An Open Circuit Voltage Estimation for Lithium-ion Batteries Using Kalman Filter

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Abstract— To the advent of renewable energy era, precise and safe management technology of lithium-ion batteries are highly required. This paper discusses a method of open circuit voltage (OCV) estimation system for lithium-ion batteries based on the join method of Kalman filter and RLS method. We use pre-measured dOCV/dSOC instead of the mean of dOCV/dSOC. As result, the OCV estimation accuracy is improved.

I. Introduction

In recent years, with the spread of renewable energy, lithium-ion batteries, capable of storing electric energy at high density, have been attracting attention.

Open circuit voltage (OCV) is a very important parameter for estimating the state of charge (SOC) and state of health (SOH). The OCV curve of the NCR18650 battery used in this paper as Fig. 1. The length of the flat part of this OCV curve is called the plateau. The length of this plateau shortens as the battery deteriorates. In addition, information such as deterioration of the lithium-ion battery can be obtained by using the dV/dQ method [1]. So, OCV estimation is a very important problem.

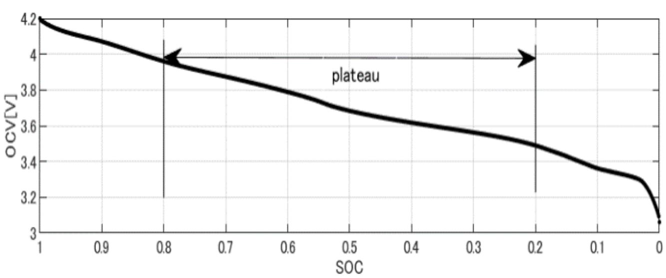

Fig1. OCV-SOC curve

We have previously developed a method for dynamically estimating OCV using the Kalman filter [2]. RLS estimates the parameters R and C required for OCV estimation. In [2], the formulation is performed using the average value of dOCV/dSOC. However, the maximum estimation error exceeds 50 mV, which is a large error. An estimation error of 5 mV or less is required as an institutional target for use in deterioration correction. In this paper, we use dOCV/dSOC curve pre-estimated at previous discharge cycle instead of the mean value of dOCV/dSOC to improve the estimation accuracy to maximum error of 30mV.

II. The Equivalent Circuit Model and Its Parameter Estimation

The battery equivalent circuit model is used as Fig. 2 [3]. This model is composed of R_a, R_b, C_b, U_OCV, R_a is the resultant resistant consisting of electrolyte and electric double layer resistance, R_b , C_b are diffusion resistance or capacitance of internal electrode, U_OCV is the electromotive force of battery same as OCV. In Fig. 2, U_L is the terminal voltage of battery, I is the terminal current of battery, U_b is the voltage of R_b and C_b parallel circuit [4].

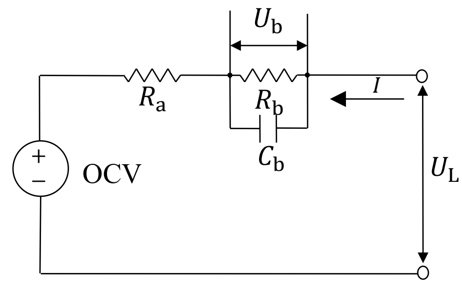

Fig. 2. The equivalent circuit model of the Li-ion battery

Equation (1) is obtained as the differential equation of the equivalent circuit model.

$$\begin{cases} C_\mathrm{b}\frac{dU_\mathrm{b}}{dt} + \frac{U_\mathrm{b}}{R_\mathrm{b}} = I \\ U_L = U_\mathrm{b} + IR_\mathrm{a} + U_\mathrm{OCV} \end{cases} \tag{1}$$

III. The OCV Estimation Method

A. Configuration of OCV estimation

Fig. 3 shows the block diagram of OCV estimation using the join method of Kalman filter and RLS. In this block diagram, the RLS block is responsible for the RC circuit parameters estimation ($R_\mathrm{a}(k)$, $R_\mathrm{b}(k)$, $C_\mathrm{b}(k)$), the Kalman filter block is responsible for the OCV estimation [5].

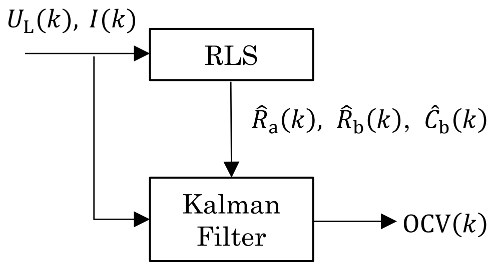

Fig. 3. Block diagram of OCV estimation using the join method of Kalman filter and RLS

B. *The OCV estimation using Kalman filter*

The Kalman filter is an approximately optimal state estimator for a stochastic process subject to Gaussian white noises using state space model [6].

$$x(k+1) = A(k)x(k) + B(k)u(k) + w(k) \tag{2}$$

$$y(k) = C(k)x(k) + D(k)u(k) + v(k) \tag{3}$$

Where (2) and (3) are the state and observation equations, respectively; $x(k)$, $y(k)$ and $u(k)$ are the state vector, observed output, and control input, respectively. The signal $w(k)$ is the process noise, and $v(k)$ is the observation noise. We assume that these noises are zero-mean white Gaussian noise processes with covariance $\sigma_w^2(k)$ and $\sigma_v^2(k)$ respectively.

In this case, we set the state vector $x(k)$ as $[\mathrm{OCV}(k) \quad U_{\mathrm{b}}(k)]^{\mathsf{T}}$, observed output $y(k)$ as $U_{\mathrm{L}}(k)$. By equation (1) and the constitution of equivalent circuit model, the detail of state space model is as next table. We give pre-measured $\frac{d\mathrm{OCV}}{d\mathrm{SOC}}$ by charging and discharging a minute current of 0.16[A]. The NCR18650 battery's gradient of the OCV curve is as Fig. 4. The FCC is the full charge capacity of battery, NCR18650 battery's FCC is 3.2[Ah].

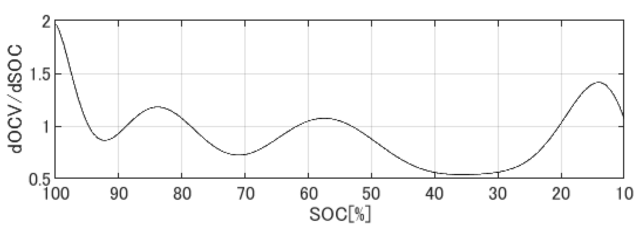

Fig. 4. The gradient of the OCV curve

The Kalman filter algorithm is described as **Algorithm 1**. This algorithm consists of three steps: Initialization value, Prediction, and Filtering. Here, $\hat{x}^-$ is the one-step prediction vector, $\hat{x}$ is the filtered estimate vector, P^- is the prediction error covariance matrix, and P is the filtering error covariance matrix.

TABLE1

The Parameter of State Space Model

$A(k) = \begin{bmatrix} 1 & \\ & 1 - \dfrac{T_{\mathrm{s}}}{R_{\mathrm{b}}(k)C_{\mathrm{b}}(k)} \end{bmatrix}$	$B(k) = \begin{bmatrix} \dfrac{T_{\mathrm{s}}}{\mathrm{FCC}} \dfrac{d\mathrm{OCV}}{d\mathrm{SOC}} \\ \dfrac{T_{\mathrm{s}}}{C_{\mathrm{b}}(k)} \end{bmatrix}$
$C(k) = [1 \quad 1]$	$D(k) = R_{\mathrm{a}}(k)$
State Vector	$x(k) = \begin{bmatrix} \mathrm{OCV}(k) \\ U_{\mathrm{b}}(k) \end{bmatrix}$
Observation Value	$y(k) = U_L(k)$

Algorithm 1 Kalman filter

Initialization Value

$\hat{x}^-(0),\ P^-(0)$

Filtering Step

$\hat{x}(k) = \hat{x}^-(k) + g(k)\big(y(k) - C(k)\hat{x}^-(k) - D(k)u(k)\big)$

$g(k) = P^-(k)C^{\mathsf{T}}(k)\big(C(k)P^-(k)C^{\mathsf{T}}(k) + R(k)\big)^{-1}$

$P(k) = P^-(k) - g(k)C(k)P^-(k)$

Prediction Step

$\hat{x}^-(k+1) = A(k)\hat{x}(k) + B(k)u(k)$

$P^-(k+1) = A(k)P(k)A^{\mathsf{T}}(k) + Q(k)$

IV. Experiment and Evaluation

In this paper, we use 3 patterns of test discharge waveforms to evaluate the stability and accuracy of the proposed OCV estimation method. Pattern 1 is a pulse discharge (Fig. 5), pattern 2 is a triangular wave discharge (Fig. 6), and pattern 3 is a pseudo-random discharge (Fig. 7). In each figure, the upper figure is the terminal current of battery, and the lower figure is the terminal voltage of battery. Simulation is done in MATLAB.

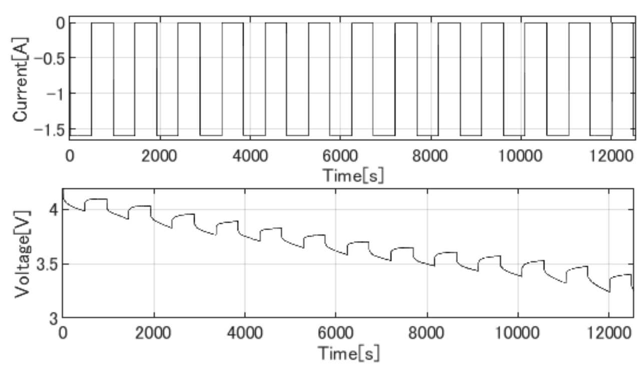

Fig. 5. The test discharge waveform pattern 1

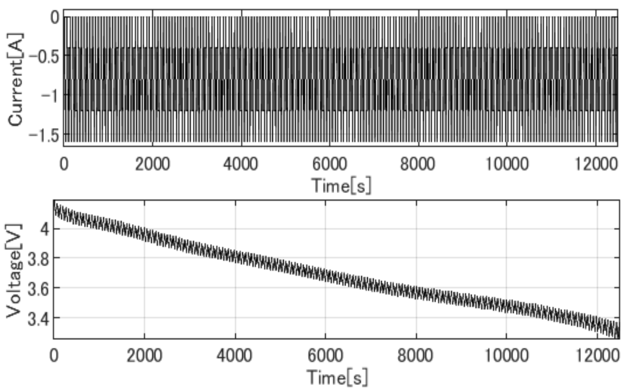

Fig. 6. The test discharge waveform pattern 2

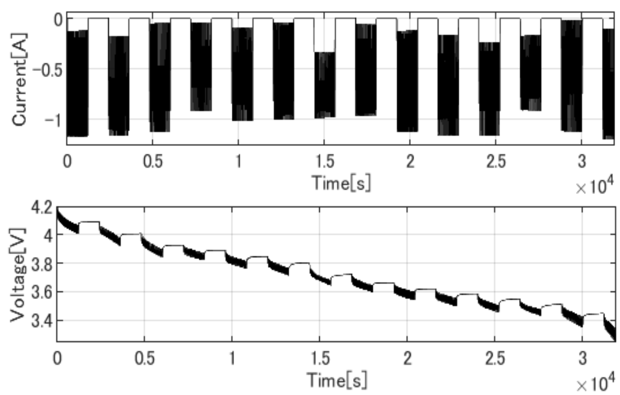

Fig. 7. The test discharge waveform pattern 1

A. OCV estimation result

The OCV estimation result of 3 patterns of test discharge waveforms is as Fig. 8~10. In each figure, the upper figure shows the result of OCV estimation, and the lower figure shows the error of OCV estimation. In the upper figures, ….line is the OCV estimation, —line is the OCV reference. In each pattern, the OCV estimation maximum is less than 30 [mV].

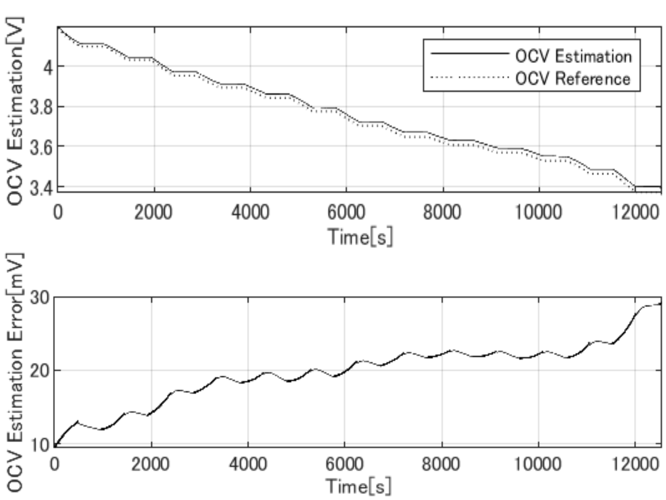

Fig. 8. The test discharge waveform pattern 1

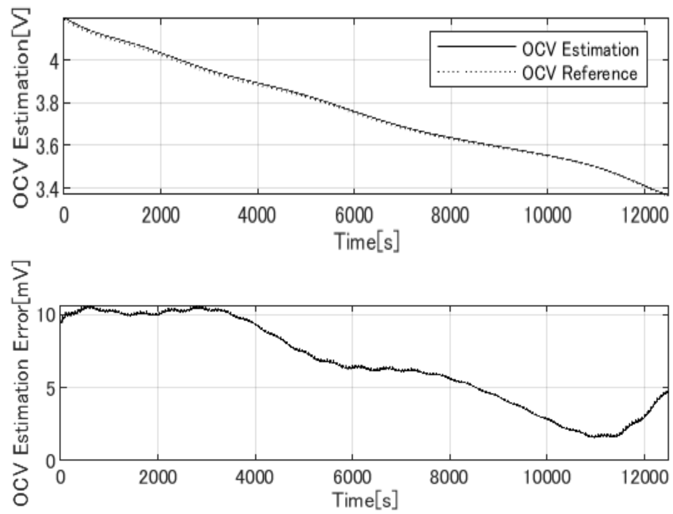

Fig. 9. The test discharge waveform pattern 2

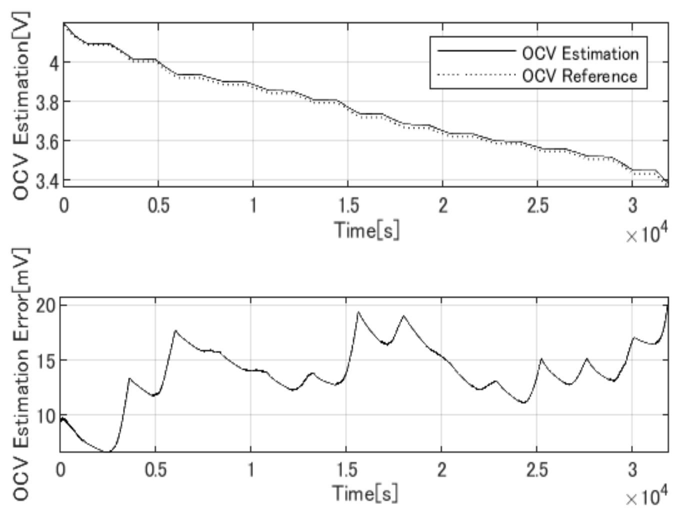

Fig. 10. The test discharge waveform pattern 3

B. OCV estimation accuracy evaluation

For evaluation, OCV estimation errors of the proposed and [2] are compared. Fig.11 shows the RMSE (Root Mean Square Error) of each methods. The unit is [mV]. The black bar is that of [2], and white bar is that by the proposed method.

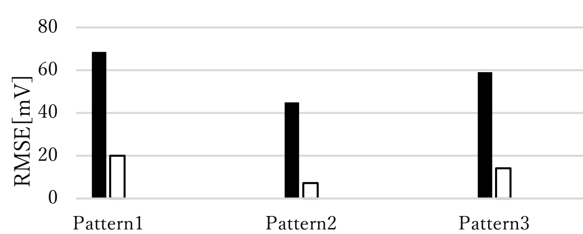

Fig. 11. OCV estimation RMSE

V. CONCLUSION

In this paper, we proposed a new method of OCV estimation using the join method of Kalman filter and RLS. We use pre-measured dOCV/dSOC instead of the mean of dOCV/dSOC. The maximum error of OCV estimation was less than 30 [mV], and it is possible to improve from the maximum error of 50 [mV]. Although there is an error, it can be used for rough deterioration diagnosis. In future, we aim to improve the accuracy of OCV estimation by FCC compensation and using deep learning to perform more detailed deterioration diagnosis.

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