A Classification Based Methodology for Estimation of State-of-Health of Rechargeable Batteries

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Abstract

This work proposes a methodology for determining the state-of-health (SOH) of rechargeable batteries. The proposed method uses a parametric approach which is based on a generic electrical circuit model for rechargeable batteries. Battery parameters of the model are identified by an algorithm based on extended Kalman filtering (EKF). Estimated battery parameters are used as classification features in quadratic discriminant analysis. Classification performance of the proposed method is investigated via a method using the concept of Bhattacharyya distance.

1. Introduction

As the usage of modern portable electronic devices increases, the measurement of the remaining battery capacity becomes important. The knowledge of the battery state-of-charge (SOC) provides the battery to be kept within safety operating limits. It is important to avoid over-charge or deep-discharge which both causes a decrease of the battery state-of-health (SOH).

To estimate the SOC, a battery model should be used. There are various types of battery models in the literature. While some of them are for specific battery types, some of them are generic models. Some battery models have a complex structure with a large number of parameters such as electrochemical models [1, 2]. Some models have the capability of the analytical insight like electrical circuit models [3-12]. In electrical circuit models, battery parameters are defined as circuit parameters to provide the understanding of battery behavior. In mathematical models, battery parameters are defined as variables which are obtained from battery tests [13]. In this work, a generic electrical circuit model, which is suitable for on-line identification of rechargeable batteries, will be used [14].

Several methods for the estimation of battery SOC are proposed in the literature. These are discharge tests, ampere-hour counting, open-circuit method [3, 6], impedance measurement methods [15, 16], Kalman-filtering based methods [1][3][10-12][13], and methods which use manufacturers' data [17-20]. Here, we use a Kalman-filtering based algorithm to estimate the battery SOC. Indeed, the SOC estimation approach we had proposed in [14] is a joint estimation method which simultaneously estimates the battery parameters.

To determine the battery SOH, we propose a quadratic discriminant classification method. We use the battery parameters obtained via the Kalman-filtering based joint estimation as a feature vector for classification. In order to estimate battery SOH, we define unused, lightly used and heavily used battery groups. These classes are defined by statistical characterization of battery parameters obtained from unused, lightly used and heavily used batteries. By this approach, we transformed the battery state-of-health estimation problem into a classification problem. Quadratic discriminant analysis [21] is used as a classification algorithm. For each class, a quadratic discriminant function is calculated at the measured battery parameters. Classification is done by assigning the battery to the class at which the maximum value of the quadratic discriminant function is achieved. The proposed classification method is tested on NiMh batteries. Classification performances are analyzed by using an inequality based on the concept of Bhattacharyya distance [22].

Joint SOH and parameter estimation method used will be briefly discussed in part 2. Proposed classification approach for SOH estimation is explained and discussed with the experimental results in part 3. We end up with a short discussion of the results in part 4.

2. Joint Battery SOC and Parameter Estimation

2.1. The Rechargeable Battery Model

In this work, a generic electrical circuit model [14] shown in Fig. 1 will be used. This model captures the basic structure and dynamics of rechargeable batteries and will be used as a generic model regardless of the type of battery.

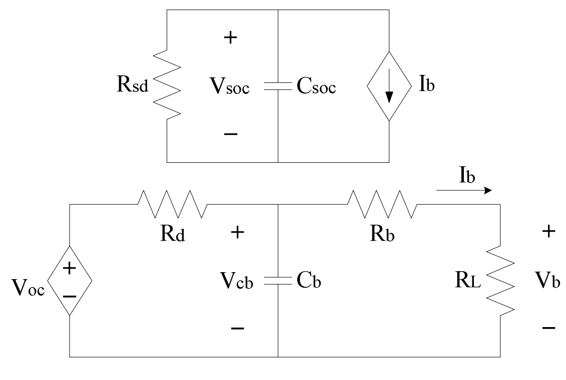

Fig. 1. Generic Rechargeable Battery Model

Here, V_{soc} is the voltage drop on the capacitor C_{soc} and will be assumed to take values between 0V and 1V. 0V will indicate that the battery is empty and 1V shows that the battery is 100% full. V_{oc} represents the battery open-circuit voltage. V_b and I_b are the battery output voltage and load current respectively. R_b is the battery internal resistance and the R_d*C_b product is the time constant of the battery voltage V_b when the battery is open-circuited. R_{sd} is the self-discharge resistance.

For this battery model, V_b and I_b are externally measureable and V_{cb} and V_{soc} will be taken as state variables in order to estimate the battery SOC. The relation between the battery open circuit voltage (controlled source) and SOC is as shown in equation (1).

$$V_{oc} = mV_{soc}+n \tag{1}$$

Here, "m" and "n" are constants and depends on the battery type. "n" and "m+n" can be calculated from the open-circuit voltage V_{oc} when the battery is empty and when the battery is 100% full respectively.

2.2. State Space Model

The state space equations of the proposed battery model in this work are as follows:

$$\dot{V}_{cb} = -\frac{1}{C_b R_d} V_{cb} + \frac{m}{C_b R_d} V_{soc} + \frac{n}{C_b R_d} - \frac{1}{C_b} I_b$$

$$\dot{V}_{soc} = -\frac{1}{C_{soc} R_{sd}} V_{soc} - \frac{1}{C_{soc}} I_b \tag{2}$$

Here, self-discharge resistance (R_{sd}) is assumed to be very large and will be ignored.

This dynamic model is sufficient to estimate the battery SOC, provided battery parameters are known. Here, we add battery parameters C_b and R_b as new state variables, and obtain an augmented state space model for the joint estimation of SOC together with these parameters:

$$x_1 = V_{cb}\ ;\ x_2 = V_{soc}\ ;\ x_3 = \frac{1}{C_b}\ ;\ x_4 = R_b$$

$$\dot{x}_1 = -\frac{1}{\mathrm{T_{cbrd}}} x_1 + \frac{m}{\mathrm{T_{cbrd}}} x_2 + \frac{n}{\mathrm{T_{cbrd}}} - x_3 I_b$$

$$\dot{x}_2 = -x_3 I_b\ ;\ \dot{x}_3 = 0\ ;\ \dot{x}_4 = 0 \tag{3}$$

Here, T_{cbrd} is the time constant of the battery voltage V_b when the battery is open-circuited and equals to the product of C_b and R_d. T_{cbrd} can be estimated via a simple open circuit test [14] and will be assumed to be known. Capacitance C_{soc} holding the electrical charge of battery is chosen according to the nominal capacity of the battery. The output variable for the state space model is defined as the battery terminal voltage:

$$y = V_b = x_1 - x_4 I_b \tag{4}$$

Kalman filter based algorithm is applied to the dynamic battery model whose input is the battery current (I_b) and the output is the battery terminal voltage. The first part of the Kalman filtering method [23, 24] is the time update.

$$x_{k+1}^- = f(x)$$

$$P_{k+1}^- = A_k P_k A_k'$$

$$A_k = \left.\frac{\partial f(x_k)}{\partial x_k}\right|_{x_k = \hat{x}_k} \tag{5}$$

Here, f denotes the dynamic of the state space model and P is the error covariance matrix. The second part of the Kalman filtering method is the measurement update.

$$K_{k+1} = P_{k+1}^- C_{k+1}' (C_{k+1} P_{k+1}^- C_{k+1}' + R)^{-1}$$

$$P_{k+1} = (I - K_{k+1} C_{k+1}) P_{k+1}^-$$

$$x_{k+1} = x_{k+1}^- + K_{k+1}(y_{k+1} - g(x_{k+1}^-))$$

$$C_{k+1} = \left.\frac{\partial g(x_{k+1})}{\partial x_{k+1}}\right|_{x_{k+1} = \hat{x}_{k+1}^-} \tag{6}$$

Here, g denotes the output equation and K is the Kalman gain matrix.

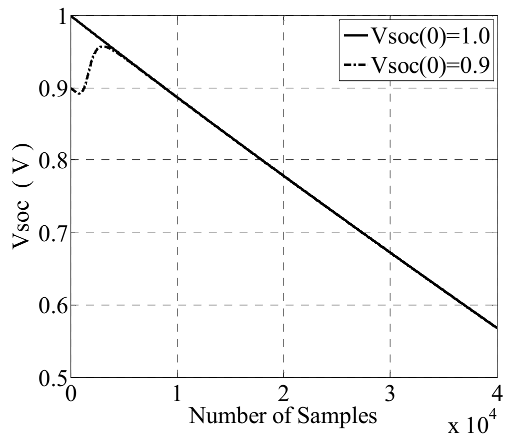

Fig. 2. The real (bold curve) and estimated (broken curve) values of the battery SOC

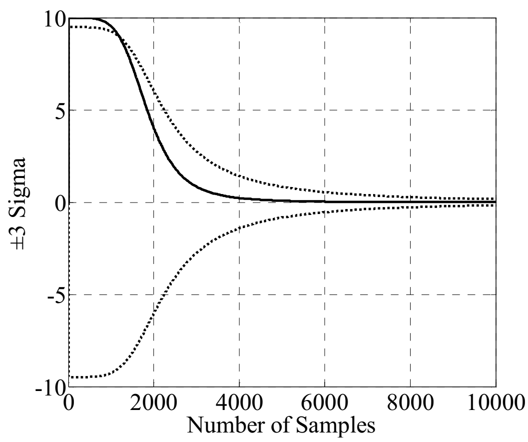

Fig. 3. Battery SOC percent error and 3-sigma curves

A simulation result for the estimation of the battery SOC is given in Fig. 2. As seen from the figure, even if the initial value of the SOC has an error of 10%, the battery model estimates the SOC without steady-state error. 3-sigma error graphic is shown in Fig. 3.

Extensive simulation studies reported in [14] has shown that this dynamical model is observable, hence can be used reliably for the joint estimation of SOC and battery parameters in a Kalman filtering estimation framework.

2.3. Experimental Study

For experimental verification of the proposed methodology, sixteen 2100mAh NiMh batteries are purchased and used as test batteries to estimate the battery SOC and parameters.

For each battery, we followed the following procedure identically. Batteries (coming partially charged from the out of package) are first discharged with a 0.2C discharge current until the terminal voltage reaches to the end voltage which is 1V. After a rest period, open-circuit terminal voltage is measured and found 1.25V for an empty battery. Then batteries are charged with 1C charge current until the battery terminal voltage is 15mV less than its maximum value during charging. Again after a rest period, open-circuit terminal voltage is measured and found 1.36V for a 100% full battery.

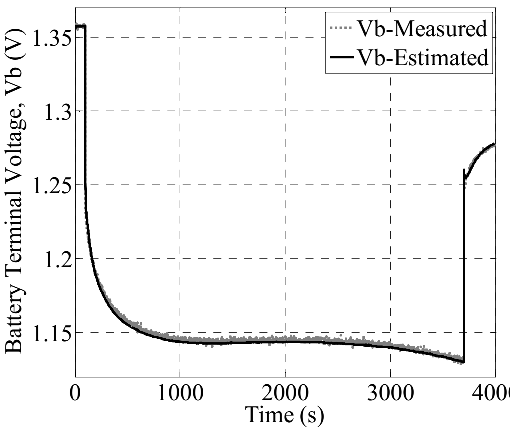

Fig. 4. Measured and Estimated Battery Terminal Voltage, V_b

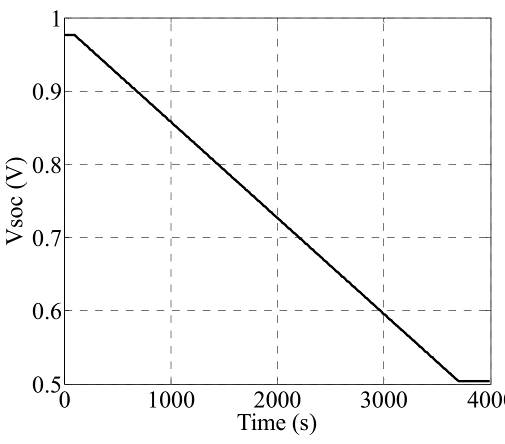

Fig. 5. The estimated battery SOC

In the second part of the test, batteries are discharged with 0.5C discharge current. Kalman-based algorithm is applied to the data and the battery SOC and parameters are estimated. The measured and estimated battery terminal voltages are shown in Fig. 4. Here, the error between the measured and estimated battery terminal voltages is less than 0.2 %. This experimental result is the unique experimental verification of the joint SOC and parameters estimation framework because the battery terminal voltage is the only variable that can be measured externally. Hence, in Fig. 5 only the estimated value of the battery SOC is given.

3. Battery State-of-Health Classification

As the number of charge-discharge cycles of a battery is increased, battery gets older. Also improper and harsh usage during charge or discharge causes battery aging. Typically battery state-of-health (SOH) is related to the real (not the nominal) capacity the battery. Here, we propose a classification methodology in order to determine the SOH instead of predicting a variable related to the SOH. Our classification methodology enables us to classify a given battery into one of the previously defined groups based on the health status of the battery. In other words, our SOH variable does take only discrete values, instead of continuous values.

3.1. Defining SOH Classes

In this study, three SOH classes are defined. These are called Group 0, Group 1, Group 2 and they associate with unused (new), lightly used, and heavily used battery classes respectively. Having a robust parameter determination method at hand, we use a parametric approach to define these SOH classes. In order to identify a battery, we used the three battery parameters: the capacitor C_b, the resistor R_b, and T_{cbrd}. In other words, we use a three dimensional feature vector for the parametric classification:

$$x = [C_b, R_b, T_{cbrd}] \quad (7)$$

It should be noted that, these three parameters uniquely define a rechargeable battery provided its type and nominal capacity are given.

In order to define Group 0, three battery parameters for the sixteen unused 2100mAh NiMh batteries are determined via the joint estimation algorithm. At the second step, eight of the sixteen batteries are similarly charged and discharged harshly several times. Then for these batteries, battery parameters are estimated. This new data forms the Group 1 which we treat as the “lightly used” batteries. At the third step, this aging procedure identically applied to the batteries in Group 1 ones again and the new set is called Group 2 which can be interpreted as “heavily used” batteries.

3.2. Quadratic Discriminant Analysis

Quadratic discriminant analysis [21] is a Bayesian classification approach in which the discriminant function is chosen as a quadratic function of the feature vector. Quadratic discriminant function is calculated as:

$$d_k(x) = -\frac{1}{2}\log|P_k| - \frac{1}{2}(x-\mu_k)^T P_k^{-1}(x-\mu_k) + \log \pi_k \quad (8)$$

for each class, where k is the class index. Here, P_k and μ_k are the covariance matrix and the mean of the k^{th} group respectively. π_k is the a priori probability of class k.

Classification is done by calculating each quadratic discriminant function at the measured feature vector (x), and assigning the measurement to the group at which the maximum is achieved:

$$\hat{d}(x) = \arg(\max_k(d_k(x))) \tag{9}$$

In our experiment, Group 0 represents the unused batteries and it has sixteen members. Group 1 is the group of 'lightly used batteries' and it has eight members. Group 2 is the 'heavily used battery' group and it has also eight members.

Table 1. Quadratic discriminant values of battery parameter sets

Battery name	Discrmt. at Group 0	Discrmt. at Group 1	Discrmt. at Group 2
01Group0	-4.02	-10.09	-9.30
02Group0	-2.13	-7.73	-8.83
03Group0	-3.26	-10.29	-9.84
04Group0	-2.25	-9.64	-9.51
05Group0	-2.44	-8.68	-9.07
06Group0	-1.70	-5.13	-8.43
07Group0	-4.12	-4.68	-8.39
08Group0	-1.70	-5.38	-8.50
09Group0	-2.36	-4.90	-8.29
10Group0	-4.53	-18.07	-10.21
11Group0	-2.27	-4.74	-8.43
12Group0	-3.63	-8.65	-8.99
13Group0	-1.45	-7.52	-9.02
14Group0	-2.86	-9.36	-9.46
15Group0	-1.85	-6.15	-8.76
16Group0	-1.70	-6.90	-8.71
01Group1	-102.88	-6.16	-8.58
02Group1	-46.37	-4.39	-7.88
03Group1	-154.37	-6.01	-7.41
04Group1	-3.60	-4.85	-8.43
05Group1	-4.25	-4.78	-8.22
06Group1	-9.09	-6.39	-7.82
07Group1	-6.94	-4.56	-8.37
08Group1	-7.82	-4.23	-7.93
01Group2	-1259.37	-49.45	-7.43
02Group2	-1082.42	-27.23	-8.01
03Group2	-2497.95	-84.95	-8.39
04Group2	-265.45	-54.17	-8.75
05Group2	-17.31	-10.06	-9.13
06Group2	-54.25	-18.48	-8.99
07Group2	-671.58	-20.14	-7.25
08Group2	-104.99	-5.96	-7.85

Quadratic discriminant functions of these three SOH classes are calculated at each of the 32 different parameter sets. These values are given in Table 1.

Based on Table 1, we applied three different classification tests for the batteries. These are tests to discriminate between unused vs. lightly used, between unused vs. heavily used, and between lightly used vs. heavily used batteries. Results of these tests are given in Table 2.

Table 2. Classification test results

Test	Number of Test Cases	Number of Correct Classification	Class. Error (%)
0 vs. 1	24	22	8.3
0 vs. 2	24	24	0.0
1 vs. 2	16	15	6.3

As seen from the Table 2; we observe that while we discriminate between unused vs. heavily used batteries without any error, there are small classification errors associated with other tests. Indeed in any classification paradigm, at which the algorithm depends on the statistical characterization of the classes, such classification errors are unavoidable. The classification performance of the proposed method is discussed in the next section.

3.3. Limits of Classification Performance

Bhattacharyya distance is a measure to determine the similarity of two probability distributions. For multivariate Gaussian distributions Bhattacharyya distance is defined as follows:

$$B = -\frac{1}{8}(\mu_1 - \mu_2)^T P^{-1}(\mu_1 - \mu_2) + \frac{1}{2}\ln\left(\frac{|P|}{\sqrt{|P_1.P_2|}}\right) \tag{10}$$

where,

$$2P = P_1 + P_2 \tag{11}$$

Here, P_k and μ_k are the covariance matrices and the means of the classes respectively. The probability of classification error (P_{err}) of any classification algorithm is bounded by the statistical similarity of the classes. As shown in [22], the probability of classification error (P_{err}) is bounded as:

$$\frac{1}{2}e^{-2B} \le P_{err} \le \frac{1}{2}e^{-B} \tag{12}$$

From this inequality, it is clear that there will be theoretical limits of performance in any classification algorithm. If the classification error of a classification algorithm is between these bounds, then there will be no need for a search for a better algorithm and we can call the algorithm as 'sufficient'. If the error performance of an algorithm approaches the upper bound from above, we can call the performance as 'reasonable'. A new method might be sought if the error probability is far above from the upper bound.

Bhattacharyya distances between SOH classes we have defined, theoretical upper bounds of the maximum classification errors and the classification errors of the quadratic classifier we employed are given in Table 3.

Table3. Comparison of classification error with theoretical limits

Test	Bhattacharyya Distance	Max. Theoretical Class. Error (%)	Class. Error (%)
0 vs. 1	1.43	12.0	8.3
0 vs. 2	2.52	4.0	0.0
1 vs. 2	1.18	15.4	6.3

As seen from the Table 3, the classification performance of the quadratic classifier proposed can be interpreted as ‘sufficient’.

4. Conclusions

This paper presents a methodology for battery SOH estimation. The methodology depends on identification of battery parameters as a member of previously defined SOH classes. Classification algorithm uses three battery parameters as the feature vector and employs quadratic discriminant analysis. We also propose a robust method for the identification of battery parameters via a Kalman-based approach. Based on a sound theoretical framework, we also showed that SOH classification performance is ‘sufficient’.

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