Commun. Fac. Sci. Univ. Ank. Series A2-A3
V.52(2) pp 1-9 (2010)

DETERMINATION OF BATTERY STATE-OF-HEALTH VIA STATISTICAL CLASSIFICATION

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(Received May 12, 2010; Accepted July 6, 2010)

ABSTRACT

This work proposes a methodology for determining the state-of-health (SOH) of rechargeable batteries. A generic electrical circuit model is used as a rechargeable battery model. Model parameters 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 by using the concept of Bhattacharyya distance.

KEYWORDS: Rechargeable battery, battery state-of-health, quadratic discriminant analysis, Bhattacharyya distance.

INTRODUCTION

As the usage of modern portable electronic devices increases, the measurement of the remaining battery capacity gains importance. The battery state-of-health (SOH) is an important factor that affects the battery capacity and battery life. The knowledge of the battery SOH provides the consumer to estimate the performance of the battery. The battery SOH is related to the maximum battery capacity that a battery can supply.

There are several factors that affect the battery SOH. These are the magnitude of the charge/discharge current, ambient temperature, depth of discharge, charge control method, over-charge and over-discharge, storage type and duration [1].

There are some studies in the literature to determine the battery SOH. Some studies use the impedance measurement method [2] while battery capacity is estimated to determine the battery SOH in some others [3,4].

In this work to determine the battery SOH, we propose a methodology based upon quadratic discriminant classification. We use the battery model 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 determination problem into a classification problem. Quadratic discriminant analysis [5] is used as a classification algorithm. For each class associated with batteries sharing the similar state-of-health, a quadratic discriminant function is calculated by using 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 Ni-Mh batteries. Classification performances are analyzed via a fundamental inequality based on the concept of Bhattacharyya distance [6].

Battery parameter estimation method is briefly discussed in the second part. Proposed classification approach for SOH determination is explained and discussed with the experimental results in the third part. We end up with a short discussion of our results in the fourth part.

BATTERY PARAMETER IDENTIFICATION

To characterize the battery SOH, a generic rechargeable battery model [1] is used in this study. Based on this model, an extended Kalman filtering based estimation algorithm is applied to the battery model in order to estimate the battery model parameters.

Battery State-Space Model

The state-space equations of the rechargeable battery model used in this work are given as follows:

$$\dot{V}_{cd} = -\frac{1}{R_d C_d} V_{cd} + \frac{m}{R_d C_d} V_{soc} + \frac{n}{R_d C_d} - \frac{1}{C_d} i_b \tag{1}$$

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

and the output equation is

$$y = V_b = V_{cd} - R_b i_b \tag{3}$$

Here, C_{soc} is the battery capacity in ampere-second. V_{soc} is the battery state-of-charge (SOC) voltage on the capacitor C_{soc} and varies between 0V and 1V. V_b is the battery terminal voltage measured at the battery terminals. The battery current i_b is the input of the dynamic model. R_b is the battery resistance. R_{sd} is the battery self-discharge resistance and will be ignored because it is assumed to be very large. The product of the diffusion resistance R_d and the diffusion capacitance C_d forms the diffusion time constant T_d which can easily be found from a simple battery test [1,7]. V_{cd} is the voltage on the capacitor C_d. "m" and "n" are constants and can be calculated from the relation between the open-circuit voltage V_{oc} and the SOC voltage V_{soc} [8] as follows:

$$V_{oc} = mV_{soc} + n \tag{4}$$

In this work, sixteen Ni-Mh batteries were tested and "m" was found as 0.11 and "n" was found as 1.25 [1]. By choosing the diffusion capacitance C_d and the battery resistance R_b as additional state variables as:

$$x_1 = V_{cd} \tag{5}$$

$$x_2 = V_{soc} \tag{6}$$

$$x_3 = \frac{1}{C_d} \tag{7}$$

$$x_4 = R_b \tag{8}$$

an augmented state-space model for rechargeable battery dynamics are written :

$$\dot{x}_1 = -\frac{1}{T_d}x_1 + \frac{m}{T_d}x_2 + \frac{n}{T_d} - x_3 i_b \tag{9}$$

$$\dot{x}_2 = -\frac{1}{C_{soc}}i_b \tag{10}$$

$$\dot{x}_3 = 0 \tag{11}$$

$$\dot{x}_4 = 0 \tag{12}$$

and the output equation of the dynamic model is

$$y = x_1 - x_4 i_b \tag{13}$$

As equation (9) and equation (13) are not linear because of the product of a state variable and the input, an extended Kalman filtering estimation procedure can be applied to the dynamic battery model to estimate the battery model parameters R_b and C_d.

Experimental Parameter Identification

In order to define an experimental procedure for SOH determination of rechargeable batteries, sixteen 2100mAh Ni-Mh batteries are purchased and used as test batteries to estimate the battery parameters. To estimate the parameters R_b and C_d, extended Kalman filtering methodology [9,10] is applied to the test batteries during a discharge test by taking equations (9-13) as the dynamical system model for the estimation. The third battery model parameter T_d was determined via a simple battery test [1,7] before applying the extended Kalman filtering.

BATTERY STATE-OF-HEALTH DETERMINATION

As the number of charge-discharge cycles of a rechargeable battery is increased, battery aging occurs. Also improper and harsh usage during charge or discharge causes battery aging. Typically, battery state-of-health (SOH) is defined as the maximum capacity of a battery under nominal charge and discharge conditions. Here, we propose a classification-based methodology for determining battery SOH, instead of estimating the maximum capacity as the State-of-Health. Our classification based approach 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, in our approach SOH variable does take only discrete values, instead of continuous values.

Defining SOH Classes

In our experimental study, three different SOH classes are defined. These SOH classes will be called Group 1, Group 2, Group 3 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 use the three battery parameters: battery resistor R_b, diffusion capacitance C_d, and diffusion time constant T_d. In other words, a three-dimensional feature vector will be used for the classification:

$$x = [R_b, C_d, T_d] \tag{14}$$

It should be noted that, in the dynamical modeling framework we use, these three parameters uniquely define a rechargeable battery provided its type and nominal capacity are given.

In order to define Group 1, three battery parameters for the sixteen unused 2100mAh Ni-Mh batteries are determined via the parameter identification algorithm as explained above. At the second step, eight of the sixteen batteries are chosen randomly, and they are exposed to an identical charge and discharge test 10 times. Then for these batteries, battery parameters are estimated again via extended Kalman filtering method. This new parameter data form the Group 2 that we treat as the "lightly used" batteries. At the third step, identical charge-discharge procedure applied 10 more times to the batteries in Group 2, and the new set is called Group 3 that can be interpreted as "heavily used" batteries. It should be noted that, batteries in a SOH class has the identical charge-discharge histories, yet they may differ in their parameters. That is the reason behind choosing a statistical classification methodology for determining state-of-health. Each SOH class is characterized by using the class mean vector and class covariance matrix (μ_k and P_k).

Quadratic Discriminant Analysis

Quadratic discriminant analysis [5] is a Bayesian classification approach in which the discriminant function is chosen as a quadratic function of the feature vector. Quadratic discriminant function is defined as:

$$d_k(x) = -\frac{1}{2} log|P_k| - \frac{1}{2}(x-\mu_k)^T P_k^{-1}(x-\mu_k) + log\,\pi_k \tag{15}$$

for each class, where k is the class index. Here, P_k and μ_k are the covariance matrix and the mean of the kth group respectively. π_k is taken as the a priori probability of class k.

Classification is carried out 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:

$$\hat{d}(x) = arg(\max_k(d_k(x))) \tag{16}$$

In our experiment, Group 1 represents the unused batteries and it has sixteen members. Group 2 is the group of 'lightly used batteries' and it has eight members. Group 3 is the 'heavily used battery' group and it has also eight members.

Quadratic discriminant functions of these three SOH classes are calculated at each of the 32 different battery 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 1: Quadratic discriminants calculated at battery parameter sets

Battery name	Discrmt. at	Discrmt. at	Discrmt. at
01Group1	-4.02	-10.09	-9.30
02Group1	-2.13	-7.73	-8.83
03Group1	-3.26	-10.29	-9.84
04Group1	-2.25	-9.64	-9.51
05Group1	-2.44	-8.68	-9.07
06Group1	-1.70	-5.13	-8.43
07Group1	-4.12	-4.68	-8.39
08Group1	-1.70	-5.38	-8.50
09Group1	-2.36	-4.90	-8.29
10Group1	-4.53	-18.07	-10.21
11Group1	-2.27	-4.74	-8.43
12Group1	-3.63	-8.65	-8.99
13Group1	-1.45	-7.52	-9.02
14Group1	-2.86	-9.36	-9.46
15Group1	-1.85	-6.15	-8.76
16Group1	-1.70	-6.90	-8.71
01Group2	-102.88	-6.16	-8.58
02Group2	-46.37	-4.39	-7.88
03Group2	-154.37	-6.01	-7.41
04Group2	-3.60	-4.85	-8.43
05Group2	-4.25	-4.78	-8.22
06Group2	-9.09	-6.39	-7.82
07Group2	-6.94	-4.56	-8.37
08Group2	-7.82	-4.23	-7.93
01Group3	-1259.37	-49.45	-7.43
02Group3	-1082.42	-27.23	-8.01
03Group3	-2497.95	-84.95	-8.39
04Group3	-265.45	-54.17	-8.75
05Group3	-17.31	-10.06	-9.13
06Group3	-54.25	-18.48	-8.99
07Group3	-671.58	-20.14	-7.25
08Group3	-104.99	-5.96	-7.85

Table 2: Classification test results

Test	Number of Test Cases	Number of Correct Classification	Class. Error (%)
1 vs. 2	24	22	8.3
1 vs. 3	24	24	0.0
2 vs. 3	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 methodology, at which the algorithm depends on the statistical characterization of the classes, such classification errors are unavoidable. Hence, performance of the proposed classification methodology will be discussed in the next section.

Limits of Classification Performance

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

$$B = -\frac{1}{8}(\mu_1 - \mu_2)^T P^{-1}(\mu_1 - \mu_2) + \frac{1}{2} ln\left(\frac{|P|}{\sqrt{|P_1 . P_2|}}\right) \tag{17}$$

where,

$$2P = P_1 + P_2 \tag{18}$$

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 [6], the probability of classification error (P_{err}) is bounded as:

$$\frac{1}{2}e^{-2B} \le P_{err} \le \frac{1}{2}e^{-B} \tag{19}$$

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'. However, a new classification method should 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.

Table 3: Comparison of classification error with theoretical limits

Test	Bhattacharyya Distance	Maximum Theoretical Class. Error (%)	Class. Error (%)
1 vs. 2	1.43	12.0	8.3
1 vs. 3	2.52	4.0	0.0
2 vs. 3	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'. In other words, classification performance of quadratic discriminant approach for the SOH determination in Ni-Mh batteries are found to be in accord with the theoretical performance limits.

CONCLUSIONS

This paper presents a classification-based methodology for battery SOH determination. The methodology depends on identifying a battery of as a member of previously defined SOH classes. Classification method uses three battery parameters as the feature vector and employs quadratic discriminant analysis. Proposed methodology is applied to a set of Ni-Mh batteries. Experimental results imply that the proposed methodology is a feasible way of determining state-of-health of rechargeable batteries. As the battery parameter identification method used in this study is a recursive approach, the proposed SOH determination method is also applicable in a real-time setting.

ÖZET

Bu çalışma, yeniden doldurulabilir bataryaların sağlık durumunun (SOH) belirlenmesine yönelik bir yöntem önermektedir. Yeniden doldurulabilir batarya modeli olarak genel bir elektriksel devre modeli kullanılmaktadır. Model parametreleri genişletilmiş Kalman filtre (EKF) tabanlı bir algoritma ile belirlenmektedir. Kestirilen batarya parametreleri, karesel ayırtaç analizinde sınıflandırmada kullanılmaktadır. Önerilen yöntemin sınıflandırma performansı Bhattacharyya uzaklığı kullanılarak incelenmiştir.

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