Estimation of SOC for Battery in Electric Vehicle Based on STUKF Algorithm

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Abstract. Lithium-ion (Li-on) battery state of charge (SOC) estimation is important for electric vehicles (EVs). To eliminate the effects of colored noise on SOC estimation, a new estimation method that based on Unscented Kalman Filter (UKF) Algorithm is proposed for high-power Li-ion batteries. First of all, based on the battery chemical properties, this paper established the improved PNGV battery model and identified the battery parameters. Then, accuracy of the model was verified under UDDS working condition. Finally, according to the influence of colored noise on estimating SOC of battery by the Unscented Kalman Filter (UKF) Algorithm, this paper proposed the Strong Tracking Unscented Kalman Filter (STUKF) Algorithm and introduced the fading factor. which forces the innovation sequence to be orthogonal and strengthens the correction of the state estimation by the new data. The result of simulation shows the STUKF Algorithm has better tracking characteristic on estimating SOC of battery.

Introduction

Along with the continuous intensification of a series of problems such as energy exhaustion, environmental pollution and greenhouse effect, the development of electric vehicles has attracted wide attention of the automobile industry, and various major automobile manufacturers have produced new electric vehicles one after another. As one of the three key technologies of electric vehicles, battery management technology has become the focus of research in major automobile enterprises, universities and research institutes [1]. Battery management system of electric vehicle is mainly responsible for battery status detection, power balance, fault protection, etc. As an important indicator of balance and fault diagnosis, SOC is related to the working stability of the whole battery management system. Therefore, the accuracy of estimating SOC of battery is particularly important [2]. The battery state of charge (SOC) is the most important point of the battery management system (BMS), whose estimation methods are often broken through in models and algorithms [3]. At present, there are many methods of building models for estimating SOC of battery. Paper [4] introduced the Rint model, Thevenin model, PNGV model and GNL model, compared with two other models, Rint model and Thevenin model are more simplified, so that the accuracy of the model was not exact. On the other hand, although the GNL model has high precision, the calculation is too much when it is applied. Besides improving the model, estimation algorithm is also very important. In [5], the SOC and capacity of batteries are estimated by double-observation algorithm under the application of reduced-order electrochemical model of composite-electrode batteries. In recent years, there have been many advanced algorithms have been applied in estimating SOC of battery, such as Extended Kalman Filter (EKF) algorithm, Unscented Kalman Filter (UKF) algorithm and NARX Neural Network algorithm. In [6], The paper proposed non-linear autoregressive control method (NARX) with the exogenous input, which is effective and large computation for the control of the system. In [7], the author used extended Kalman Filtering algorithm to estimate SOC of battery with the PNGV model. In this model, RC circuit was added, however, the capacitance did not participate in identification which describes open circuit voltage variations because of charge accumulation. EKF algorithm depends more strongly on the accuracy of the model parameters, which are difficult to achieve, so that the estimated results are not accurate because the EKF algorithm can only simplify the system into a first order approximation model. Due to the disadvantages of Extended Kalman
algorithm, some scholars proposed to use the Unscented Kalman Filter (UKF) algorithm to estimate SOC of battery. In [8], the UKF algorithm was used to estimate SOC of battery. The UKF algorithm mainly adopts sample and UT transformation of sampling data to approximate the nonlinear model. Compared with the EKF algorithm, model order of the highest can retain to third order, but the same problem is that the system can't be estimated accurately because of noise changed. Generally speaking, for a nonlinear system like battery, the system model is built on the basis of ignoring some factors. There is a difference between the model and the actual system and the system noise cannot be predicted accurately, these lead to the phenomenon of inaccuracy of estimation and divergence of the filter. In addition, UKF algorithm is feasible when the system noise is Gaussian white noise, but it will lose the ability to track the state when the state variables of the system are superimposed with colored noise. To eliminate this problem, a new SOC estimation algorithm based on the UKF algorithm is proposed in this paper. The key of the new algorithm is to put forward a calculation method of fading factor to make sure that the innovation sequence is orthogonal under model’s noise uncertainty, thus, the accurate of SOC estimation is improved. The simulation results show that the accuracy of proposed method is higher than that of conventional UKF algorithm.

**Building Model and Parameters Identification**

The accuracy of SOC estimation largely depends on the accuracy of the model. In this paper, based on PNGV equivalent circuit model, the model is added a set of RC circuit to simulate to distinguish different polarization characteristics of the battery. The equivalent circuit diagram is shown in Figure 1 and the parameters of the equivalent circuit model are shown in Table 1.

![Figure 1. Improved PNGV model](image)

**Table 1. Model parameters**

| Parameter | Meaning |
|-----------|---------|
| $U_{ocv}$ | Open circuit voltage |
| $R_0$     | Ohm resistance |
| $C_0$     | Describes open circuit voltage variations because of charge accumulation |
| $R_{1,2}$ | Polarization resistance |
| $C_{1,2}$ | Polarization capacity |
| $U_L$     | Terminal voltage |

Parameters identification of equivalent circuit model needs voltage and current data which obtained from HPPC experiment. In this paper, the battery is used in this experiment from cylindrical lithium battery batteries manufactured by Tianjin li Shen battery co, LTD, whose specific parameters are shown in Table 2.
Table 2. Li-on battery parameter

| Parameter       | The maximum capacity | rated voltage | cut-off voltage | Max discharge current |
|-----------------|----------------------|---------------|----------------|-----------------------|
| Mean value      | 2400mAh              | 4.2V          | 3V             | 7.2A                  |

Figure 2 shows the voltage change in the HPCC experiment when SOC is 0.7. The \( U_1-U_2 \) voltage drops vertically at the time of discharge and the \( U_3-U_4 \) voltage rises abruptly, which is caused by the ohm internal resistance of the battery. Therefore, the calculation formula of ohm internal resistance of battery can be represented.

\[
R_o = \frac{(U_1 - U_2) + (U_3 - U_4)}{2I}.
\]  

(1)

The \( U_1 \) voltage before discharge pulse is higher than the \( U_5 \) voltage when discharge reaches a stable state at the end of discharge, the voltage difference caused by the integral of discharge current on capacitance \( C_0 \). Therefore, the identification calculation formula describing the open circuit voltage capacitance \( C_0 \) can be represented.

\[
C_o = \frac{\Delta Q}{\Delta U_{ocv}}, \Delta U_{ocv} = U_1 - U_5.
\]  

(2)

At the end of the discharge, the voltage of \( U_4-U_5 \) slowly increases. Due to polarization of the battery and it is the zero-input response of the \( RC \) parallel circuit. When the battery discharging, the voltage of \( U_2-U_3 \) drops slowly which is the zero-state response of the \( RC \) parallel circuit. The calculation formula of the voltage response can be represented.

\[
U_{\text{zero-input}} = U_{ocv} - U_1(0)e^{-\frac{t}{R_1C_1}} - U_2(0)e^{-\frac{t}{R_2C_2}} \quad U_{\text{zero-state}} = U_{ocv} - IR_1 - U_1(0)e^{-\frac{t}{R_1C_1}} - U_2(0)e^{-\frac{t}{R_2C_2}}.
\]  

(3)

Considering that the battery stops discharging at time of \( U_3 \), and the voltage at both ends of the capacitor can remain unchanged at the moment when the current is interrupted, the initial voltage of the zero-state response is the same as the voltage at the end of the zero-input, thus, the calculation formula of \( R_1, R_2 \) be established.

\[
U_1(0) = IR_1(1 - e^{-\frac{t}{R_1C_1}}) \quad U_2(0) = IR_2(1 - e^{-\frac{t}{R_2C_2}}).
\]  

(4)

The sampling time of HPCC experiment was 1s and the working temperature is at 25°C. In the process of HPCC experiment, the open circuit voltage of SOC from 0 to 0.9 could be obtained by full static. The parameter identification results under different SOC are shown in Table 3.
Table 3. Fitting results of improved PNGV model

| SOC | R0  | R1  | C1   | R2  | C2   | C0    |
|-----|-----|-----|------|-----|------|-------|
| 0.0 | 46.8| 3.2 | 15.16| 0.9 | 488.11| 734   |
| 0.1 | 39.6| 2.4 | 18.77| 0.6 | 532.83| 1058  |
| 0.2 | 37.8| 1.9 | 23.99| 0.6 | 543.31| 1119  |
| 0.3 | 35.0| 1.3 | 31.89| 0.6 | 1199.54| 1376  |
| 0.4 | 34.4| 0.9 | 46.26| 0.1 | 2443.81| 1495  |
| 0.5 | 34.2| 0.9 | 50.80| 0.1 | 2780.48| 1395  |
| 0.6 | 36.5| 1.4 | 28.18| 0.2 | 1476.29| 981   |
| 0.7 | 36.0| 1.1 | 37.33| 0.1 | 2668.85| 1008  |
| 0.8 | 35.7| 1.5 | 29.88| 0.2 | 1655.81| 1051  |
| 0.9 | 35.3| 1.1 | 40.85| 0.1 | 2731.64| 1113  |

Note that the unit of resistance is $m\Omega$ and the unit of capacitance is $F$. By using the table lookup method, the results of parameter identification data are put into the battery model. Then, the simulated voltage is compared with the real voltage under UDDS working condition. It is found that the experimental simulation voltage can trace the real voltage well, and the error is below 1.5%, as shown in Figure 4. It can be proved that the improved PNGV model can simulate the real-time status of battery well.

**SOC Estimation Based on STUKF Algorithm**

The STUKF algorithm is a new algorithm that based on UKF algorithm, UKF abandoned the traditional method of linearizing nonlinear functions, but it adopted Kalman linear filtering framework and UT transformation. The principle of UT transformation is to obtain some sample points in the original distribution according to a definite rule, so that the mean and covariance of these sampling points are equal to the mean and covariance of the original state distribution, then, these points are substituted into the nonlinear function, and the value point set of the nonlinear function is obtained correspondingly. The mean value and covariance of the transformation can be obtained through these point sets.

For the nonlinear system, the state equation and observation equation are shown in Eq.5.

\[
\begin{align*}
    x_{k+1} &= f(x_k, u_k) + w_k, \quad Q = E[w_k w_k^T] \\
    y_k &= g(x_k, u_k) + v_k, \quad R = E[v_k v_k^T]
\end{align*}
\]  \hspace{1cm} (5)

In Eq.5, $x_k$ is a system state variable, $y_k$ is the system output variable, $u_k$ is the system input variable, $w_k$ and $v_k$ respectively indicate the state noise and measurement noise of the system. When the $w_k$ and $v_k$ are Gaussian white noise, $R=Q=0$, because Gaussian white noise is uncorrelated random variables.

In Kalman linear filtering framework, the final state variable $x_k = x_k + K_k r_k$, $K_k$ is Kalman gain; $r_k = y_k - y_k^*$, $r_k$ is innovation sequence. According to the minimum variance principle.
Innovation sequence $r_k$ is orthogonal, UKF algorithm can estimate the state variable well, but in the actual system, the state variable is superimposed a lot of colored noise, the color noise are not uncorrelated random variables, innovation sequence $r_k$ is not orthogonal. This may cause UKF estimated error increases. In order to solve this problem. This paper puts forward the STUKF and introduces the fading factor, the fading factor can adjust the predicted error covariance matrix in real time, so the output innovation sequence can be guaranteed to be orthogonal to each other, so that the filter has strong tracking properties. Besides, the introduction of fading factor can reduce the influence of old data on the estimation value.

The first step of the simulation experiment is establishing discrete state equations of the improved PNGV model.

The second step is to use the algorithm to process the voltage and current data to realize the estimation of SOC. Firstly, the variable is initialized.

$$X_0 = x_{k-1}$$

$$X_i = x_{k-1} + (\sqrt{N+\lambda})P_{k-1},i = 1,...,N$$

$$X_i = x_{k-1} - (\sqrt{N+\lambda})P_{k-1},i = 1+L,...,2N$$

Where $\lambda = a^2(L+k)-L$ and $L$ represent the window size of covariance matching. $N$ is the dimension of the model. In general $a=0.1$, $k=0$, the sigma points were updated backward according to the state space expression of the battery and the prior estimate of the battery state can be obtained.

$$X_{i,k-1} = f( X_{k-1},i_k ) + w_{k-1},i = 1,...,2N$$

$$x_k = \sum_{i=0}^{2N} W_i^m X_{i,k-1}.$$  

The $W_i^m$ and the $W_i^c$ are the weight coefficient.

$$W_0^m = \frac{\lambda}{\lambda + N}$$

$$W_i^m = \frac{\lambda}{2\lambda + 2N}, i = 1,...,2N$$

$$W_0^c = \frac{\lambda}{\lambda + N} + (1-\alpha^2 + \beta)$$

$$W_i^c = \frac{\lambda}{2\lambda + 2N}, i = 1,...,2N$$

The covariance matrix of the prior estimate is
\( P_{x,k-1} = \lambda_k \sum_{i=0}^{2N} W^r_i \left( X_{i,k-1} - x_k^i \right) \left( X_{i,k-1} - x_k^i \right)^T + Q \). \tag{12} \\

\( \lambda_k \) is the fading factor and \( \lambda_k > 1 \). The introduction of the fading factor changes the matrix and which will change the Kaman gain. For the solution method of fading factor, the nonlinear programming method should be used to solve the optimal fading factor, but the calculation amount of this method is too large to be suitable for online calculation. In Eq.13, the calculation method of the first-medium quadratic fading factor is given.

\[
\lambda_k = \begin{cases} 
    e_k & (e_k > 1) \\
    1 & (e_k \leq 1)
\end{cases}
\tag{13}
\]

Where, \( e_k = \frac{tr \left( N_k \right)}{tr \left( M_k \right)} \), \( tr \) is a kind of operation to find the trace and the \( M_k \) and \( N_k \) are defined.

\[
M_k = P_{x,k} - V_{i-1} + N_k \quad N_k = V_k - \beta R - \frac{P_{r,k}}{P_{x,k}} Q \frac{P_{r,k}}{P_{x,k}} P_{r,k} \quad V_k = \begin{cases} 
    r_k r_k^T & (k = 1) \\
    \rho V_{i-1} + \beta R & (k > 1)
\end{cases}
\tag{14}
\]

Where \( \beta \) is the weakening factor and \( 1 < \beta < 2 \). The weakening factor can make the state estimation of SOC smoother and improve the filtering performance. \( \rho \) is the forgetting factor, usually \( \rho = 0.95 \). The reconstructed covariance matrix of state variables is introduced into the process of STUKF algorithm, and the \( K_k \) is changed to improve the accuracy.

According to the system measurement equation, the mean of the measured estimate is calculated by propagating the sigma sampling point backward to the sigma point of the output variable.

\[
y_{i,k-1} = g \left( X_{i,k-1}, i_k \right) + v_{i-1} \quad y_k = \sum_{i=0}^{2N} W^m_i y_{i,k-1} \cdot \tag{15}
\]

After propagating backward on both sides, the covariance matrix of the output variable can be obtained.

\[
P_{x,k} = \sum_{i=0}^{2N} W^r_i \left( Y_{i,k-1} - y_k^i \right) \left( Y_{i,k-1} - y_k^i \right)^T + R \quad P_{y,k} = \sum_{i=0}^{2N} W^r_i \left( X_{i,k-1} - x_k^i \right) \left( X_{i,k-1} - x_k^i \right)^T \cdot \tag{16}
\]

\[
K_k = \frac{P_{x,k}}{P_{y,k}} \cdot \tag{17}
\]

\[
x_k = x_k^i + K_k \left( y_k - y_k^i \right) \cdot \tag{18}
\]

\[
P_{x,k} = P_{x,k} - K_k P_{x,k} K_k^T \cdot \tag{19}
\]

Where \( P_{x,k} \) is the common covariance of the state variable and output variable, \( K_k \) is Kalman filter gain, \( x_k \) is final state variable estimate and \( P_k \) is correction of state covariance.

### Simulation and Results

In order to verify that the STUKF algorithm has better traceability, the simulation was conducted under UDDS working condition, including 3000 data points were collected. Figure 5 shows that when the noise signal is Gaussian white noise, the UKF algorithm and the STUKF algorithm have the same estimation accuracy. Both filtering algorithms can well track the actual SOC of the battery. Figure 6 shows the errors between the two algorithms and the actual SOC, the initial error is up to 0.6%. In the later tracking, the error gradually shrinks to -0.1~0.2%.
In Figure 7 and Figure 8, with the noise change to colored noise, STUKF algorithm show better traceability, which compare with the actual SOC of the battery, STUKF algorithm estimated errors does not increase, that still can track the actual SOC of the battery well. On the contrary, the estimation error of the UKF algorithm is increasing. In the later stage of simulation, the estimated value diverges.

Conclusion

As an essential parameter for the energy control of an electric vehicle, the SOC of the battery needs to be accurately estimated to improve battery life and vehicle performance. In this paper, the improved PNGV model of the battery is established, and the STUKF algorithm is used to reduce the estimated error caused by the noise uncertainty. Summarize three main conclusions:

1. The improved PNGV model can simulate the actual condition of the battery well. Due to the addition of first order $RC$ circuit and capacitance $C_0$ which identified results are added to the model, so that the model accuracy is improved prominently.
2. The STUKF can ensure the orthogonality of the innovation sequence and weak the influence of old data on filter values by introducing the fading factor.
3. The STUKF Algorithm has better tracking characteristic that face to interference of colored noise.

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