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Li-ion battery capacity estimation: A geometrical approach

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HIGHLIGHTS

- A geometrical metric is proposed to estimate the battery capacity.
- Four geometrical features being sensitive to battery degradation are extracted.
- The law of battery degradation is recognized on an intrinsic manifold.
- Geodesic on the intrinsic manifold is used to estimate the battery capacity.
- A promising approach to battery assessment under different operating conditions.

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ABSTRACT

The majority of methods used for lithium-ion (Li-ion) capacity estimation are usually restricted to certain applications. Such methods often are time consuming and inconsistent with actual experimental data as well as depending on complicated battery operating and/or aging conditions. A geometrical approach to Li-ion battery capacity estimation is presented in this work. The proposed method utilizes four geometrical features that are sensitive to slight changes in the performance degradation of a Li-ion battery. The Laplacian Eigenmap method is used to establish an intrinsic manifold, and the geodesic on the manifold is used to estimate battery capacity. Tests are conducted based on data obtained under different operating and aging conditions provided by NASA Prognostics Center of Excellence. The evaluation results suggest that the proposed geometrical approach can be used to estimate Li-ion battery capacity accurately for the conditions given in this article.

1. Introduction

The high energy density of lithium and the lightweight of lithium batteries [1] have sparked interest in Li-ion batteries and resulted in a remarkably high number of studies aimed at improving the performance of such batteries [2]. The rate of capacity loss highly depends on operating conditions and permanent capacity loss over time; thus, accurate estimation of available battery capacity is often desired for reliability and better management of energy use [3].

Battery modeling and simulation [4–6] have undergone significant advancements over the past decade because of significant improvements in software capability and modern experimental techniques. Few attempts have been made to estimate Li-ion battery capacity. Zhang et al. [7] focused on characterizing the shifting electrical, chemical, and physical properties of anode, cathode, electrolyte, and current collectors. Fuller et al. [8] used a "first-principle" electrochemical model to estimate Li-polymer cell capacity. Spotnitz [9] incorporated solid electrolyte interphase (SEI) growth into Fuller's model and investigated the correlation of impedance change with capacity fade. In Ref. [4], an equivalent-circuit model was used to simulate cell performance, particularly the capacity fade phenomenon as influenced by thermal aging, which is one of the most influential factors affecting battery calendar life during storage, standby, or operational periods. An equation was proposed in Ref. [10], where two accurate state-of-charge (SOC) values are regarded as functions of the open circuit voltage (OCV), and the integrated current between these two values are sufficient to estimate the capacity of the battery cell. Chan et al.

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[11] applied an artificial neural network with single input and single output to build a correlation between discharge current and capacity for lead–acid batteries. They assumed that battery aging and degradation do not significantly affect capacity estimation. However, this assumption does not apply to Li-ion batteries. An extended Kalman filter [12] has also been used for capacity estimation based on the specific state/parameter models involved. In Ref. [13], a multivariate linear model was established to determine the relationship between capacity and a multitude of inputs, including internal DC resistance, OCV, and temperature.

So far, most of the abovementioned models have largely contributed to accurate capacity estimation. However, some issues should be dealt with before battery capacity estimation models can be fully applied to real-world applications:

(1) Dependence on accurate models representing the dynamic behavior of batteries, which have been proven difficult to establish [14], as in Refs. [4–6,12,13];
(2) Electrochemical parameters and properties of batteries are required, as in Refs. [4,7–9];
(3) Reliance on accurate SOC values, which are also part of a significant and difficult research field, as in Ref. [10];
(4) OCV values are needed, which always require considerable time of rest, as in Refs. [10,13];
(5) Being inappropriate for different operating conditions, as in Refs. [11–13].

Based on the aforementioned issues, a geometrical approach that can effectively reflect the intrinsic degradation or health state of Li-ion batteries is proposed. First, four geometrical features that are highly sensitive to slight changes in the degradation of Li-ion batteries are used to adjust to real applications. Second, the Laplacian Eigenmap (LE) method is applied to establish an intrinsic manifold where geodesic distances are calculated as the metric of the estimated capacity of a Li-ion battery. Meanwhile, the approach removes the need to study complex electrochemical mechanisms, to establish models, and to consume various times of rest for testing.

2. Related works

2.1. LE

In this paper, LE is applied not only for dimensionality reduction but also for the establishment of a low-dimensional manifold where Li-ion battery capacity will be estimated. A manifold, in mathematics, is a topological space where each point of an n-dimensional manifold has a neighborhood that is homeomorphic to the n-dimensional Euclidean space [15].

2.1.1. General description of LE

We assume that a d-dimensional manifold M^d (nominated as output space) embedded in an m-dimensional space $\alpha_N \in \mathbb{R}^m$ (nominated as input space, $d < m$) can be described by a function

$$f : C \subset \mathrm{M}^d \rightarrow \mathbb{R}^m,$$

where C is a compact subset of M^d with open interior. A set of data points $\alpha 1,\ldots,\alpha N$, where $\alpha_i \in \mathbb{R}^m$, are sampled with noise from the intrinsic manifold M^d; the relationship can be represented as follows:

$$\alpha i = f(\beta i) + \xi i, \quad i = 1,\ldots,N, \tag{1}$$

where ξ_i denotes noise. LE can be recognized as: The original data set α_i's in the higher dimensional manifold $\mathbb{R}^m$ is mapped (nonlinearly) to the data point β_i's in the estimation of the unknown lower dimensional manifold M^d, with $d < m$ [16].

2.1.2. Theory of LE

Given a data set with N points, for arbitrary point $A \in \mathrm{M}^d$ with k nearest neighborhoods, we construct a weighted graph $G = (V,E)$ with edges connecting nearby points to one another with the assumption that the graph is connected. We consider the problem of mapping the weighted graph G to a line, such that the connected points stay as close together as possible. Let

$$\boldsymbol{y} = (y_1, y_2, \cdots, y_N)^T \quad \boldsymbol{x} = (x_1, x_2, \cdots, x_N)^T, \tag{2}$$

where $x_i, y_i \in \mathbb{R}$ is a coordinate value of the ith point in $\mathbb{R}^m$ and M^d. A reasonable map is to choose y_i's$\in$R to minimize $\sum_{ij}(y_i - y_j)^2 W_{ij}$ under the appropriate constraints. The objective function minimizing the coordinate is an attempt to keep the similarity of distances between x_i and x_j in the lower dimensional manifold, where y_i and y_j lie. As a result, for any $\boldsymbol{y}$, we have

$$\frac{1}{2}\sum_{i,j}\left(y_i - y_j\right)^2 W_{ij} = \boldsymbol{y}^T L \boldsymbol{y}, \tag{3}$$

where, as before, L=D–W, which is positive semidefinite. Notably, W_{ij} is symmetric, and $Dii = \sum_j Wij$. Thus, $\sum_{i,j}(y_i - y_j)^2 W_{ij}$ can be written as

$$\sum_{i,j}\left(y_i^2 + y_j^2 - 2y_i y_j\right)W_{ij} = \sum y_i^2 Dii + \sum y_j^2 Djj - 2\sum y_i y_j W_{ij} = 2\boldsymbol{y}^T L \boldsymbol{y}, \tag{4}$$

Therefore, the minimization problem reduces to fining

$$\arg\min_{\boldsymbol{y}^T D \boldsymbol{y} = 1} \boldsymbol{y}^T L \boldsymbol{y}$$

The constraint $\boldsymbol{y}^T D \boldsymbol{y} = 1$ removes an arbitrary scaling factor in the embedding. Matrix D provides a natural measure on the graph vertice. A larger value of D_{ii} (corresponding to the ith vertex) makes the vertex more "important." From Eq. (3), L is shown as a positive semidefinite matrix, and the vector $\boldsymbol{y}$ that minimizes the objective function is given by the minimum eigenvalue solution to the generalized eigenvalue problem $L\boldsymbol{y} = \lambda D \boldsymbol{y}$ with an additional constraint of orthogonality

$$\arg\min_{\substack{\boldsymbol{y}^T D \boldsymbol{y} = 1 \\ \boldsymbol{y}^T D \boldsymbol{1} = 0}} \boldsymbol{y}^T L \boldsymbol{y}$$

More generally, the embedding is given by the $N \times d$ matrix $Y = [\boldsymbol{y}_1 \boldsymbol{y}_2 \ldots \boldsymbol{y}_d]$, where the ith row, denoted by Y_i^T, provides the embedding coordinates of the ith vertex. Similarly, we need to minimize

$$\sum_{i,j}\|Y_i - Y_j\|^2 W_{ij} = tr\left(Y^T L Y\right), \tag{5}$$

This condition reduces to finding [17]

$$Y_{\mathrm{opt}} = \arg\min_{Y^T D Y = \boldsymbol{1}} tr\left(Y^T L Y\right), \tag{6}$$

2.2. Time-window for mapping updating

LE provides a mapping $g = f^{-1}$ for the fixed set of data from high-dimensional space to low-dimensional space. Therefore, the mapping from $\mathbb{R}^m$ can be conveniently extracted to M^d. Theoretically, one can receive a corresponding low-dimensional point through