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Study on Stable Estimation Method for Lead-acid Battery SOC by Extended Kalman Filter

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Abstract

A stable state of charge (SOC) estimation method which can adapt to variable current environment through adjusting noise covariance is proposed in this study. The accuracy of battery SOC estimation is the important factor in battery management system. First, the cause of instability on SOC estimation using Kalman filter is analyzed, and then an extended Kalman filter (EKF) is used to build up state space equation. The experimental results show that the SOC estimation error within 10%. Meanwhile, the variety of SOC is decreased from 1% to 0.6%.

Keywords: *SOC, noise covariance, battery management system, EKF, estimation error*

1. Introduction

As an important core component of new energy vehicles, battery system is essential for vehicle power system including economy and security [1, 2]. In order to improve battery efficiency and safety, battery system needs rational management. To avoid over-charging and over-discharging, which are the main faulty operations to damage batteries, it is necessary to online estimate battery SOC.

SOC is defined as the percentage of the remained charge inside the battery to the full charge, which is one of the most important parameters on batteries [3]. Accurate SOC estimation owns a great of significance to the vehicle. So SOC estimation is a key research area and it should be exploited within designed limits. Common SOC estimations includes current integration method, discharge test method, open circuit voltage method, electrochemical impedance spectroscopy, resistance predication method, linear models method, neural networks and Kalman filtering algorithms [4]. These methods have their advantages and disadvantages respectively. Kalman filter algorithm just needs a small amount of computation and storage which solve the multidimensional nonlinear stochastic signal filtering problem, especially suitable for current violent fluctuation conditions.

Fei Zhang [5] studied a method using the Kalman filter to estimate lead-acid battery SOC, but its battery modeling purpose is indeterminate and state equation parameter need to be online identified that highly require a precise acquisition device. So the method could not apply to battery management system. Based on the electrochemical reaction mechanism of lead-acid batteries, Michael Knauff [6] introduced a new battery model as SOC observer which receives a good result to a single cell. Unfortunately, the

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method ignores the differences between each cell, which cannot give an overview of battery system force an obstacle to battery SOC estimation. Jie Xu [7] used Kalman filter method combined with current integration method into SOC estimation, the initial SOC indirectly obtained by measuring open circuit voltage (OCV) while current integration obtain initial SOC increment, with the help of Kalman filter recursion formula SOC estimation error is less than 6.5%. However, initial SOC assurance needs enough laid-aside periods to get precise OCV which cannot be satisfied in practice. To solve above problems, combined with instable SOC estimation of EKF, this paper studied a stable SOC estimation method using EKF based on process noise covariance regulation.

2. Lead-acid Battery Model

In this section, battery modeling is presented for lead-acid battery with nominal voltage of 12V and nominal capacity of 100Ah. SOC estimation methods can be divided into classes, non-model based estimation and model based estimation. A reasonable and effective battery model owns important significance for battery SOC estimation and hardware-in-loop simulation [8, 9]. Battery SOC is a variable which cannot be measured directly so that we have to estimate SOC based on relative battery parameter and mathematical algorithm.

To reflect battery modeling significance in more intuitive degree, we adapt two models, the internal resistance model (shown in Figure 1), where OCV describes the battery capacity, Ro indicates the battery ohm resistance. Figure 2 shows a first-order RC model, except for OCV and Ro, consist of R_1 and C_1, which describe the diffusion impedance caused by electrode material. Ro, R_1 and C_1 can be identified by test method. According to the model, an accurate state space and output equation would be got, (1) and (2) is described the characteristics of the model.

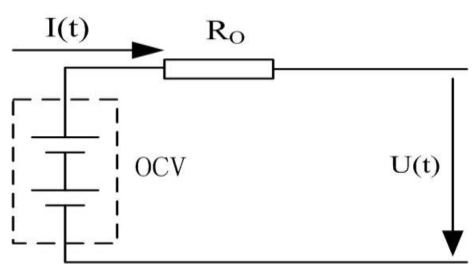

Figure 1. Battery internal resistance model

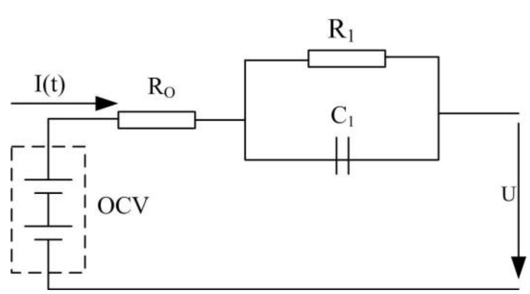

Figure 2. Battery RC model

$$\begin{bmatrix} SOC(k+1) \\ U_{R1C1}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\Delta t/\tau} \end{bmatrix} \times \begin{bmatrix} SOC(k) \\ U_{R_1C_1}(k) \end{bmatrix} + \begin{bmatrix} \dfrac{\eta\Delta t}{C_e} \\ R_1(1-e^{-\Delta t/\tau}) \end{bmatrix} \times I(k) \quad (1)$$

RC model output can be expressed:

$$U(k) = OCV(SOC(k)) - U_{R_1C_1}(k) - I(k) * Ro \quad (2)$$

where Δt is sampling period, k is the sample point and η is coulomb efficiency. We assume that η <1 for charge, η = 1 for discharge. I represents the current and I >0 for charge and I<0 for discharge. U is pack's terminal voltage, and $OCV(SOC(k))$ describes the relationship between *OCV* and *SOC*, τ is the time constant for R_1C_1 circuit, that is $\tau = R_1 * C_1$, $U_{R_1C_1}(k)$ is the voltage on C_1.

Internal resistance state and output equation can be expressed by (3) and (4):

$$SOC(k+1) = SOC(k) - \frac{\eta i_k \Delta t}{C_e} \quad (3)$$

$$U(k) = OCV(SOC(k)) - I(k) * Ro \quad (4)$$

To the RC model, its parameter identification result is shown table 1

Table 1. Battery internal parameter identification at different SOC

SOC	$R_O(\Omega)$	$R_1(\Omega)$	C_1(F)
0.1	0.01113	0.0139	271.44
0.2	0.0085	0.0174	574.48
0.3	0.0090	0.0148	672.03
0.4	0.0087	0.01400	713.98
0.5	0.0086	0.0126	790.27
0.6	0.0079	0.01397	715.45
0.7	0.0067	0.0148	674.18
0.8	0.0094	0.0086	541.41
0.9	0.0075	0.0135	530.76

3. Lead-acid Battery SOC Estimation on EFK

Kalman filtering algorithm provides optimal estimation method to system observation and state vectors. Due to the nonlinear characteristic for battery [10], this paper mainly uses discrete nonlinear system formula.

$$X(k+1) = f(x_k, u_k) + w_k \quad (5)$$

$$Y(k) = g(x_k, u_k) + v_k \quad (6)$$

(5) is state equation, (6) is system output equation, $f(x_k, u_k)$ and $g(x_k, u_k)$ is nonlinear function, to meet the requirement of EKF, using linearization method to obtain discrete linear

state space equation, the process noise and the sensor noise of the system are w_k and v_k respectively, which w_k is uncorrelated with v_k, x_k is system state at time point k, u_k is the input of the system and y_k is the output of the system.

where x_k^- represents optimal estimation value and x_k^+ represents optimal filtering value.

Adding 1th Taylor expansion into $f(x_k,u_k)$ and $g(x_k,u_k)$, the EKF is summarized as following equations:

$$A_k = \left.\frac{\partial f}{\partial x}\right|_{x=x_k^+} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\Delta t/\tau} \end{bmatrix} \tag{7}$$

$$C_k = \left.\frac{\partial g}{\partial x}\right|_{x=x_k^-} = \begin{bmatrix} \left.\dfrac{dOCV(SOC_k)}{dSOC_k}\right|_{SOC=SOC(k)} & -1 \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} SOC(k+1) \\ U_{R_1C_1}(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\Delta t/\tau} \end{bmatrix} \times \begin{bmatrix} SOC(\mathrm{k}) \\ U_{R_1C_1}(\mathrm{k}) \end{bmatrix} + \begin{bmatrix} \dfrac{\eta \Delta t}{C_e} \\ R_1(1-e^{-\Delta t/t}) \end{bmatrix} \times I(k) + w_k \tag{9}$$

$$U(k) = OCV(SOC(k)) \text{-} U_{R_1C_1}(K) \text{-} R_o * I(k) + v_k \tag{10}$$

The Kalman filtering problem, namely, the problem of jointly solving the process and output equations for the unknown state in an optimum manner [11] may now be formally stated as follows:

$$\tilde{\mathrm{x}}_{\mathrm{k}} = \arg\min E[(x_k - \mathrm{x}_k^+)(x_k - \mathrm{x}_k^+)^T \,|\, u(0), u(1), \ldots.., u(k), y(0), y(1), \ldots.., y(k)] \tag{11}$$

Essentially, EKF initialization is similar to traditional Kalman filtering [12];

$$\begin{aligned} & k = 0 \qquad \mathrm{x}_0^+ = E(x_0) \\ & \textstyle\sum_{\mathrm{x}_0}^{+} = E[(x_0 - \mathrm{x}_0^+)(x_0 - \mathrm{x}_0^+)^{\mathrm{T}}] \\ & \textstyle\sum_w = E(w \times w^{\mathrm{T}}) \\ & \textstyle\sum_v = E(v \times v^{\mathrm{T}}) \end{aligned} \tag{12}$$

As K arising, its recursive equations are expressed as following:

$$\mathrm{x}_{\mathrm{k}}^- = f(\mathrm{x}_{k-1}^+, u_k) \tag{13}$$

Error covariance propagation:

$$\textstyle\sum_{x_k}^{-} = A_{k-1} \sum_{x_{k\text{-}1}}^{+} A_{k-1}^{\mathrm{T}} + \sum_w \tag{14}$$

Kalman gain matrix:

$$L_k = \textstyle\sum_{x_k}^{-} C_k^{\mathrm{T}} / (C_k \sum_{x_k}^{-} C_k^{\mathrm{T}} + \sum_{\mathrm{v}})^{-1} \tag{15}$$

State estimate update:

$$\mathrm{x}_{\mathrm{k}}^+ = x_k^- + L_k[y_k - (C_k x_k^- + D_k \mathrm{u}_k^-)] \tag{16}$$

Error covariance update:

$$\sum\nolimits_{x_k}^{+} = (I - L_k C_k)\sum\nolimits_{x_k}^{-} \tag{17}$$

where I represents unit matrix, $\sum_w$ and $\sum_y$ describe the mathematical expectation of w_k and v_k, $\sum_{x_k}^{+}$ reflects the state estimation uncertainty which is inversely proportional to the state vector. The initial state estimation is incorrect in general, but with the help of estimation and correction equations, as the time period arising, SOC would converge to the true value.

To verify the presented battery model accuracy, the model is evaluated by comparing the measured and the estimated battery voltage corresponding to several current profiles. As the Figure 3 and 4, the battery was charged and discharged under pulse current.

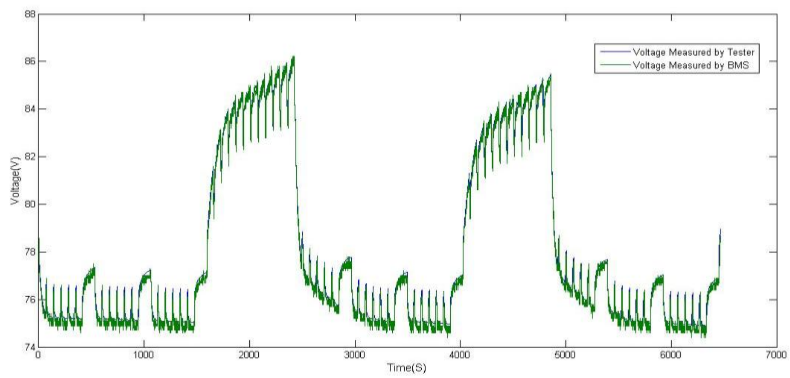

Figure 3. Battery voltage profile

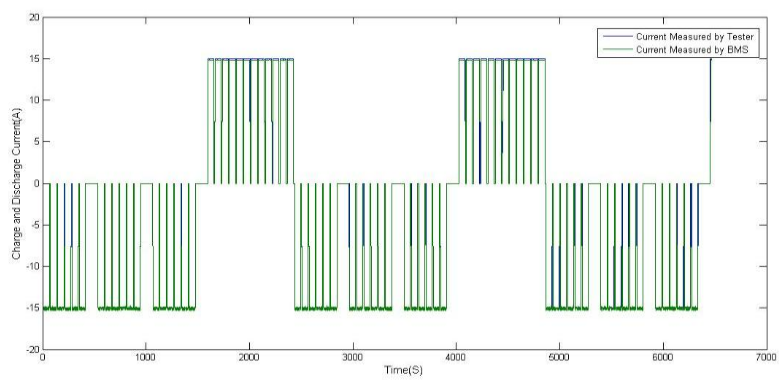

Figure 4. Battery current profile

Using equations (2) and (4) to estimate battery voltage, which compared with the measured voltage, Figure 5 is the comparison of estimated voltage by RC model and internal resistance model.

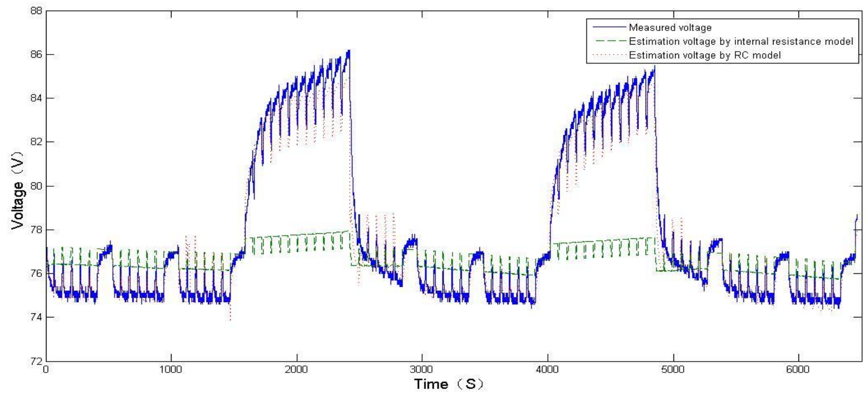

Figure 5. Voltage estimation compared with RC model and internal resistance model

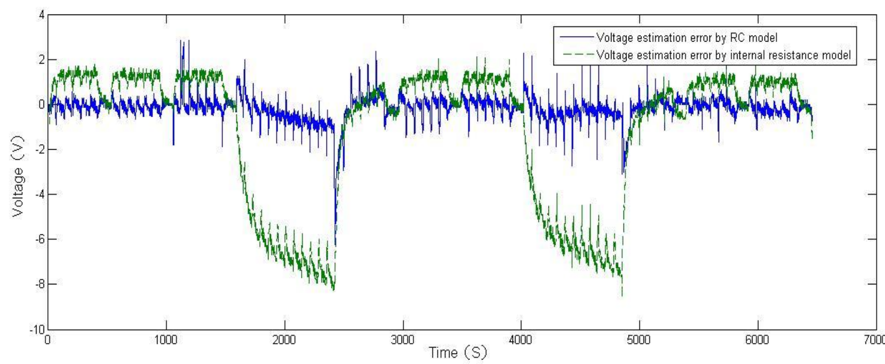

Figure 6. Voltage estimation error by RC model and internal resistance model

From Figure 5, it can be seen the estimated terminal voltage with RC model are more consistent with the measured one. From Figure 6, it is seen that RC model keep the voltage error within 2V while internal resistance is 8V. Due to battery has polarization effect at charging and discharging period, its internal parameters would change as current period and strength causing internal electrolyte concentration changed, as the result, battery emerges voltage drop phenomenon. Internal resistance characteristic just has impendence that cannot describe battery nonlinearity. In contrast, RC circuit accurately describes the polarization effect on appearance and disappearance. But RC model estimated voltage appear some large error as figure 6 shown, except for the error by battery modeling, it is mainly OCV is confirm by SOC which has inherent error existed, in addition to battery parameter identification does not take temperature element into account. But as a whole, RC model estimation is much better to describe battery characteristics.

4. SOC Estimation Result Based on Parameter Adjustment

The above section has discussed EKF algorithm theory. And due to the algorithm defects [13], battery model error is accordance to SOC estimation error. Especially, terminal voltage estimation error deeply affects SOC estimation accuracy. Although EKF would keep the error into a controllable range, in Dramatic change phase, battery terminal voltage brings about fluctuation on SOC estimation, as the result, driver may receive the wrong information and make the wrong behavior.

In EFK equations, $\sum_y$ and $\sum_w$ are taken as constants, $\sum_y$ is related to hardware and its characteristic has little relationship to other conditions, so it is reasonable to set as constant. The process noise covariance $\sum_w$ represents the uncertainty caused by modeling which is not the same during charging and discharging. To improve SOC estimation stability, using Σ_w adjustment when there is large difference between measured voltage and estimated voltage, increase Kalman gain to update state vectors while decrease Kalman gain at small error period.

Based on these above, this paper set three adjustment conditions respectively for three battery processes. Although this EFK has the disadvantage of large matrix operations due to the high dimensionality of the resulting augmented model, it could be written into 16-bit microcontroller. And SOC estimation operation diagram is shown in Figure 7.

To verify our SOC estimation method, the experiment is based on Figure 5 and 6, tradition EKF initial SOC is dependent on OCV, Kalman filter algorithm using its effective recursion computing equations could constrain SOC to true value which keep estimation error within 2%, especially when violent changes in current, parameter adjustment, according to voltage estimation error, decrease the phenomenon of estimation instability.

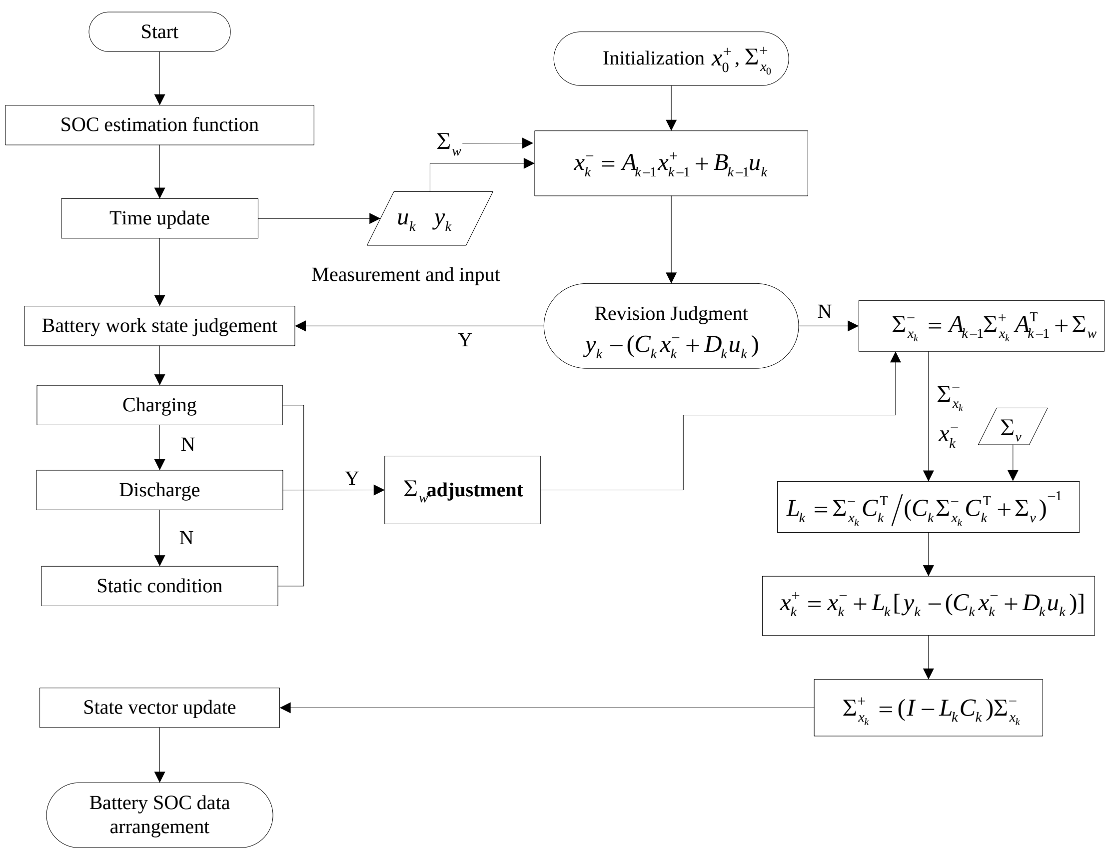

Figure 7. The operation of EKF

Due to true SOC is hard to obtain, we just compare with Ah counting method. Initial SOC is calculated by OCV, figure 8 is shown SOC estimation curve.

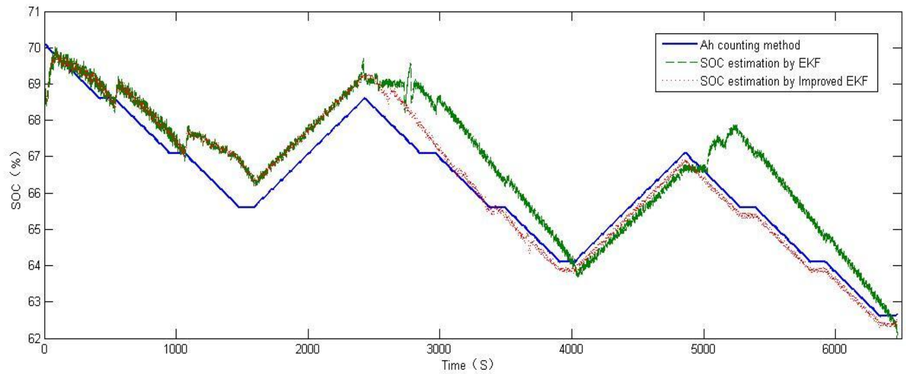

Figure 8. SOC estimation curve by three methods

From the simulation experiments, it shows EFK algorithm owns estimation accuracy and has a strong revision for initial SOC, as Figure 9 seen, using Σ_w adjustment has decreased estimation instability, especially, in the test latter period, its estimation error is appeared to linear. In contrast to traditional EFK estimation curve, our method is more accuracy and more reasonable. Figure 10 shows that the method adapted by the paper has decreased SOC variety from 1% to 0.6%.

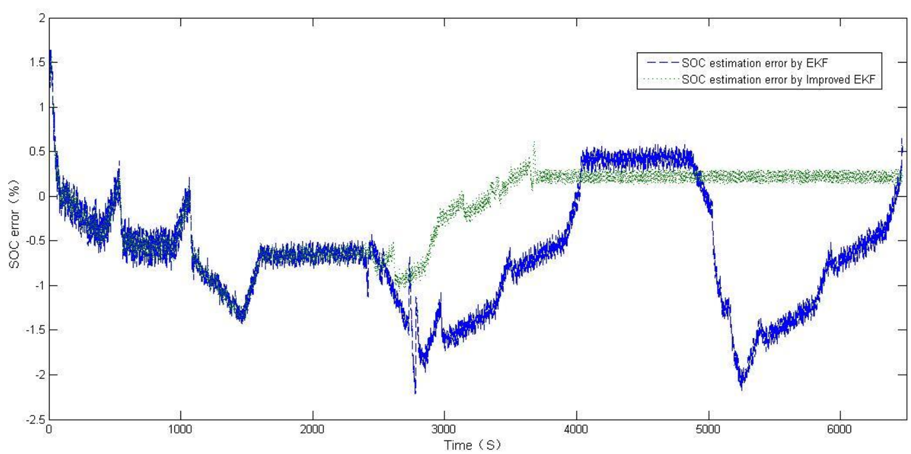

Figure 9. SOC error profile by two methods

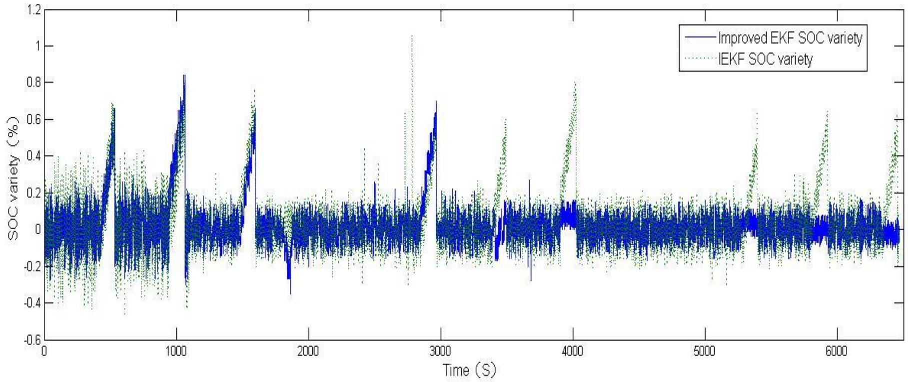

Figure 10. SOC vary rate by two methods

5. Conclusion

This paper has studied a stable SOC estimation method based on EFK, we have described EKF characteristic and SOC estimation requirement, building up battery equivalent model and define the relation between the model physical quantity and the state vector, in the final, with the help of EKF and parameter adjustment, SOC estimation maximum error constrain to 10%, the result has reflected battery model and its parameter plays an important role in SOC estimation, meanwhile, using parameter adjustment improve estimation stability. The method is easy to transfer into 16-bit microcontroller. Unfortunately, this paper does not take temperature and model parameter variety into account, the focus of research would be online parameter identification.

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