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An online method to simultaneously identify the parameters and estimate states for lithium ion batteries

Qianqian Wang [a, c], Jianqiang Kang [a, c, *], Zuxian Tan [b], Maji Luo [a, c]

[a] Hubei Key Laboratory of Advanced Technology for Automotive Components, Wuhan University of Technology, Wuhan 430070, PR China
[b] Shenzhen Pengcheng New Energy Technology Co., LTD, Shenzhen 518102, PR China
[c] Hubei Collaborative Innovation Center for Automotive Components Technology, Wuhan University of Technology, Wuhan 430070, PR China

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ABSTRACT

Currently, state of charge (SOC) estimation on the basis of Kalman filter (KF) is realized to be applied online, but the parameters of the battery model that is implanted in KF are commonly identified offline. The offline identification is not only a time-consumed process but also provides the inaccurate results. Considering the complex and changeable operating conditions of batteries employed in electric vehicles, the parameters are also varied in fact and need to be identified online, by which the real state of the battery is reflected. In this study, the online identification of parameters and estimation of SOC are fulfilled simultaneously by using a novel algorithm named dual unscented Kalman filter (DUKF). Results show that the parameter identification on the basis of the DUKF accurately simulates the dynamic performance of the terminal voltage. By using the proposed algorithm and under three different operating conditions, the state of the battery is effectively estimated. The maximum error of SOC estimation is less than 3%, which is better than the results by using the extend Kalman filter (EKF) and unscented Kalman filter (UKF). Furthermore, the online identification of parameters that are changeable and related to the fading state of the battery, enables the state of health (SOH) to be estimated online.

1. Introduction

Currently, the contradiction between automobiles and energy supply, environmental protection as well as other social carrying capacity has become increasingly prominent with the expansion of the car ownership [1]. Rational distribution of electric vehicles as the representative of the new energy automotive industry has become an important direction of the future economic development. As the core component of electric vehicles, the power battery is the key factor that determines the healthy and rapid development of electric vehicles. Because of its high energy density, long cycle life, low self-discharge rate, no memory effect and green environmental protection, the lithium-ion battery has become the first choice for electric vehicles. Although lots of progress and achievements have been made in research and industrial application of lithium-ion batteries, the problem of safety and life still restricts the popularity of electric vehicles and large-scale applications. This case requires an accurate battery management system (BMS) to control the batteries in real time, especially to estimate the actual state of charge (SOC) [2]. The real time SOC is the basis for the BMS to obtain energy, power and safety information from the battery and feedback to the vehicle. Therefore, the accurate estimation of SOC has a significant impact on the vehicle's dynamic performance and safety.

The SOC estimation methods are mainly consisted of the current integration [3], the open circuit voltage [4,5], the black-box model based method [6,7] and the model based filtering method [8–11]. The current integration method is easy to calculation but have no automatic error correction function which causes a large number of error accumulations. The open circuit voltage method requires a lot of time and energy for measurement. The black-box model based methods, such as support vector regression, fuzzy control and neural networks need sufficient offline training data, thus they are hard to achieve online estimation. For a real application, the model based filtering method seems to be the most promising, especially the Kalman filter-based methods, such as extend Kalman filter (EKF) [12–14], sigma points Kaman filter (SPKF) [15–17], and the interacting multiple model (IMM) Kalman filter [18]. This method is believed to meet the common requirements of the BMS, such as the real-time response performance, low-cost hardware, high accuracy

* Corresponding author. Hubei Key Laboratory of Advanced Technology for Automotive Components, Wuhan University of Technology, Wuhan 430070, PR China.
E-mail address: kjqiang@sohu.com (J. Kang).

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etc.

The accurate identification of dynamic battery parameters is the premise that ensures the safe and reliable operation of a lithium-ion battery system. At present, the parameters are commonly identified by HPPC test that is an offline method. The offline identification is not only a time-consumed process but also provides the inaccurate results, for the detection quantity is accompanied by the uncertainty noise signal in the process of modeling. The errors generated by the noise in real time can be compensated if parameter identification is carried out by an online method. The Kalman filtering has been widely used in online parameters identification, providing a direct solution of random noise [33,34]. The random noise is filtered out to obtain the exact space state value by treatment of the measured data. Lately, using the Kaman-based methods or observers to estimate parameters and states seems to be very promising [26]. To estimate the state and parameters of the system simultaneously, joint Kalman filtering (JKF) [19–22] or dual Kalman filtering (DKF) [23–33] can be employed. The JKF algorithm considers the online identified parameters as the system state, and thus needs to expand the dimension of the original system state variables, may leading to high-dimensional vectors and complex matrix operations. The DKF algorithm uses two independent Kalman filters to estimate the system state and to identify the parameters, respectively, and thereby avoiding the increase of dimensionality that leads to the complicated calculation. Therefore, the DKF algorithm is more widely used. Dave Andre [26] introduced a dual filter consisting of a standard Kalman filter and an Unscented Kalman filter to estimate the parameters and SOC. Despite of this method with good results, the capacitance was treated as a constant so that a lot of time is needed to off-line measure the specific capacitance and thus is difficult to achieve online estimation. Jonghoon Kim [32] proposed an algorithm based on dual extended Kalman filter (DEKF) to estimate SOC/SOH and B. S. Bhangu [33] used Kalman filter to estimate SOC and extended Kalman filter to estimate SOH. Both the abovementioned methods used extended Kalman filter for dimensionality reduction. However, the extended Kalman filter leads into derivative calculation in the process of linearizing, increasing the operating load of Micro Control Unit (MCU). The specific literature comparison is shown in Table 1.

After review of the previous literatures, we find that some parameters were assumed as constants when SOC estimation was implemented. The assumed parameters not only cause the long time data calibration but also reduce the precision. Some papers only partially identified the model parameters. And some estimation algorithms have the disadvantages of low accuracy, large dimensions, and high complexity. Therefore, a better approach is to find a suitable method with high efficiency and accuracy, realizing simultaneously the estimation of the states and the identification of all parameters. To overcome the above-mentioned shortcomings, it is necessary to propose a new algorithm.

In view of the above deficiencies, a dual Unscented Kalman filter (DUKF) is proposed in this study to fulfill online the parameters identification and the SOC estimation on the basis of the dual polarization (DP) model that considers both electrochemical polarization and concentration polarization. For the state estimation, the algorithm takes the real time change of parameters into account, compensates the noise signals during the operation and avoids the influence of the ambient factors in practice, so the accuracy and efficiency of the method are better than that of EKF and UKF. In terms of parameters online identification, the DUKF algorithm used in this study can estimate not only SOC but also SOH in real time, since the changeable parameters are related to the fading state of the battery.

2. Experiments

Experimental studies were conducted on a graphite/$LiNi_xCo_yMn_{1-x-y}O_2$ battery that had a rated capacity of 35 Ah and a nominal voltage of 3.7 V. As shown in Fig. 1(a), the experimental bench comprised a Neware battery test system (BST 7.5.3 Newaresles) for battery charging and discharging, a host PC (Intel(R) Core(TM) i7-4770 CPU@3.40 GHz) for signal acquisition, and a thermal chamber (GDJS-150 WuXi Youlian Ltd.) for temperature control. To ensure the consistency of the measurement conditions, the cell was placed in a constant temperature of 25 °C during the whole test. The battery test system acquisition module has temperature sensors to collect the surface temperature of the battery. Although the collected data show a slight increase in temperature, it can be ignored since the battery performance is changed slightly with a little increase of the temperature.

The experiment projects were designed to test the basic performance and dynamic adaptability. The entire tests include a static capacity test, a constant current discharge (CCD) test, a hybrid pulse power characterization (HPPC) test referred to Ref. [37] and a dynamic stress test (DST) referred to Ref. [35]. The HPPC test shown in Fig. 1(b) can not only be used to realize the offline battery parameters identification, but also be regarded as an operating condition. The DST test shown in Fig. 1(c) is mainly used to test the dynamic performance of the battery and simulate the running condition of the vehicle with variable power. Before the DST test the peak power

Table 1
Literatures comparison.

	Algorithm	Parameter identification	State estimation	Advantage or Disadvantage	Reference
1	KF-UKF	Partial parameters	SOC and SOH	The polarization capacitances are treated as constants.	[26]
2	DEKF	Partial parameters	SOC and SOH	This paper only studied the online changes of parameter R_{Diff}.	[32]
3	KF-EKF	All parameters	SOC and SOH	The KF algorithm is only suitable for handling linear problems, and the EKF algorithm can only achieve first-order estimation accuracy.	[33]
4	EKF-UKF	All parameters	SOC and SOH	The EKF algorithm uses a first-order Taylor expansion to deal with nonlinear problems. Although this method can linearize the problem, it ignores the discrete distribution of random variables.	[30]
5	JEKF	All parameters	SOC and SOH	The joint Kalman filter algorithm causes the dimension of the state variable to increase and the amount of calculation is larger; The EKF algorithm only achieves first-order accuracy, which easily leads to loss of precision.	[19]
6	JUKF	All parameters	SOC and SOH	The joint Kalman filter algorithm causes the dimension of the state variable to increase and the amount of calculation is larger.	[20]
7	DUKF	Partial parameters	SOH	This paper only studied the online changes of internal resistance.	[39]
8	DUKF	All parameters	SOC and SOH	The DUKF algorithm used in this study has superior theoretical advantages.	This study