

# A Review of Nonlinear Kalman Filter Applying to Sensorless Control for AC Motor Drives

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(Invited)

**Abstract**—Sensorless control of AC motor drives, which takes the advantages of cost saving, higher reliability, and less hardware, has been developed for several decades. Among the existing speed sensorless control methods, nonlinear Kalman filter-based one has attached widespread attention due to its superb estimation accuracy and inherent resistibility to noise. However, the determination of noise covariance matrix and robustness of model uncertainties are still open issues in practice. A great number of studies try to solve these problems in recent years. This paper reviews the application of extended Kalman filter (EKF), unscented Kalman filter (UKF), and cubature Kalman filter (CKF) in speed sensorless control for AC motor drives. As an iterative algorithm, EKF has advantages in processor implementation. However, EKF suffers from the linearization error and model uncertainties when applying to sensorless control system. This paper presents the predominant improvements of EKF which is also applicative in UKF and CKF mostly.

**Index Terms**—AC motor drive, nonlinear Kalman filter, robustness, sensorless control.

## I. INTRODUCTION

IN modern high performance adjustable-speed drives of AC motor, the speed measurement is a crucial link to achieve an accuracy control of rotor speed. In general, the rotor speed is obtained by encoder or other position sensors. However, the robustness and reliability of system suffer from the installation of mechanical position sensors, which simultaneously cause an increased cost of drive system. Moreover, an extra mounting space is need in AC motor drive system. Therefore, sensorless control is a promising way to solve these problems.

In the past three decades, a number of researchers have sought to find a perfect sensorless control for induction motor (IM) and permanent magnet synchronous motor (PMSM). The method has an ability to achieve the performance of high-precision, wide range of speed and strong robustness.

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Numerous sensorless control methods have been proposed in existing studies, and these methods can be classified as signal injection-based method and AC motor model-based method [1]. High-frequency signal injection method is generally used to sensorless control system for PMSM, at low speed region especially [2]. It is also suitable for sensorless starting of aircraft starter/generator [3]. The performance of this method is outstanding at low speed or even zero speed. However, the performance is limited as the speed increase. Moreover, the injection of signal inevitably brings about the electromagnetic and audible noise problem in spite of a mitigation method has been proposed in literature [4].

The model-based methods are widely used in the AC motor drives, which mainly include sliding-mode observer (SMO) [5], adaptive full-order observer (AFO) [6], model reference adaptive systems (MRAS) [7], artificial neural networks (ANN) [8], and extended Kalman filter (EKF) [9-65]. These methods are developed on the basis of the mathematical model of AC motors, and the back EMF plays an significant role in estimation process. Unlike other model-based sensorless control methods, nonlinear Kalman filter-based one is the optimal estimation algorithm for a stochastic system, which is an attractive solution of state estimation for sensorless control system when the system and noise model is uncertain. The statistical properties of stochastic state variables are updating in real time and used to obtain an optimal Kalman gain matrix. The estimated value is corrected to the optimal one by Kalman gain matrix as the iteration progresses, and the error covariance matrix converges to minimum when the system achieves steady state. The nonlinear Kalman filter-based sensorless control method mainly includes EKF, unscented Kalman filter (UKF) and cubature Kalman filter (CKF). These methods are not widely used as a result of the limited performance of microprocessor in earlier years. However, with the rapid development of microprocessor, these methods have been attracted much attention of scholars, in speed sensorless control of AC motors especially.

This paper concentrates on reviewing the most up-to-date researches of the nonlinear Kalman filtering-based sensorless control method for AC motor drive. The paper is organized as follows: Section II shows the basic idea of EKF and its implementation details in sensorless control system. Moreover, various improved EKF methods for sensorless control are reviewed. UKF and CKF, the evolutionary algorithms of EKF, applying to sensorless control area, are shown in Section III. At the end of the paper, the challenge in low speed and

development tendency of the three methods are discussed in Section IV. The summary and prospect for nonlinear Kalman filtering-based sensorless control methods are discussed in Section V.

## II. SENSORLESS CONTROL BASED ON EKF

An optimal recursive algorithm for the stochastic dynamic system, named Kalman filter (KF), is proposed by R. Kalman in 1970s [9]. The well-known EKF is derived from the linear Kalman filter, which firstly proposed by Bucy and Sunahara. The application in sensorless control based on KF theory was firstly found in [10], [11]. In 1991, EKF was applied to sensorless control for IM and PMSM, which can be found in [12], [13]. The researches drop a hint that EKF takes a great advantage on sensorless control of AC motor. Due to the insufficient development of the microprocessor, however, the sensorless control based on EKF in the true sense was not implemented in real-time in these literatures. Owing to the rapid development of digital signal processor, the implementation of EKF is becoming easier in terms of the computational burden. In [14], the speed sensorless vector control of IM based on EKF is realized by a TMS320C30 DSP chip. In the work, a fifth-order IM mathematical model is built, which takes the state variables of stator current, rotor flux and rotor speed. Furthermore, with this method, the rotor speed and rotor flux are estimated online. The sensorless control for PMSM based on EKF is similar to IM, which employs a forth-order PMSM mathematical model with the state variables of stator current, rotor speed and rotor position. In this way, the position sensor is replaced by estimation of the position [15], [16].

Although EKF has been successfully applied in the field of speed sensorless control of AC motors, there are still many problems to be solved in EKF. Since EKF was proposed, related improvements have been studied in an increasing number of literature. At present, the research of EKF in speed sensorless control of AC motor drives mainly includes:

- (1) Implementation and performance analysis to EKF-based sensorless control system.
- (2) Sensorless control based on EKF with motor parameter estimation.
- (3) Sensorless control based on reduced-order EKF.
- (4) Determination of noise covariance matrix offline.
- (5) Sensorless control based on noise covariance adaptive EKF.
- (6) Sensorless control based on strong tracking EKF.
- (7) Sensorless control based on multiple-model EKF.

### A. Implementation and performance analysis to EKF-based sensorless control system

The basic idea of EKF is essentially different from other model-based estimation methods. The most remarkable characteristic of EKF is that the selected state variables are considered to be random variables. On this basis, the transformation of state variables is a nonlinear stochastic process in mathematics.

In general, considering the noise, the mathematical model of

discrete nonlinear systems can be expressed as follows

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}) + \mathbf{B}_k \mathbf{u}_{k-1} + \mathbf{v}_{k-1} \quad (1)$$

$$\hat{\mathbf{y}}_k = \mathbf{H}_k \hat{\mathbf{x}}_k + \mathbf{w}_k \quad (2)$$

where  $\mathbf{x}_k$  is the state vector,  $\mathbf{f}(\cdot)$  is the nonlinear function of  $\mathbf{x}_k$ ,  $\mathbf{u}_k$  is the input vector,  $\mathbf{B}_k$  and  $\mathbf{H}_k$  is the input matrix and output matrix respectively, the system noise and measurement noise can be expressed to vector  $\mathbf{v}_k$  and  $\mathbf{w}_k$ .

On the basis of the framework of KF, the mathematical description of EKF is as follows

1) Prediction process

$$\tilde{\mathbf{x}}_k = \mathbf{f}(\hat{\mathbf{x}}_{k-1}) + \mathbf{B}_k \mathbf{u}_{k-1} \quad (3)$$

$$\tilde{\mathbf{P}}_k = \mathbf{G}_k \hat{\mathbf{P}}_{k-1} \mathbf{G}_k^T + \mathbf{Q}_{k-1} \quad (4)$$

where  $\tilde{\mathbf{x}}_k$  and  $\tilde{\mathbf{P}}_k$  is the predicted state value and covariance matrix,  $\mathbf{G}_k$  is the Jacobian matrix of nonlinear function, and  $\mathbf{Q}_k$  is the system noise covariance matrix. This process transmits the mean and covariance of state variables from the moment  $k-1$  to moment  $k$ . It is noteworthy that the value of  $\tilde{\mathbf{x}}_k$  and  $\tilde{\mathbf{P}}_k$  are not the optimal after this process.

2) Update process

$$\mathbf{K}_k = \tilde{\mathbf{P}}_k \mathbf{H}_k^T (\mathbf{H}_k \tilde{\mathbf{P}}_k \mathbf{H}_k^T + \mathbf{R}_k)^{-1} \quad (5)$$

$$\hat{\mathbf{x}}_k = \tilde{\mathbf{x}}_k + \mathbf{K}_k (\mathbf{y}_k - \mathbf{H}_k \tilde{\mathbf{x}}_k) \quad (6)$$

$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \tilde{\mathbf{P}}_k \quad (7)$$

where  $\mathbf{K}_k$  is the Kalman filter gain,  $\mathbf{R}_k$  is the measurement noise covariance matrix,  $\mathbf{y}_k$  is the measurements corresponding to the output equation,  $\hat{\mathbf{x}}_k$  and  $\hat{\mathbf{P}}_k$  are the optimal value of state and covariance matrix in EKF calculation cycle.

EKF has been widely used to sensorless control of AC motor drives, e.g., IM, PMSM, and permanent magnet synchronous linear motor (PMSLM), etc. However, the implementation of EKF in different kinds of motors are quite similar, this paper takes the application of IM as an example.

The block diagram of an IM sensorless control system based on EKF is presented in Fig. 1. The sampled stator voltage and the three phase current of the induction machine are transformed to  $\alpha\beta$  reference frame, which are the inputs of EKF. The estimated rotor speed  $\omega_r$  is feedback to the input of speed controller.

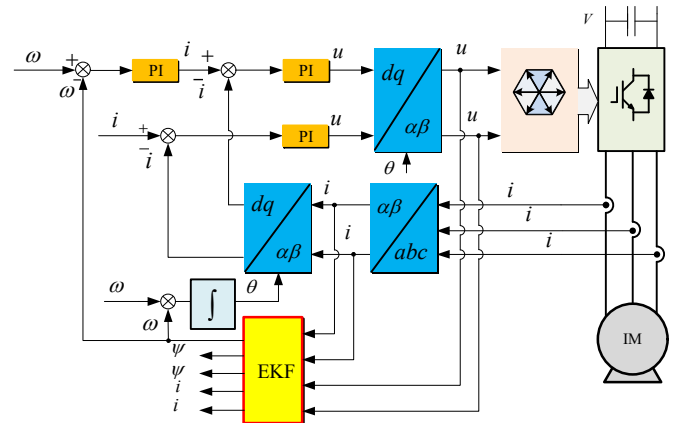


Fig.1. Block diagram of IM sensorless control based on EKF.

EKF is well received in the speed sensorless control system due to its following advantages:

- (1) The EKF is known for its high convergence rate, which improves transient performance significantly.
- (2) Considering the system noise and measurement noise inherently, EKF has high estimation accuracy and strong anti-interference ability.
- (3) Less memory is needed when EKF algorithm is implemented in a microprocessor.

Although the advantages of EKF are obvious, the shortcomings exist inevitably. The inherent defects mainly include:

- (1) As the implementation of first order approximation of Taylor expansion to EKF, linearization error exists in estimation process inevitably. The estimation accuracy reduced significantly when the sampling time is increased.
- (2) The computation of Jacobi matrix brings great computational cost to the implementation of EKF.
- (3) It is difficult to determine the value of noise covariance matrices.

In general, the increment of rotor speed is assumed to be a constant, which forms the fifth-order IM model and fourth-order PMSM model. The EKF estimator based on the assumption can be found in [12]-[16]. As the sampling time increases, the estimation accuracy inevitably suffers from a loss as a result of the introduction of the assumption. The loss of estimation accuracy would be increased when the load changes instantaneously [17]. This problem can be alleviated by introducing the equation of motion into the modeling process. In [18], a sixth-order EKF is built by extending the mathematical model of IM, in which the state variables include stator current, rotor flux, rotor speed, and load torque. The sensorless control system can operate in a wide speed range, and the improvement of performance is great at low speed especially. However, the comparison between the fifth-order and sixth-order EKF is not studied, and the extension to mathematical model of IM leads to the additional computation burden. A contrastive work between the fifth-order and sixth-order EKF is conducted in [19]. As a part of this work, the behavior of two methods at low speed is investigated by means of changing the stator and rotor resistance under half of the rated load torque. Compared to the sixth-order EKF-based sensorless control system, less deviation from the given speed with smaller estimation error is presented in the fifth-order EKF-based one. However, the comparative tests of the two methods are conducted under different sampling time, which lead to unfairness in terms of the state expansion of EKF.

As a result of first-order Taylor approximations from KF to EKF, the sampling time of EKF plays an important role in speed estimation. On the one hand, a large sampling time may cause EKF divergence due to the excessive linearization error, on the other hand, the reduction of sampling time helps to improve the estimation accuracy and expand the convergence range of EKF in consideration of the determination to noise covariance matrices. In other words, EKF can be convergent under a large scope of noise covariance matrices value change. In [20], the convergence analysis of EKF based on an sixth-order discrete-time model is presented. Besides, the influence of Euler discretization is analyzed theoretically.

### B. Sensorless Control Based on EKF with Motor Parameter Estimation

The motor parameters play a significant role in the sensorless control system of an AC motor drive. Accuracy parameters of motor are needed in high performance and precision control system, especially in low speed control area. As a result of the rise in temperature and magnetic saturation, the parameters of AC motor change correspondingly, and the slip produce an effect on rotor resistance of IM [21]. EKF takes an inherent advantage to resist against the model uncertainties, which including modeling error and parameter mismatch. In [22], an analysis of stator and rotor resistance variation on EKF performance is conducted by simulation. EKF can works normally under two times variation of parameter mismatch by adjusting  $Q$  and  $R$ . However, little working condition is tested and no experimental verification is shown in the literature. The robustness analysis of an EKF for sensorless control of IM is discussed in [23], in which the susceptibility of EKF to motor parameters (stator resistance, rotor resistance, mutual inductance, and inertia coefficient) is studied, and the system is sensitive to the change of stator resistance and mutual inductance at low speed. The variation of rotor resistance has a moderate effect on estimation performance at low speed, but the effect is aggravated as the speed increases. Moreover, the estimation performance shows low sensitivity to the change of inertia coefficient. The study indicates that there is a increasingly requirement of online parameter identification in the sensorless control system based on EKF.

In [24], the rotor resistance estimation of IM is proposed, in which the EKF is employed. The combination between the method and the sensorless control based on EKF is presented in [25]. The intention of estimating rotor resistance is to get an accurate rotor time constant, which has significant influence on the dynamic and loading performance. The rotor time constant estimation based on EKF can be found in literatures [26], [27].

In [28], [29], the braided EKF is proposed to estimate the stator resistance  $R_s$ , rotor resistance  $R_r$ , rotor speed  $\omega_r$ , and load torque  $T_L$  simultaneously. The braided EKF consists of two EKF models, which are carried out consecutively in a switching way. The method also goes by the name of switching EKF [30]. In the method, one EKF model is set to estimate  $R_s$ , another is set to estimate  $R_r$ . The  $\omega_r$  and  $T_L$  are estimated in both EKF models. The estimated resistance value is used by each other. The block diagram of the braided EKF is shown as Fig. 2.

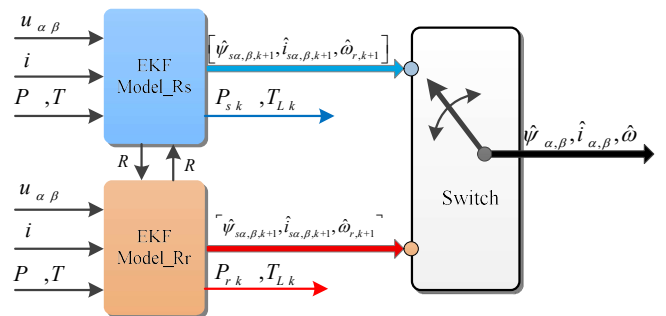


Fig.2. Block diagram of braided EKF.

Compared with single resistance-based EKF, the estimation accuracy of speed, resistances, and load torque in low or zero

speed are improved by using braided EKF. However, the sampling time and required memory area of the alternately-executed EKF increase two times than single EKF, and the loading performance of the method in low and zero speed is not researched in detail. The [21] has a comment on this method that it is impossible to know the existence of the persistent excitation condition a priori in practical applications, which is a mandatory condition for an exact parameter estimation.

Bi input-extended Kalman filter (BI-EKF), considering one EKF model and two inputs calculated from the two extended IM models, takes the advantages of helping to implementation in real time and estimating the  $R_s$  and  $R_r$  simultaneously [31], [32]. The block diagram of the BI-EKF is shown as Fig. 3.

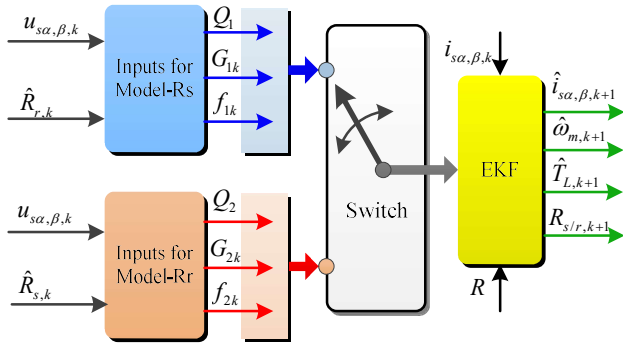


Fig.3. Block diagram of BI- EKF.

This method is very similar to braided EKF in essence, and the contrastive test between braided EKF and BI-EKF is not found in the literature. However, it is a heuristic and promising way to alleviate the bad effect on sensorless control system caused by changing parameters.

Parameter estimation in sensorless control of AC motor drives is still an open issue, and the research on transient performance of parameter estimation is still needed because of the contribution to speed estimation.

### C. Reduced-order EKF

Reduced-order EKF (ROEKF) is developed to alleviate the computational burden when implement it in a microprocessor. ‘Reduced -order’ means to reduce the order of controlled object model rather than EKF. Therefore, the advantages of EKF remain unchanged.

Considering the stator currents are sampled in real time in the speed sensorless control system of IM, the currents can be removed from the state variable. Based on this, a third-order EKF is designed in [33]. The state variable consists of rotor speed and flux, and the state equation is simplified in the third-order EKF. However, the observation equation of the third-order EKF is more complex than the full-order EKF, and the differential operations for current are brought to observation equation. In [34], a robust reduced-order EKF (RROEKF) is proposed to estimate the rotor speed of IM. The key to improve ROEKF lies in the amendment of the error covariance matrix. Compared to ROEKF, RROEKF has a better robustness to gross external error and estimated error. Another ROEKF is realized by rearranging the state variable as rotor flux and rotor resistance or speed. In this way, the rotor

resistance or speed are identified simultaneously [35].

Application of reduced-order EKF in PMSM can be found in [36], which is different to that used in IM sensorless system. In this study, the parallel reduced-order EKFs are designed for speed and position estimation. One ROEKF is developed considering the state variable of stator current  $i_\alpha$  and EMF components  $(e_\alpha, e_\beta)$ , another ROEKF takes the state variable with stator current  $i_\beta$  and EMF components. The aim of parallel ROEKF is to estimate the EMF components, which contains the information of rotor speed and position. The method is realized in a FPGA chip and the complexity between full-order EKF and ROEKF is investigated. A better estimation performance in position and speed is shown in comparison with the full-order EKF and the sliding mode observer. Different from [36], another kind of ROEKF, which takes the state variables with EMF components and angular speed  $\omega_r$ , is developed to identify the rotor speed and position in sensorless control system of IPMSM [37]. The method shows an equivalent performance to EKF, and an angle compensation method is introduced into the system to enhance the robustness of parameter change.

### D. Determination of noise covariance matrix offline

In a sensorless control system of an AC motor based on EKF, the system noise covariance  $\mathbf{Q}$  mainly consists of system disturbances, model indeterminacy, motor parameter mismatch, as well as rounding and truncation error caused by limited word length of DSP. The noise covariance  $\mathbf{R}$  includes A/D quantization and measurement noise brought by the current sensors. In most cases, the value of  $\mathbf{Q}$  and  $\mathbf{R}$  can be determined by trial and error. The method could be easier to achieve if the sampling time of EKF is small, and it requires experience to adjust repeatedly. The relationship between noise covariance matrix and bandwidth of KF is discussed in [38], which provides the intuitive understanding of KF and is suitable for nonlinear KF. In the study, the KF is considered as a deterministic filter with a time-varying bandwidth that determined by Kalman filter gain  $\mathbf{K}$ . Moreover,  $\mathbf{K}$  is proportional to  $\mathbf{Q}/\mathbf{R}$ . That is to say the bandwidth of KF depends on the noise covariance matrix. The regulation of  $\mathbf{Q}$  and  $\mathbf{R}$  can be summarized as follows:

1) The increase of elements in  $\mathbf{Q}$  shows intuitively that the uncertainty of the system model increases, which directly affects the increase of the gain matrix of KF, which is equivalent to increase the credibility of measurement information. Therefore, the transient response rate is getting faster, and bandwidth of KF increases.

2) The larger the element value in  $\mathbf{R}$  is, the more uncertainty of measurement will be. A large value of  $\mathbf{R}$  leads to the reduction of  $\mathbf{K}$  directly. Therefore, the transient response rate of the algorithm is becoming slower and the bandwidth of KF decreases.

3) In the practical application of KF, the ratio of  $\mathbf{Q}$  to  $\mathbf{R}$  is often the main factor affecting the performance of the filter. When implementing the trial and error method, one noise matrix is usually fixed, another is adjusted to get a better performance.



It is extremely difficult to find the optimal value of  $\mathbf{Q}$  and  $\mathbf{R}$  by means of the time-consuming trial and error method. Many researchers try to find a convenient way to determine the noise covariance matrix of EKF. In [39], a normalization technique is adopted to PMSM sensorless control system. Both PMSM control system and EKF are normalized to develop a self-tuning procedure of the noise covariance matrix. This off-line procedure is very instrumental in the AC motor drive with EKF-based sensorless control.

In recent years, some intelligent methods are employed to find the best  $\mathbf{Q}$  and  $\mathbf{R}$  of EKF. In [40], genetic algorithm (GA), a stochastic global search method, is applied to optimize the noise covariance matrix  $\mathbf{Q}$  and  $\mathbf{R}$  simultaneously. The similar work can be found in [41], in which a different fitness function is selected. In these methods, the training sequence, consisting of stator current, rotor flux and rotor speed, which contains information on the dynamic and steady state, is sampled to optimize  $\mathbf{Q}$  and  $\mathbf{R}$ . An excellent speed estimation accuracy of optimized EKF is acquired. However, the optimal  $\mathbf{Q}$  and  $\mathbf{R}$  are changed under different working conditions, and there is a trade-off between dynamic performance and steady state performance inevitably. Furthermore, it is difficult for sampled training sequence to cover all working conditions. Another commonly used optimization algorithm is differential evolution algorithm (DEA) [42], [43]. Similar to GA, an evolutionary algorithm is employed to optimize the overall response of the drive in literature [42], in which the objective function based on speed errors and current errors is constructed. The optimization methods in [40], [41] are based on single objective. In [43], [44], multi-objective optimization approaches are proposed to improve the multi-dimensional performance of sensorless control system by means of selecting several fitness functions that based on the speed estimation error, current estimation error, and torque estimation error. These methods provide promising ways to determinate the value of  $\mathbf{Q}$  and  $\mathbf{R}$  in application. There are other intelligent algorithms, such as particle swarm optimization (PSO) [45], simulated annealing (SA) [46], for determining  $\mathbf{Q}$  and  $\mathbf{R}$  offline.

On one hand, these offline parameter determination methods can only determine a set of parameter values.  $\mathbf{Q}$  and  $\mathbf{R}$  are still fixed when EKF runs. The performance degradation of the EKF-based sensorless control system will happen under extreme conditions. On the other hand, the optimization procedure costs a long time, which caused the impossible implementation online. Therefore, it is necessary to determine the noise covariance matrix online, which will be discussed in the next part.

*E. Noise covariance adaptive EKF*

To enhance the adaptability and robustness of EKF, the desirable ways to adjust noise covariance matrix adaptively are explored by many researchers.

The fuzzy theory can be used to tune the noise covariance matrix of EKF online [47]-[49]. An adaptive EKF based on fuzzy theory named fuzzy extended Kalman filter (FEKF) is proposed in [47], [48], in which the fuzzy factor is introduced to adjust the measurement noise covariance matrix  $\mathbf{R}$  in real time. The speed estimation block diagram based on FEKF is shown

in Fig. 4.

The fuzzy factor  $S_k$ , calculated by an exponential function in fuzzy logic reasoning system, tune  $\mathbf{R}$  directly. If the proper fuzzy control rules are designed, the estimation performance of EKF can be improved effectively. Other similar applications of fuzzy theory in tuning system covariance matrix  $\mathbf{Q}$  are shown in [49]-[51]. The basic idea of fuzzy control is the utilization of the field operator's control experience and knowledge of relevant experts, so the design process of fuzzy control rules is quite complicated.

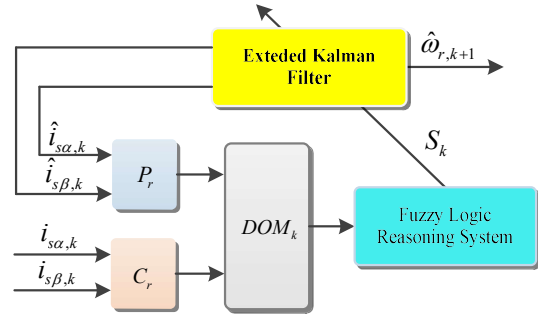


Fig.4. Speed estimation block diagram based on FEKF.

In [52], system covariance matrix estimation method based on innovation residual is proposed to tune the  $\mathbf{Q}$  in real time. The innovation residual is the difference between measured stator current and estimated one. The significant advantages of this approach are simplicity and less computation in comparison with other improved methods. However, the size of estimation window, which is the length of innovation residual sequence, plays an important role in the performance of AEKF estimator, especially in transient performance. Therefore, how to determine the size of estimation window is another issue needing to be discussed. In [53], an adaptive EKF is employed to provide the position information of IPMSM. With this method, the system noise and measurement noise are simultaneously estimated and the experimental results show that the proposed scheme has a higher estimated accuracy compared to EKF. However, the implementation of the simultaneously estimated system noise and measurement noise is easy to cause the observer divergence in practice when both of them are uncertain, which is pointed in [54].

On the whole, the improvement of EKF based on adaptive noise covariance matrix is a promising way to enhance the adaptability and robustness of the sensorless control system. It is noteworthy that simultaneous estimation of both  $\mathbf{Q}$  and  $\mathbf{R}$  should be avoided.

*F. Strong tracking EKF*

In a sensorless control system of AC motor, there are a lot of uncertainties of the system model owing to the simplification of model, the inaccurate statistical characteristics of noise, the deviation of initial state, and parameter change in actual system. EKF has poor robustness to model uncertainty. However, the strong tracking filter takes the advantages of the robustness to model uncertainty and strong tracking ability to state mutation. Therefore, the combination of EKF and STF come into a natural way, called strong tracking EKF (STEKF). Another term is sub-optimal fading extend Kalman filter [55], or

adaptive fading extended Kalman filtering (AFEKF) [56]. AFEKF and STEKF introduce the fading factor into the prediction of error covariance matrix. The construction of fading factor in two methods are slightly different. In [57], [58], STEKF is employed to estimate the rotor speed in sensorless control system of induction motor. The application in PMSM can be found in [55], [56]. The basic implementation of STEKF is presented in [57], in which the fifth-order model is built. To improve the low speed and transient performance, a sixth-order model with STEKF is studied in [58]. This method helps to reduce the influence of badly-tuned  $Q$  and  $R$ . In [59], a seventh-order model, taking the torque and rotor resistance into account, is utilized to cope with the problem caused by the change of torque and rotor resistance. The STEKF working with seventh-order model can restrain the decreased performance from changing torque and rotor resistance to some extent. However, the higher-order model increases computation time of STEKF inevitably.

In [60], an improved version of STEKF is used to estimate the rotor speed of induction motor, named symmetric strong tracking extended Kalman filter (SSTEKF). Fig.5 presents the speed estimation block diagram based on SSTEKF.

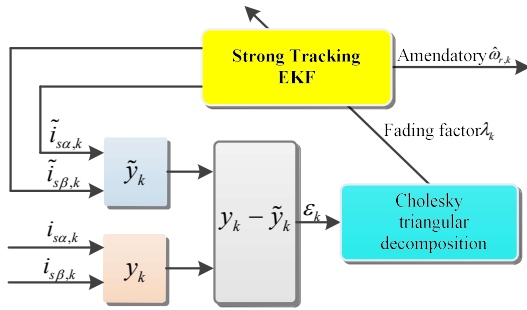


Fig.5. Speed estimation block diagram based on SSTEKF.

The innovation of this method lies in the introduction of Cholesky triangular decomposition which modify the action mode of the multiple fading factor matrix in the error covariance matrix. The residual information keeps symmetry in the process of estimation. In this way, the stability and tracking ability of SSTEKF is improved effectively.

Another improvement approach to STEKF is proposed in [61]. In this method, least-square algorithm is introduced to the fading factor. The improvement is on the basis of the aforementioned innovation sequence. The role of least-square algorithm is to extract the information in innovation sequence effectively. The tracking ability and robustness of two kinds of improved STEKF are well enhanced. However, the stability analysis are absent in the literatures.

### G. Multiple-model EKF

The implementation of conventional EKF takes a set of fixed noise covariance matrices into account, which leads to mismatches between the optimal noise covariance matrix and the changed working conditions. A single noise covariance matrix-based EKF model cannot meet the requirement of frequently changed operating conditions in EKF-based sensorless control system. Therefore, an idea of multiple-model is introduced into EKF for improvement of model adaptive

ability [62]. An improved version of multiple-model EKF, named interfacing multiple-model EKF (IMM-EKF), is often used for speed sensorless control [63], [64]. Fig. 6 is the block diagram of IMM-EKF, the specific working principle of the method can be found in [65].

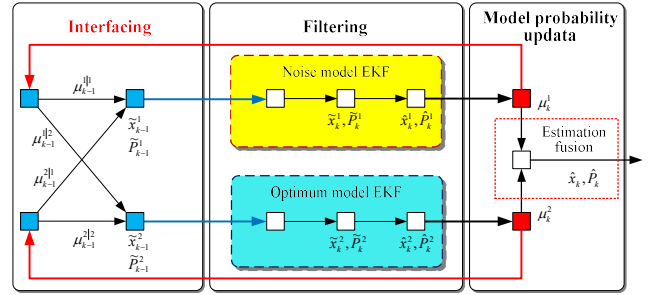


Fig.6. Block diagram of IMM-EKF.

IMM-EKF is a favorable improvement to conventional EKF due to the consideration of different noise model and optimal model. It is essentially a process of finding the optimal working point of EKF between noise model and optimal model dynamically. Compared with the intelligent algorithm mentioned above, searching for the optimal  $Q$  and  $R$  offline, this method can realize the on-line regulation to  $Q$  and  $R$ . Therefore, the disturbance in IMM-EKF-based sensorless control system can be reduced effectively in comparison with EKF. A significant factor influencing the estimation accuracy in IMM-EKF is the input interaction, which is determined by the switching probability of different models. However, the interaction parameters determined by the prior information suffers from a tradeoff between mode switching and non-switching. In addition, the switching speed and the estimation accuracy of the EKF models are influenced by hysteretic probability and noise. In [65], Markov chain is employed to improve the interaction process. Fig. 7 is the block diagram of multiple-model EKF based on the Markov chain (MC-MM-EKF). In block diagram,  $\pi^{ij}$  represents the transition probability from the model  $i$  to the model  $j$ , which is updated according to Markov chain algorithm.

With this method, EKF is more efficient to find the best working condition, and the adaptability of EKF to the actual system and the working conditions variations are enhanced. However, a number of different EKF models are required to cover all possible working conditions, which lead to a huge amount of computation of multiple-model EKF. It is unfavorable to implement in a sensorless control system.

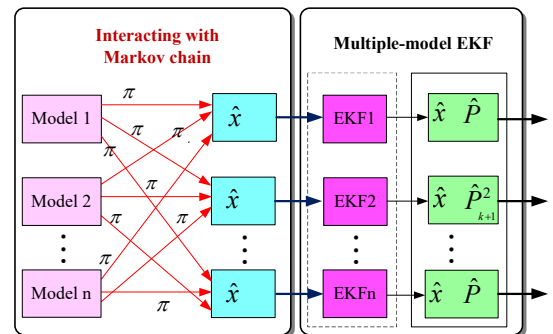


Fig.7. Block diagram of MC-MM-EKF.

III. SENSORLESS CONTROL BASED ON UKF AND CKF

Although EKF has many attractive advantages, the linearization error exists inevitably when it is applied to speed estimation. UKF appears to alleviate the linearization error of EKF, which is proposed by Julier and Uhlman [66]. The estimation accuracy is higher than EKF. The computational cost of UKF is the same order of magnitude as the EKF, and it can be applied in many highly nonlinear filtering and control applications. The strict theoretical derivation of UKF is unexplored, which is one of the advantages of CKF. Besides, it has the better numerical stability and filtering accuracy than UKF in high order system (usually higher than 3). The tuning method of CKF can be easier due to the absence of scaling parameter, and the CKF requires lower computational effort than the general UKF, because the CKF does not apply the center sampling point [89].

A. UKF

The filtering framework of KF is still adopted in UKF. The key step of UKF is unscented transformation (UT), which is used to transform the state (mean and covariance) from moment  $k$  to moment  $k+1$  by selecting the fixed number of sigma points. The structural schematic diagram of UT algorithm is presented in Fig.8. It is essentially a nonlinear approximation process. Compared to EKF, UKF takes the following advantages:

- (1) Computation of complex Jacobian matrix is avoided in UKF as a result of the employment of UT.
- (2) EKF takes only the first-order approximation of a nonlinear function. Due to the consideration of effect caused by higher order terms of Taylor expansion, the estimation accuracy of UKF is higher than EKF.
- (3) The computational complexity of UKF is the same order as that of EKF. The calculation of UKF is acceptable when the order of the system is not too high.

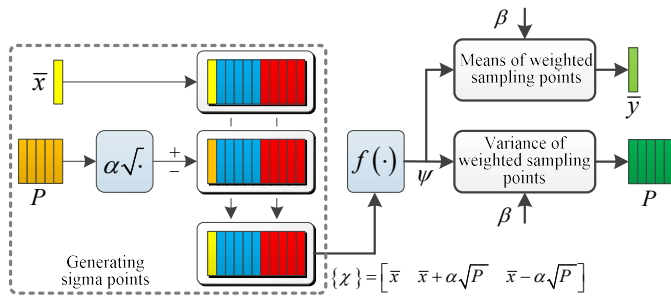


Fig.8. Structural schematic diagram of UT algorithm.

Owing to the limitation of microprocessor performance, UKF has not been widely used to the sensorless control system in early time. In recent years, The application of UKF to sensorless control has attracted many attention.

In [67], UKF is firstly used to sensorless control system for IM. A fifth-order IM model is developed for the implementation of UKF, and the estimation performance between EKF and UKF is compared in the study. The simulation results show that the estimation accuracy of EKF performs is at least as good as UKF, but the experiments are not carried out in the study. A comprehensive work of UKF is reported in [68], in which the load torque is considered as a

state variable, and a sixth-order UKF is formed to estimate speed and torque of IM simultaneously. A better robustness of UKF at low speed is shown in comparison with EKF. However, the computational cost of UKF increased significantly as the order increases.

To reduce the numerical errors in application, square root unscented Kalman filter (SRUKF) is proposed in [69]. The triangularization technique is employed to get the square root matrix  $S$  of error covariance matrix  $P$ , and the propagation of  $P$  is replaced by  $S$ . In this process, the Cholesky factorization is avoided. In this study, three methods of EKF, UKF, and SRUKF are compared in the respects of estimation accuracy and computational cost. SRUKF has the highest estimation accuracy, but the amount of calculation and code size is the largest. The simultaneous estimation of rotor speed and rotor resistance for IM sensorless control system can be found in literatures [70], [71].

Application of UKF in PMSM sensorless control is reported in [72]-[77]. The speed and position estimation based on fourth-order UKF is studied in [72]-[74], and fifth-order UKF considering disturbance variable is developed in [75]. Furthermore, the improvements of UKF such as adaptive UKF [76], improved UKF [77], and neural network aided UKF [78] are reported in recent years. In [79], application of UKF in switched reluctance motor (SRM) is presented.

Although UKF has a higher estimation than EKF, it does not show a dominant advantage to replace EKF in sensorless control system of AC motor. Moreover, the improvement of low speed performance is still an open issue.

B. CKF

To overcome the numerical instability and reduced accuracy of UKF using in higher dimensional system, cubature Kalman filter (CKF) is proposed by Ienkanan Arasaratnam and Simon Haykin [80]. This is an optimal estimation algorithm which is developed by strict mathematical reasoning. The difference between CKF and UKF is that the cubature point set replaces the sigma point set. In recent years, CKF has entered the eyes of scholars who study the sensorless control of AC motor.

Application of CKF in speed sensorless control of PMSM can be found in [81]-[86], and its application of IM is reported in [87] and [88]. References [81]-[83] employ the CKF to estimate the speed and position of PMSM. The performance of EKF and CKF is explored in simulation, and almost the same is shown in simulation results [81]. The implementation of CKF with experiments are carried out in [82]. In [87], CKF is utilized to estimate the speed of IM. A seventh-order IM equation of state is developed to get the essential variables for sensorless control system, which is an unfavorable factor in implementation of CKF.

The commonly used improvement of CKF is Square root Cubature Kalman filter (SCKF), which intends to enhance the numerical stability for convergence. The implementation to SCKF in PMSM sensorless control system is studied in [84], in which the performance is compared to EKF and a slightly better transient response is obtained during reversal. The improvement to CKF is quite similar with EKF. Other

improvements, such as SCKF with joint parameter estimation [85], and adaptively tuned SCKF [86], are reported in existing literature. In [88], especially, a novel improvement to CKF, considering the non-Gaussian environments, is proposed. The robust M-estimation theory is used to obtain the unknown measurement noise statistics. The validity of this method is proved by adding different types of noises.

A comparative work of EKF, UKF, and CKF applying to the sensorless control of IM is conducted in [89]. The estimation performance of three methods in low speed region are explored in terms of root-mean-square error (RMSE) values of the estimated speeds, and average execution time. In contrast, the UKF and the CKF show higher accuracy in the low speed region, and UKF-based method provides the highest estimation accuracy in the low speed region. Furthermore, the estimation accuracy of CKF is the best of three methods when stator resistance mismatches with the actual value. As for average execution time, UKF and CKF show the same level of time cost and the EKF is the shortest one. However, the three methods are investigated only in open-loop and without external load disturbance.

#### IV. CHALLENGE AND DEVELOPMENT TENDENCY

##### A. Challenge in low speed operation

In general, estimating the flux (which is the main component of speed estimation algorithm) in medium-and high-speed regions is not a major problem. The problem is more pronounced in low-speed regions, near zero stator frequency, whereby the magnitude of the induced rotor voltages and currents become very small [19]. The estimation performance in low speed is vulnerable to the change of motor parameters. Moreover, the low speed performance of nonlinear KF suffers from the sampling time and measurement noise significantly. Unlike other model-based sensorless control methods, which considered to be deterministic and can be easily polluted by noise and require parameter adaptation algorithms, especially at very low speed. Nonlinear KF is highly suitable under conditions where parameter uncertainties and presence of noise are unavoidable. The EKF-based estimator has good disturbance rejection which can take into account model uncertainties and the effect of unmeasured disturbances. Although this property makes it show a better performance in low-speed regions, the challenge remains to exist.

The sensorless control system based on EKF can operate at 3rad/s (0.5Hz) with 50% of rated load torque in [19]. It is very sensitive and more challenging region as authors supposed to be. Reference [18] shows the experimental results for very low (10rpm/0.33Hz) and zero velocity operation of an IM sensorless control system based on EKF. The experiments are carried out under a very small load torque (5% of rated load torque). The performance of sensorless control system in low-speed regions can be enhanced by simultaneous estimation of motor parameters and speed. In [32], the stator resistance, rotor resistance and speed are estimated simultaneously by using an BI-EKF, and the system works well at 9 rpm (~1% of the rated speed) under 1.5 N·m. Moreover, the experimental

results for stator resistance change (50% of rated value) are presented and the speed estimation performance is good under such a situation. The author claimed that the IM cannot be applied to high load torque at very low speed operation. Based on a symmetric strong tracking EKF, operation of an IM sensorless control system at 30 rpm (2% of the rated speed) with 100% of rated load torque is presented in [60]. For an UKF-based IM sensorless control system, the operation at 18 rpm (0.6Hz) can be found in existing literatures. The very low or zero speed operation of UKF-based sensorless control system is rarely reported in existing literatures. In a word, to improve the performance of nonlinear KF-based sensorless control system under very low or zero speed with high load torque is still an open issue.

##### B. Development tendency

The general application of nonlinear KF in industry has not been realized owing to its computational burden. However, this is a disappearing problem with the rapid development in high performance processing technology. The increase of compute speed necessitate a cooperation of the wide-bandgap power semiconductor switches[90]. In the future, the following development tendency of nonlinear KF, from the author's point of view, will be research increasingly.

- (1) As mentioned above, to improve the performance under very low or zero speed is a key point to sensorless control system based on nonlinear KF.
- (2) Precise parameters of motor play a significant role in the improvement of nonlinear KF, in low or zero speed especially. Therefore, simultaneous estimation of speed and parameters is a promising way to enhance the sensorless control system based on nonlinear KF.
- (3) As pointed out in [3], data fusion of estimates from model-based methods and high frequency signal methods could be an alternative way to make up for the deficiency of nonlinear KF in low speed regions. Moreover, the combination of optimal controller and observer is still an open issue.
- (4) The regenerative operation mode of sensorless control system based on nonlinear KF arises in various applications. However, the observability and stability in such a working condition is rarely studied in existing literatures. In the future, this issue takes the increasing importance in nonlinear KF-based sensorless control system of AC motor drives.
- (5) Owing to the high estimation precision, UKF and CKF will be studied increasingly as the rapid development of high performance processing technology. However, EKF is hard to replace by UKF or CKF in practical applications because of its simplicity and comparable estimation performance.

#### V. CONCLUSION

This paper reviews the application of nonlinear Kalman filter theory in speed sensorless system of AC motor drives. Three methods, including EKF, UKF, and CKF, are mainly introduced in this paper. Among them, EKF is the most widely



used method in the field of speed sensorless control of AC motors. EKF algorithm is simpler than UKF and CKF, but it has linearization error. Therefore, it is crucial to select a small sampling time when implement EKF. Another important issue is to determine the noise covariance matrix of three methods. Due to the employment of KF filtering framework in the three methods, they have common characteristics in determining noise matrix. Several online and offline determination methods are introduced in this paper. Online determination methods are considered as the promising way to improve the performance of three nonlinear Kalman filter. However, accurate motor parameters are required in low speed or dynamic conditions of the system, thus the simultaneous estimation of motor parameters and speed/position is a trend in sensorless control system. Moreover, the observability and stability at low speed or in regenerative operation mode are still open issues.

UKF and CKF have higher estimation accuracy than EKF in theory, but their increase in computational complexity cannot be neglected. Almost the same performance between EKF and UKF, CKF is shown in existing studies when applying three methods to sensorless control system of AC motor. For the moment, EKF is the most practical algorithm among the three methods. The performance of microprocessor acts as a direct stimulus to the development of the application of three methods in sensorless control system of AC motor drives.

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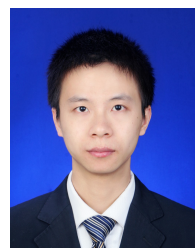


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