor flux identification method based on UKF, PF, UPF algorithm and algebraic identification algorithm are proposed. The identification performance of UKF, PF, UPF and algebraic identification algorithm is studied and compared in gaussian distribution noise and non-gaussian distribution noise by means of simulation, and the identification performance of algebraic identification algorithm is verified by experiment.

The simulation and experimental results show that the proposed four algorithms all can achieve accurate identification of PMSM rotor flux linkage with gaussian distribution measurement noise, and the algebraic identification algorithm has the obvious advantages on time consuming. With the non-Gaussian distribution measurement noise, UKF algorithm has obvious identification error, the other three identification algorithms can still achieve accurate identification, and the algebraic identification algorithm still has the least amount of computation among the four algorithms, which is conducive to achieve the online identification of PMSM rotor flux linkage.

All of the research achievements provide some effective references to realize high-performance control and reliable permanent magnet demagnetization fault diagnosis of PMSM drive system.

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