

State of charge prediction for UAVs based on support vector machine

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Abstract: Unmanned aerial vehicle (UAV) is a power-driven aircraft that is unmanned and reusable. The purpose of this study is to accurately estimate the state of charge (SOC) of lithium-ion batteries for UAVs. A support vector machine (SVM) method, SVM is a type of learning machine based on statistical learning, is used as the input variable of the battery charging discharge data (current, voltage and temperature). The kernel of the radial basis function is the best kernel of authors' experiment, where the C , ν and g values are 1, 0.012 and 0.0125, respectively. The experimental results from the lithium-ion battery data at NASA Ames Prognostics Center of Excellence demonstrate the potential application of the proposed method as an effective tool for battery SOC prediction. The accuracy of the whole experiment is 98.42%. Mean-squared error is 1.783%. The experimental results show that the model has higher accuracy in predicting the discharge capacity of lithium battery SOC-training samples.

1 Introduction

Owing to its small size, light weight, flexible maneuver and low cost, UAV has been widely used in military and commercial [1] (transportation, communications, agriculture, disaster reduction and environmental protection), such as high-resolution mapping in various fields, environmental situation monitoring, traffic flow monitoring, emergency relay communication, anti-terrorism prevention and control and public safety. Most of the UAVs use batteries as power [2] supplies, such as MH-Ni batteries, Li-Po [3] batteries, Li-ion batteries and so on. Due to its long life, small self-discharge, high energy, easy access, light quality and so on, Li-ion battery has become the most choice power supply for UAVs, where a suitable battery management system (BMS) is needed to ensure the safety and efficiency of battery usage. However, even how well a complex systems is designed, the system will deteriorate over time or usage and even appear some dangerous situations. Therefore, there are many key technical problems to be noted in [4] BMS. After the battery has been used for a long time, it is particularly important to estimate the state of charge (SOC) of lithium-ion batteries in real time for the effective use of batteries. The precise estimation of battery SOC allows users to understand the remaining battery capacity in real time so as to make reasonable operation, such as return or land in time. SOC estimation can also be used to avoid harmful conditions, such as over discharge and overcharge, which will lead to a reduction in battery life. Therefore, accurate SOC instructions are important for user convenience and prolonging battery life. There are many ways [5] to estimate SOC, each of which has its merits and demerits. The commonly used methods for estimating SOC are Combining Ampere-Hour integral method and open-circuit voltage (OCV) method, model-based approaches and machine learning methods, which the most commonly used algorithm is the combination of OCV method and time integration method. This method is relatively simple and easy to calculate, but due to the complex internal state of the battery, which it shows very strong non-linear characteristics. Therefore, this method is difficult to estimate the real-time state of battery accurately. In machine learning methods, support vector machine (SVM) [6] is the most suitable for estimating the battery SOC. This method can establish a model with high precision according to the selected kernel function and adjust the corresponding parameters, so it has high accuracy in the existing SOC estimation.

2 Methods and data-set

2.1 Support vector machine

SVM [7–9] can solve the practical problems such as small sample, non-linear, high dimension and local minima. The main function of the algorithm is to map the sample data with non-linear characteristics and map the input sample data into a high-dimensional feature vector through its kernel function. Thus, the non-linear relationship between input data and output results is formed. SVM is often used to solve vector classification problems and support vector regression (SVR) problems. When using SVM to solve the problem, we need to select a kernel function (linear, SIG, polynomial). In theory, as long as the function satisfying the Mercer condition can be selected as a kernel function, different kernel functions will result in the effect of the classifier completely different. The battery test platform is composed of the National [10] 11 Instrument LabVIEW™ software.

2.1.1 Support vector regression: SVM can be applied to regression problems using SVR [11] algorithm, in which the objective is to find an optimal function [12]:

$$y(x) = \omega^T \varphi(x) + b. \quad (1)$$

The goal of SVR is to find the function (1), making the maximum deviation of $y(x)$ from the arbitrary training data less than the user-defined value, while maintaining the highest possible flatness. There is a form of optimisation problem:

$$\Phi(\omega, \xi) = \frac{1}{2} \|\omega\|^2 + C \sum_i \xi_i, \quad (2)$$

constraint condition:

$$y_i - (\omega, x_i) - b \leq \varepsilon + \xi_i. \quad (3)$$

The required function is the optimal function of Lagrangian:

$$\begin{aligned} \Phi(\omega, b, \alpha, \beta) = & \frac{1}{2} \|\omega\|^2 + C \sum_i \xi_i - \sum_i \alpha_i (\omega^T x_{i+b} - y_i + \varepsilon + \xi_i) \\ & - \sum_i \beta_i \xi_i. \end{aligned} \quad (4)$$

The optimised objective function has the form:

$$y(x) = \sum_{i=1}^L \alpha_i \langle x_i, x \rangle + b, \quad (5)$$

where x_i are the support vectors. The main advantage of SVR algorithm is the final formula in support vector, which condenses large training data to a significantly smaller SV subspace. In addition, the formula does not require any computationally intensive mathematical operations. The proposed method utilises the advantages of SVM to get computationally efficient SOC estimation algorithm.

2.2 Experimental data-set

The discharge and charging data of Li ion batteries under different conditions are analysed in this paper. The battery cycling data is provided by Prognostics Center of Excellence (PCoE) at NASA Ames [13] Research Center. It includes the available lithium ion 18,650 size rechargeable battery, ammeter, programmable electronic load, voltmeter, power supply, environment chamber, thermocouple sensor, electrochemical impedance spectrum and DAQ based on the PXI chassis [13]. Impedance measurement is based on electrochemical impedance spectroscopy (EIS) from 0.1 Hz to 5 kHz frequency scan to measure battery capacity. The data of #21 battery will be used to estimate the SOC in the study. Data sets have a total of 36 battery charging points. A set of #21 battery were run through three different operational profiles (charge, discharge and impedance) at room temperature (24°C). No. 21 battery is charged in a constant current (CC) mode until the battery voltage reaches 4.2 V, and then continues in a constant voltage (CV) mode until the charging current falls to 20 mA, indicating that the battery capacity is filled up to 100%. The discharge is carried out in 4 A until the battery voltage drops to 2.0 V, indicating that the battery capacity reaches 0%. Impedance measurement was carried out through an EIS frequency sweep from 0.1 Hz to 5 kHz. Battery charge and discharge data-set are mainly included: Current_measured: Battery output current (Amps), Voltage_measured: Battery terminal voltage (Volts) and Temperature_measured: Battery temperature (degree Celsius). In this study, the data-set of charge and discharge from No. 1 to No. 51 is selected as the input variables using in the following algorithm. The data-set of charge and discharge from No. 1 to No. 51 of #21 battery charge and discharge data-set is shown in Fig. 1.

3 Experiments and results

3.1 Experiments processing

3.1.1 Selection of input variables: The main purpose of this study is to use SVR technology and battery measurable parameters to obtain a model to estimate SOC. The battery input variables considered in this study are shown in Table 1.

The battery current (Fig. 1a), voltage (Fig. 1b) and temperature (Fig. 1c) are given as input train data and the battery SOC (Fig. 1d) as input train label to the SVM model. The training data set will be trained by using the No. 1–51 charge and discharge data-set of the #21 battery to train the SVM model, while using No. 52–53 charge and discharge data-set as test data and SOC data-set as test label to test the accuracy of the model.

3.1.2 Kernel selection: There are many types of kernel functions in (5), such as linear kernel function, polynomial kernel function, radial basis function (RBF) etc. Due to the non-linear characteristics of battery power changes, RBFs ((6)) with better non-linear characteristics are used in this paper. In terms of form, RBF is translation invariant [14] kernel. From the function point of view, RBF implements the local mapping of the input space to the characteristic space, because RBF is a non-negative function of the radial symmetric decay of the local distribution. The RBF kernel has fewer adjustment parameters than the polynomial kernel, making the choice of parameter processing simpler. In addition, compared with the RBF kernel function, sigmoid kernel functions will have some validity problems to be solved under certain [15] parameters.

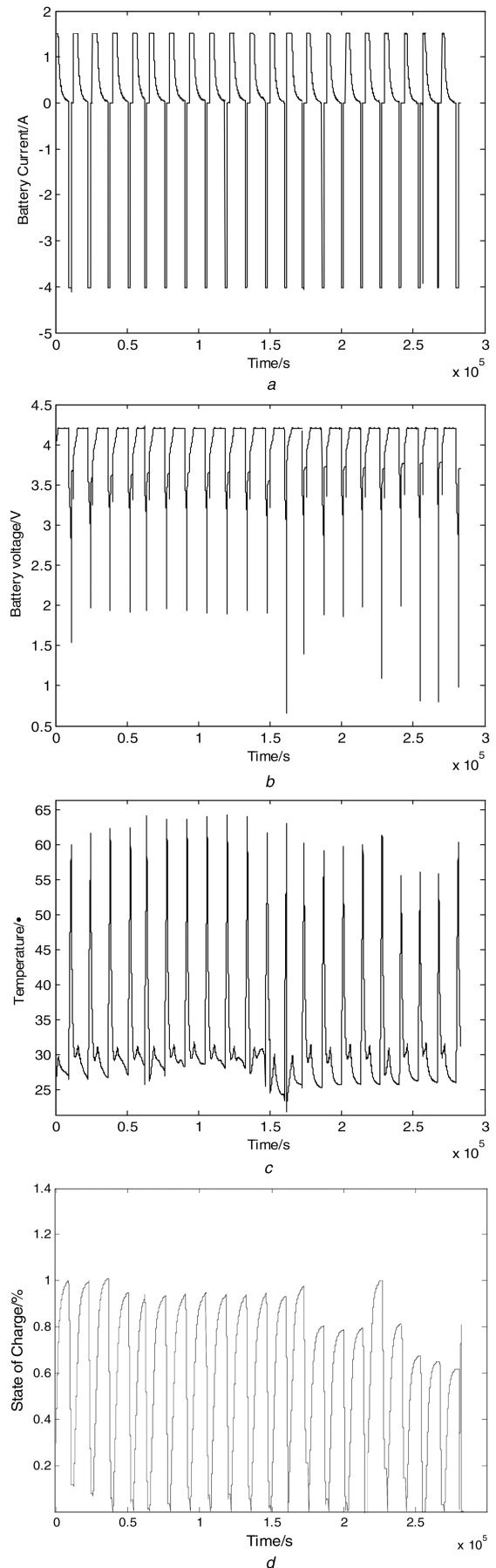


Fig. 1 #21 battery No. 1–51 charge and discharge data-set

(a) Battery charge and discharge current vs. time, (b) Battery charge and discharge voltage vs. time, (c) Battery charge and discharge temperature vs. time, (d) Battery charge and discharge SOC vs. time

$$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / 2\gamma^2). \quad (6)$$

In addition, support for SVM relies heavily on SVM parameters (C , ν , γ). We select C as the default parameter 1 of the system. After repeated experiments, $\nu = 0.012$ is the best parameter $\gamma = 0.0125$. Therefore, after repeated experiments, Table 2 is the optimal parameter set of SMV.

3.2 Results

The comparison between predicted SOC results and experimental SOC values is shown in Fig. 2.

The accuracy of the whole experiment is 98.42%. Mean-squared error is 1.783%. The results show that predict and experimental data are almost completely fitted in the CC discharge process, but there is a large error in the charging process. Especially in the process of CC charging to CV overcharge, the prediction result has a larger error.

In practice, the RBF kernel performs better in the high non-linearity problem and chooses the SVR technology with RBF core. This special kernel selection achieves better results than other kernels in this application.

4 Conclusion

For the UAV with battery as the main power supply system, it is very important to estimate the SOC accurately. However, due to the time-varying speed of UAV during flight, Li-ion battery itself has the characteristics of non-linear system. It is difficult to establish a more accurate SOC correspondence.

This paper mainly uses the NASA data-set of Li-ion battery and establishes a more perfect single-cell model by using SVM method and tests the accuracy of the model through the other recharge discharge data of the same battery. The SOC estimation method is suitable for low-cost BMS.

The result of this experiment is more accurate in the discharge process, but in the charging process, especially in the process of CC charging to constant pressure charging, there is a big error. Therefore, in the future, when using SVR to set up a precise SOC model, we will focus on the charging process, especially the part of the accuracy of SOC prediction in CC steering and CV. Moreover, the data-set used in this paper contains a lot of battery charging and discharging data, so it can also be used in the estimation of remained useful life (RUL) [3, 16–18].

Finally, the combination of SOC and RUL can finally accurately estimate the SOC and RUL of the battery under multiple conditions, so as to improve the efficiency of the battery [19].

In addition, static battery charging and discharging data are used in this paper. During the actual operation of UAV, there will be more external factors affecting the remaining battery capacity. For example, variable current discharge caused by variable speed flight, different environmental flight causes battery temperature changes and other external factors. By collecting the charge and discharge data of the UAV battery in more environment, the more accurate SOC and RUL model of the battery can be set up, and the effective and safe use of the UAV battery system is improved. Additionally, when SVR is used to train data, the training time is longer. Therefore, future research can also be carried out to reduce the training time of model. Finally, the author has information on the experimental method in this paper and can use the same method for similar battery research.

Table 1 Input variables used in this experiment

Input variables	Variable
battery voltage(V)	voltage
battery current(A)	current
battery temperature (°C)	temperature

Table 2 Optimal parameters of the fitted SVM model

Parameters	Value
SVM_Type	ν – regression
SVM_Kernel	radial basis function
C	1
γ	0.0125
ν	0.012

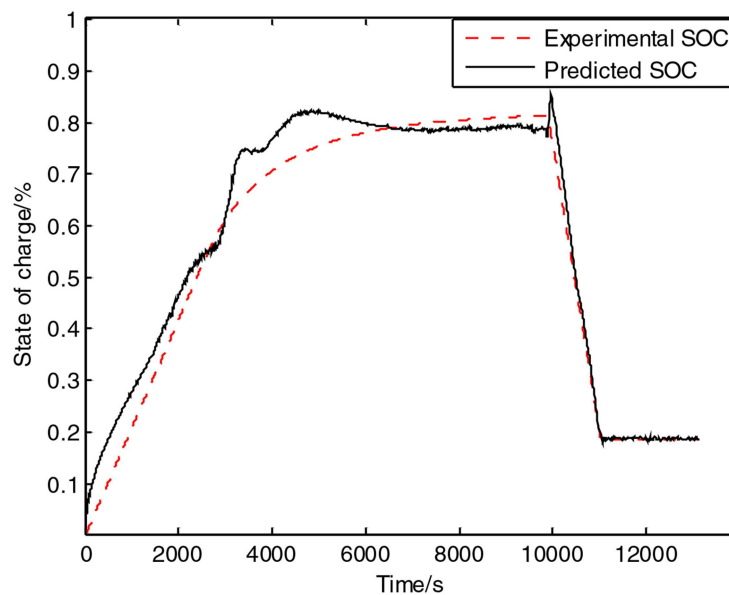


Fig. 2 Predicted SOC results versus experimental SOC values

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