State estimation of lithium-ion battery based on Gaussian process regression

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Abstract. The state of charge (SOC) of lithium-ion battery is one of the important parameters of battery management system (BMS). Accurate estimation of SOC can improve the safety of battery. Therefore, in order to improve the accuracy of SOC estimation, a new method based on Gaussian process regression (GPR) is proposed. The SOC estimated value at the previous time is used as the feedback vector, together with the current and voltage measured at the current time are used as the input vectors of the model to estimate the SOC at the current time. The experimental results show that the error of the proposed method is controlled within 2%, which verifies the effectiveness of the proposed method.

1. Introduction

With the increasing global petrochemical crisis, a global consensus has been reached on the development of new energy hybrid vehicles, and the key technology of new energy hybrid vehicles is the research of power battery system [1]. Lithium ion battery has the advantages of high energy and power density, long cycle, long calendar life, low self-discharge rate, and has become the preferred battery for electric vehicles. The state estimation (SOC) is one of the most important parameters of battery management system (BMS), but the complex chemical reactions inside the battery lead to the strong nonlinear and time-varying characteristics of the external characteristics of the battery, which increases the difficulty of SOC estimation. Therefore, accurate SOC estimation is still a challenging topic.

At present, there are many methods to estimate SOC, including ampere hour integration method [2], open circuit voltage method (OCV) [3], Kalman filter model [4]. The ampere integration method is widely used in industry, but the error of initial capacity and current measurement will accumulate continuously, which leads to low accuracy of SOC estimation. When the OCV is applied to estimate SOC, it needs a long time of standing, so it cannot be applied to on-line battery estimation. At present, many kinds of model-based methods are studied[5]. Among several models, the equivalent circuit model based on Kalman filter (KF) is presented. Kalman filter(KF) estimators [6] has a closed-loop correction structure, which can solve the difficulty of the initial SOC error. Zhang Wet al. [7] proposed an adaptive UKF for SOC estimation and parameter identification that can achieve self-adjustment of the noise covariance. Although this estimation method can obtain better estimation accuracy of SOC, the reliability of estimation is limited because the different battery types and health conditions usually have different charging and discharging rates, health levels and other performances.

To improve the battery model estimation performance, an increasing number of machine learning algorithms have also been used in recent years. The neural network (NN) is the most widely studied
data-driven method and has achieved considerable success in SOC estimation [8]. However, the NN method is prone to fall into a local optimum when obtaining parameters. The support-vector-machine (SVM) uses structural risk minimization to improve generalization ability [9]. Although NN and support vector machine have achieved good performance in SOC estimation, these methods are easy to fall into local optimization, which brings uncertainty to SOC estimation. The Gaussian process regression (GPR) [10] is an estimation method based on statistical mathematics theory. It can avoid local optimization in parameter optimization, and can well solve complex problems such as high dimension and nonlinearity. So, in order to get the better estimation accuracy of SOC, the GPR model is used to estimate SOC.

2. The principle of GPR

Given a set of data \( M(x_i,y_i) \), where \( x_i \) represents input vectors, \( y_i \) represents output vectors, suppose there is a potential function \( f(.) \), which injects the input \( x_i \) to the corresponding output value \( y_i \), as follows:

\[
y_i = f(x_i) + \xi_i
\]

where \( \xi_i \) is Gaussian noise, obeys the normal distribution with mean value of 0 and variance of \( \sigma_n^2 \), \( y_i \) also obeys Gaussian distribution:

\[
y_i \sim N(0, k(x_i,x_j) + \sigma^2 I)
\]

among them, \( k(x_i,x_j) \) is the corresponding function, \( I \) is the corresponding unit matrix, given the new sample input vectors \( x^* \), the corresponding output is \( y^* \), according to the Bayesian principle, the joint distribution of the output value \( y^* \) and the training set sample \( y \) is:

\[
\begin{bmatrix}
y \\
y^*
\end{bmatrix} = N(0, \begin{bmatrix}
k(x,x) + \sigma_n^2 I & k(x,x^*) \\
k(x^*,x) & k(x^*,x^*)
\end{bmatrix})
\]

Therefore, the corresponding posterior distribution \( y^* \) can be calculated, and the predicted output \( y^* \) can be expressed as:

\[
y^*|x, y, x^* \sim N(\mu, \Sigma)
\]

where

\[
\mu = k(x^*,x)(k(x,x) + \sigma_n^2 I)^{-1}y
\]

\[
\Sigma = k(x^*,x^*) - k(x^*,x)(k(x,x) + \sigma_n^2 I)^{-1}k(x,x^*)
\]

Because the square exponential covariance function (SE) has strong anti-interference ability, therefore the SE is selected as the kernel function in this paper. The maximum likelihood estimation is used to solve the parameters in kernel function, including \( \sigma, \sigma_f \) and \( l \). The SE kernel function is defined as follows:

\[
k(x_i,x_j) = \sigma_f^2 e^{-\frac{|x_i-x_j|^2}{2l^2}}
\]

The SOC, ranging from 0% to 100%, is a parameter that characterizes the residual capacity of LIBs. This paper presents a framework of GPR to estimate SOC. The input vector of GPR consists of current and voltage LIBs.

![Figure 1. Battery SOC estimation model based on GPR.](image-url)
Figure 1 shows the battery SOC estimation model based on GPR, in which the input vectors are the voltage and current at time $t$, expressed as $V(t)$ and $I(t)$ respectively, and the $SOC(t)$ represents the estimated value at time $t$. The model training method is shown in Table 1.

### Table 1. Algorithm flow.

| Step | Description |
|------|-------------|
| 1.   | Select the working condition to obtain the training set $M(x, y)$. $x$ represents voltage and current, $y$ represents the SOC. |
| 2.   | Normalize the selected data. |
| 3.   | Select the covariance function and initialize the corresponding parameter $\theta(\sigma, \sigma_f, l)$. |
| 4.   | Using conjugate gradient method to solve the log likelihood function and obtain the optimal parameter value. |
| 5.   | After the parameter value is obtained, the input vectors $x$ is selected to obtain the corresponding prediction distribution: $\mu_e = k^T_e (k + \sigma^2_n I)^{-1} y$. |

### 3. Battery model

In the process of battery measurement, due to the influence of internal factors of battery with charging and discharging time, and the influence of acquisition equipment, it will affect the SOC estimation. While it will be found that SOC will not change dramatically in the instantaneous time. Therefore, a new model based on GPR is proposed. The SOC estimated at the previous moment is added to the input vector to form a closed-loop system, together with the voltage and current at the current time to estimate the SOC at the current time. The model structure is shown in Figure 2.

![Figure 2. GPR-1: GPR model based on feedback loop.](image)

### 4. Experimental verification of algorithm

To verify the validity of the proposed model, 18650 LIB is used for testing, the detailed parameters are shown in Table 2. Table 2 shows the specific parameters of the battery.

### Table 2. The information of the battery.

| Parameters                  | Values   |
|-----------------------------|----------|
| Battery capacity (Ah)       | 2.4      |
| Heat capacity (J/g*K)       | 1232     |
| Upper cut-off voltage       | 4.2±0.05V|
| Lower cut-off voltage       | 3.0      |

In this experiment, the battery charging and discharging equipment (Arbin-BT2000) is used to carry out relevant experiments on the battery, and the selected RGD-500 is used to control the temperature during the experiment, and the data is collected through Fluke. Figure 3 shows the data collected under the FUDS working condition, and the collection interval time is 1s.

In this paper, two evaluation criteria are used to compare model performance: root mean square error (RMSE) and maximum absolute error (MAE):

$$RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (y_k - y)^2}$$  \hspace{1cm} (8)
\[ MAE = \max |y_* - y| \]  

Where \( y_* \) is the estimated value, \( y \) is the actual value.

**Figure 3.** The FUDS conditions cycle: voltage, current and SOC.

From Figure 4 to Figure 7, it indicates that the accuracy of SOC prediction based on the proposed model is better than that of traditional GPR, and the RMSE is reduced from 3.42% to 1.15%, which shows that the stability of the model is improved by 66.3%, the MAE is reduced from 6.54% to 1.49%. The experimental results present that the feedback of SOC value estimated at the previous time is added to the input vectors, it can effectively improve the estimation accuracy of SOC. It is shown that the SOC estimated at the previous time is added to the input vector of the model as the feedback value to form a closed-loop system, which can effectively adjust the estimation performance of SOC and greatly improve the estimation accuracy of SOC. It can be seen from Table 3 that compared with LSSVM and NN, the battery SOC estimation based on GPR-1 have better estimation performance.

**Figure 4.** SOC estimation results based on GPR.  
**Figure 5.** SOC estimation results based on GPR-1.
Figure 6. SOC estimation results based on LSSVM.

Figure 7. SOC estimation results based on NN.

Table 3. SOC prediction accuracy of each estimator.

| Methods | RMSE (%) | MAE (%) |
|---------|----------|---------|
| NN      | 14.39    | 18.69   |
| LSSVM   | 5.18     | 5.45    |
| GPR     | 3.42     | 9.54    |
| GPR-1   | 1.15     | 1.67    |

5. Conclusions

It is very important to estimate SOC accurately for electric vehicles. Because batteries are nonlinear systems, it is difficult to estimate SOC accurately. In order to improve the accuracy of SOC estimation, a novel model based on GPR is proposed. The SOC estimated value at the previous time is used as the feedback vector, together with the current and voltage measured at the current time are used as the input vectors of the model to estimate the SOC at the current time. Compared with LSSVM and NN, the SOC estimated by proposed method has high accuracy.

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