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Discrete wavelet transform-based denoising technique for advanced state-of-charge estimator of a lithium-ion battery in electric vehicles

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ABSTRACT

Sophisticated data of the experimental DCV (discharging/charging voltage) of a lithium-ion battery is required for high-accuracy SOC (state-of-charge) estimation algorithms based on the state-space ECM (electrical circuit model) in BMSs (battery management systems). However, when sensing noisy DCV signals, erroneous SOC estimation (which results in low BMS performance) is inevitable. Therefore, this manuscript describes the design and implementation of a DWT (discrete wavelet transform)-based denoising technique for DCV signals. The steps for denoising a noisy DCV measurement in the proposed approach are as follows. First, using MRA (multi-resolution analysis), the noise-riding DCV signal is decomposed into different frequency sub-bands (low- and high-frequency components, A_n and D_n). Specifically, signal processing of the high frequency component D_n that focuses on a short-time interval is necessary to reduce noise in the DCV measurement. Second, a hard-thresholding-based denoising rule is applied to adjust the wavelet coefficients of the DWT to achieve a clear separation between the signal and the noise. Third, the desired de-noised DCV signal is reconstructed by taking the IDWT (inverse discrete wavelet transform) of the filtered detailed coefficients. Finally, this signal is sent to the ECM-based SOC estimation algorithm using an EKF (extended Kalman filter). Experimental results indicate the robustness of the proposed approach for reliable SOC estimation.

1. Introduction

Rechargeable lithium-ion batteries have become preferable in portable devices, power electronics, and renewable energy storage applications [1–3]. Lithium-ion batteries have been increasingly recognized as a promising solution for electric-powered transportation such as EVs (electric vehicles) and HEVs (hybrid electric vehicles) because of their high specific energy densities, long cycle lives, and low self-discharge [4–6]. With the increased interest in EVs and HEVs, the need for accurate and reliable knowledge to guarantee the overall system performance, namely a BMS (battery management system), has also significantly increased [7–10]. Failure to use a well-designed BMS, leading to over-discharging and over-charging conditions, may cause permanent internal degradation [10]. Thus, numerous studies have investigated the design of an improved BMS that overcomes the above weaknesses, in particular, focusing on SOC (state-of-charge), which is considered a key factor in BMSs for supporting optimal battery performance and safety in EVs and HEVs [11–13]. Precise SOC information is critical in practical applications in which it is necessary to determine both how long the battery will last when predicting a reliable operating range and when to stop discharging and charging to prevent the batteries in EVs and HEVs from over-discharging and over-charging [14,15].

In recent years, much research has been devoted to developing more accurate methods of SOC estimation [16–24]. Specifically, adaptive methods such as the EKF (extended Kalman filter) [16–20] and other observed-based approaches [21–24] by means of non-linear ECM (equivalent circuit modeling) have been extensively studied because of their advantages of being closed-loop and online, and having the dynamic SOC estimation error range available. In general, the state-space ECM structure is used to describe the battery voltage behavior; it is applied in adaptive methods for SOC estimation. This structure is generally composed of the OCV (open-circuit voltage) and RC (resistance-capacitance) networks (such as first-, second-, and third-order RC), which capture the dynamic I–V characteristics of a lithium-ion battery. Through physical

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Nomenclature

EV/HEV	electric vehicle/hybrid electric vehicle
BMS	management system
SOC	state-of-charge
EKF	extended Kalman filter
ECM	equivalent circuit model
DCV	discharging/charging voltage
DWT	discrete wavelet transform
MRA	multi-resolution analysis
A_n	approximation component
D_n	detail component
$\phi_{j,k}(t)$	scaling function of the signal at level j
$\psi_{j,k}(t)$	wavelet function of the signal at level j
$a_{j,k}$	approximation coefficients of the signal at level j
$d_{j,k}$	detail coefficients of the signal at level j
$h(n)$	filter coefficient of the low-pass filters
$g(n)$	filter coefficient of the high-pass filters
$f_s(f_s^{1\ \text{sec}})$	sampling frequency (based on the sampling period of 1 s)
$f(f^{1\ \text{sec}})$	supply frequency (based on the sampling period of 1 s)
$n\ (n^{1\text{sec}})$	decomposition level (based on the sampling period of 1 s)
δ^T	threshold value
$\widehat{\sigma}$	noise variance related to the detailed coefficients
MAD	median absolute deviation
N_d	length of the vector of the DWT coefficients
σ_x	standard deviation of the original signal
σ_e	standard deviation of the noise
SNR	signal-to-noise ratio

parameterization of the ECM, the electrochemical behavior of a lithium-ion battery can be better understood. In the model-based SOC estimation, this behavior is considered the estimated terminal voltage.

When various typical discharging/charging pulse currents are applied to the batteries, experimental voltages are measured. As previously mentioned, the EKF and other observer-based methods are known to yield an optimum adaptive algorithm based on recursive estimation. Thus, to achieve high-accuracy SOC estimation, there must be little voltage difference between the measurement and the estimated result, under the assumption of the correctness of the ECM. Elaborated data regarding the experimental DCV (discharging/charging voltage) of a lithium-ion battery is required for comparison with voltage data estimated by adaptive methods. However, there is the possibility of unexpected and instantaneous sensing of noise in the BMS. It is inevitable, therefore, that an uncorrected battery voltage is measured and applied to the BMS. In spite of using an optimum SOC estimation algorithm, low BMS performance (such as an increased SOC estimation error and long run-time operation) is, therefore, unavoidable. To solve this problem, in this work, an innovative approach to one of the key technologies of the BMS is investigated. Unfortunately, thus far, no comprehensive and qualitative methodologies dealing with the aforementioned issue have been presented in the literature.

This study introduces a new approach to the design and implementation of DWT (discrete wavelet transform)-based denoising of DCV signals. The DWT has been widely considered as an effective mathematical function that is capable of analyzing a DCV signal with non-stationary and transient phenomena in accordance with scale and resolution [25–30]. Specifically, a representative characteristic of the DWT is MRA (multi-resolution analysis) with a precise function for both time and frequency localization. Greater resolution in time is provided by the high-frequency components of a signal, and a greater resolution in frequency is provided by the low-frequency components. However, unexpected and instantaneous noise occurs in the DCV signal, creating high frequency components in the spectrum of the signal. Then, although this noise-riding DCV signal is decomposed by the MRA, it is absolutely certain that the high frequency components still contain noise. Fortunately, the DWT-based denoising technique proposed in this study enables us to obtain DCV signals that have no noise. The concept of wavelet denoising was introduced by Donoho and Johnstone [42], and a wide variety of related research methods and techniques have been investigated in many different fields [31–36]. The proposed procedure for denoising a noisy DCV signal is as follows. First, the noise-riding DCV signal is decomposed into different frequency sub-bands (low- and high-frequency components, A_n and D_n). Specifically, to eliminate noise from the DCV, the signal processing of the high frequency component D_n (which concentrates on short-time intervals) is essential. Second, a suitable hard thresholding-based denoising technique is implemented to adjust the wavelet coefficients of the DWT so as to minimize the noise effect from the signal. Third, the desired de-noised DCV signal is reconstructed by taking the IDWT (inverse DWT) of the filtered coefficients. For reference, the order 3 Daubechies wavelet (dB3) [37,38] with scale 5 is properly used as the mother wavelet in decomposition and reconstruction processes of the DWT. In addition, to determine the threshold value in hard-thresholding, *VisuShrink* (which performs visually calibrated adaptive smoothing on noisy DCV signals) is used. Finally, the recently de-noised DCV signal is applied to the ECM-based SOC estimation algorithm using the EKF. Consequently, this proposed study makes an effort to provide a reliable estimation of the SOC. This approach has been validated by extensive experimental results conducted on prismatic 18650 lithium-ion batteries that had a rated capacity of 1.3 Ah produced by Samsung SDI [39].

The remainder of this manuscript is organized into six sections, including this introduction section. In Section 2, a review of the theoretical background of classical DWT is simply presented. Section 3 shows the experimental test setup used to perform discharging/charging of lithium-ion batteries and to obtain noise-riding DCV signals. The proposed DWT-based MRA (decomposition and reconstruction process) and denoising technique is described in the following section; in this section, a basic introduction to wavelet-denoising techniques is also provided. Section 5 presents high-accuracy model-based SOC estimation using the EKF. Then, to compare the SOC estimation accuracy with and without the proposed approach, the SOC estimation results are compared with those of ampere-hour counting. In the final section, some conclusions and final remarks are given.

2. Basic concept of the DWT

The DWT [25–30,43] has been widely researched in new mathematical approaches that decompose a time-domain signal into different frequency groups, and provides effective methods for analyzing non-stationary signals. The DWT is a function of $\psi(t) \in L^2(R)$ with zero basis [40–42] and can be defined as