Estimating Lithium-ion Battery State of Charge and Health with Ultrasonic Guided Waves Using an Efficient Matching Pursuit Technique

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Introduction

Electric vehicle energy storage, particularly lithium-ion (Li-ion) batteries, are extremely complex systems with a very narrow operating range and are prone to premature, unexpected failure. Optimizing battery performance, lifespan, and most importantly, safety requires continuously monitoring the state of charge (SoC), as well as accurately predicting degradation, or state of health (SoH). It is a true detriment to the field that the practical implementation of battery systems is still extremely challenging, owing to the lack of a field-deployable and accurate, yet affordable, battery management system \cite{1}. The current techniques have not come to exploit the fact that a Li-ion undergoes mechanical evolution, most notably modulus and density distribution, during electrical cycling and aging \cite{1}. Ultrasonic guided wave inspection is one of the most elegant and widely-used solutions in the context of ultrasonic non-destructive evaluation (NDE) and structural health monitoring (SHM). Mechanical stress waves are propagated in a structure, allowing the mechanical properties and internal damage to be accurately monitored almost in real time.

Problem Statement and Approach

Therefore, the objective of this investigation is to develop a similar built-in acousto-ultrasonic guided wave technique to monitor SoC and SoH of Li-ion batteries. Pitch-catch guided wave
experiments were performed to correlate the waveform signals with battery SoC and SoH. An efficient time-frequency representation algorithm was developed based on the Matching Pursuit technique to extract predictive features from the information-rich signals. A preliminary statistical analysis was then performed to evaluate the SoC/SoH prediction accuracy of the proposed techniques, while maintaining a model complexity level that is applicable for field applications.

**Preliminary Experiments and Indicative Results**

Pitch-catch guided wave propagation experiments were performed on 3,650mAh off-the-shelf Li-ion pouch batteries (Figure 1) [2, 3]. Guided wave signals were gathered at various battery SoC and SoH from surface-mounted, small-footprint piezoelectric disc transducers. One of the piezoelectric discs can be chosen as an actuator to generate acousto-ultrasonic guided waves. The other piezoelectric disc then serves as a receiver to record the transmitted guided wave signals. The so-called “pitch-catch” experiments used five-peak Gaussian-windowed tone bursts with center frequencies between 100 to 200 kHz. The ultrasonic data acquisition was synchronized with a battery cycler, which performed battery charging, discharging, and aging. A representative time-domain actuator-sensor response from the pouch cell experiment is shown in Figure 2A. The changes in the time-domain signals due to SoC and SoH could be clearly observed, and these were the results of the distribution and redistribution of electrodes’ mechanical properties – namely, moduli and densities.

**Feature Extraction Using Matching Pursuit**

In our previous work, we showed the potential of the guided wave method for SoC and SoH monitoring by performing state prediction, using only two simple features from time-domain analysis (time of flight and signal amplitude) [2, 3]. However, using time-frequency analysis, numerous predictive features can be extracted from the guided wave signals owing to their feature-rich nature and the intertwined mechano-electrical coupling. This potentially allows prediction accuracy to be
significantly improved and/or greatly simplifies the structure and complexity of the prediction model. Therefore, we developed an efficient algorithm based on the Matching Pursuit technique [4], which is a time-frequency representation method widely used in the field of guided wave SHM for analyzing guided wave data with reference to SoC/SoH prediction. We used the Matching Pursuit approach based on the Gabor dictionary (a collection of scaled, translated, and modulated versions of Gaussian-windowed tone bursts) to decompose the guided wave responses into representative “atoms” (Figure 2B). We first obtained an optimal set of parameters for the constituent atoms by performing decomposition on signals at a reference state. Signals at subsequent states were decomposed by imposing constraints using baseline information to greatly improve the efficiency and computation expense of Matching Pursuit. The information-rich guided wave data were then “mined” by extracting the parameters of each atom at different SoC and SoH to serve as features for state prediction (Figure 3).

**Prediction Model and Results**

A basic statistical analysis was performed by creating prediction models based on a Generalized Additive Model (GAM) [5]. GAMs are a non-parametric regression technique, which allows dependent variables to be described by smooth non-linear functions of covariates. Thin-plate regression splines were employed as smoothed non-linear fits of covariates using maximum penalized likelihood to prevent overfitting. While SoC and SoH prediction is model-agnostic, GAMs with regression splines, unlike other statistical learning methods, were chosen because they are easy to interpret and allow model structures of different complexity levels to be systematically compared. The statistical parameters of the models used in this study are summarized in Table 1. Overall, it can be shown that SoC and SoH could be accurately predicted using guided wave data from in-situ, small-footprint sensors/actuators. Particularly interesting is the significantly improved accuracy when a larger set of features extracted via Matching Pursuit were used, as compared to a model that used only time of flight and amplitude as
predictors. The prediction accuracy was improved, owing to the feature-rich nature of the data whose features were extracted using the efficient Matching Pursuit time-frequency representation. Moreover, we also showed that more features allowed equivalently good prediction accuracy, since using the time-domain-based features were achieved at a considerably lower model complexity and model order.

**Conclusions**

This work established a preliminary evaluation of estimating battery SoC and SoH with ultrasonic guided waves using small footprint, built-in piezoelectric transducers. Experimental pitch-catch guided wave propagation was conducted on commercial Li-ion pouch batteries that were retrofitted with low-profile, surface-mounted piezo transducers. An efficient algorithm was developed based on the Matching Pursuit time-frequency time representation technique, in order to extract predictive features from the information-rich guided wave signals. Compared to time-domain-only predictors, numerous useful features extracted from the decomposed signal ‘atoms’ allowed the SoC and SoH to be predicted very accurately with simplified model structures.

**References**


Figure 1. A) Schematics of pitch-catch guided wave propagation. B) Experimental pouch cell with built-in piezos.

Figure 2. A) Raw guided wave signals at two different SoC. B) First three decomposed atoms. Each atom is an optimal scaled/translated/modulated version of Gaussian-windowed tone bursts.

Figure 3. Gabor parameters of the first three atoms as a function of SoC. $\alpha$ is the translation parameter. $\sigma_s$ and $b_0$ are coefficients of the sine and cosine terms in the Gabor function.

Table 1. Prediction performance of models using Gabor parameters as predictors. Model 2 uses fifteen predictors resulting in an order of magnitude improvement as compared to time-domain-only features. Model 3’s complexity is the same as the time-domain-only Model 1, but showing a significant increase in accuracy.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Two predictors: time of flight (ToF) and signal amplitude (SA)</td>
<td>0.265</td>
<td>0.034</td>
<td>0.138</td>
</tr>
<tr>
<td>GCV score</td>
<td>896</td>
<td>-343</td>
<td>519</td>
</tr>
<tr>
<td>AIC</td>
<td>19.2</td>
<td>96.1</td>
<td>19.4</td>
</tr>
<tr>
<td>10-fold CV error</td>
<td>0.45</td>
<td>0.04</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Approximate significance levels ($p$-value) and degrees of freedom (d.f.) are displayed for each of the covariates.