Transportation robot battery power forecasting based on bidirectional deep-learning method

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Abstract

This paper proposes a data-driven hybrid model for forecasting the battery power voltage of transportation robots by combining a wavelet method and a bidirectional deep-learning technique. In the proposed model, the on-board battery power data is measured and transmitted. A WPD (wavelet packet decomposition) algorithm is employed to decompose the original collected non-stationary series into several relatively more stable subseries. For each subseries, a deep learning–based predictor – bidirectional long short-term memory (BiLSTM) – is constructed to forecast the battery power voltage from one step to three steps ahead. Two experiments verify the effectiveness and generalization ability of the proposed hybrid forecasting model, which shows the highest forecasting accuracy. The obtained forecasting results can be used to decide whether the robot can complete the given task or needs to be recharged, providing effective support for the safe use of transportation robots.

Keywords: robotic power management; transportation robot; time series forecasting; wavelet packet decomposition; bidirectional long short-term memory

1. Introduction

Against the background of the general promotion of improved intelligent manufacturing environments, the development of mobile robots has become a top priority in the field of modern intelligence research. To ensure the high efficiency and safety of robots, many scientific aspects need...
to be taken into consideration, such as navigation [1], trajectory tracking [2], obstacle avoidance [3] and so on. The energy-perception capabilities of robots are also important in an intelligent operation and maintenance environment. Stable control is a precondition for all types of robots. For the long-term operation of transportation robots under high-load conditions, endurance is often limited by the amount of vehicle power. If a robot is stuck in the running automatic assembly line due to power failure, it may lead to the overall collapse of the collaborative operation [4]. Realizing the power feedback of transportation robots is therefore of great significance to ensure the safe operation of robots in intelligent manufacturing operation and maintenance environments.

Several approaches have been utilized for the power management of mobile robots. Forecasting when battery power depletion will reach a critical threshold is an important basis for determining whether a mobile robot requires recharging or returning to the base station. Hamza et al. [5] proposed a framework for predicting the onboard power of robots for specific tasks. The specific description formula for all specific tasks was derived into the parameterization index related to the robot, and the task was then mapped to the nonlinear relationship of the electricity by training the neural network using experimental data. The experimental results of the model on Turtlebot 2 proved that the recurrent neural-network model was effective in power prediction. Liu et al. [6] proposed a new framework for predicting and managing the battery voltage of mobile robots. The original measurement data was decomposed into sub-series using wavelet methods, and an ANFIS was constructed and predicted for all the decomposed sub-series. Finally, the sub-layer prediction results were integrated to make the final prediction of the original online voltage data. Shen et al. [7] proposed using discharge and regeneration capacity distribution to describe a discharge current curve. Neural networks were used to estimate the complicated nonlinear relationships between the amount of electricity and the capacity distribution at different temperatures. The predicted results by the neural network were compared with the calculated results from experimental data. The results confirmed that the proposed method was able to provide accurate power description for lead-acid batteries. Pentzer et al. [8] proposed a model for predicting the power trend of skid-steering robots using terrain and motion parameters. The extended Kalman filter was used to learn the position of the instantaneous centre of rotation, and the recursive least squares method was used to learn the terrain-related power-model parameters. The algorithm used a kinematic model of the robot wheel’s centre of rotation to provide accurate power-usage estimates. The field test results showed that the method did not require prior terrain information. It needed to know only the geometry and mass distribution of the robot, intermittent GPS, and direction and tire odometer information, and was able to use the kinematics model of the instantaneous centre of rotation of the robot wheel to provide accurate battery usage forecasting.

As shown in the above-mentioned literature, the management of on-board robot battery power is gaining increasing attention. Forecasting the future trends of battery power helps us to make appropriate decisions ahead of time. However, most of the existing methods require multidimensional parameters such as voltage, temperature, load current and battery internal resistance. The time series forecasting-based method is rarely analysed. Moreover, the deep-learning method has not been adopted.

In this study, two sets of recorded voltage data for on-board robot batteries were used as training data to construct a deep learning–based forecasting model. The battery power data was directly measured and transmitted. The rest of this paper is organized as follows: Section 1 sets out the framework of the proposed model; Section 2 expounds the theory of wavelet packet decomposition (WPD); Section 3 describes the predictor (bidirectional long short-term memory; BiLSTM); Section 4 sets out the experimental results and analysis; and Section 5 concludes the paper.

2. Framework of the proposed model

As shown in Fig. 1, the measured data was decomposed into multiple stable subseries using WPD, with the result that the forecasting ability was reduced. For each subseries, a BiLSTM was constructed to obtain forecasting results. The results were then summed up to produce the final forecasting results, which helped to determine whether the robot was able to complete the given task or had to be recharged. Fig. 2 shows the measured robot power voltage data. Data 1–1200 were utilized to train predictors, while data 1201–1600 were set as testing data to evaluate the performance of the forecasting results.
Wavelet packet decomposition can only subdivide the low-frequency components of each layer, however, WPD can further divide all subseries in each layer. In the proposed model, three-layer WPD was utilized to decompose the power data, whose binary tree is shown in Fig. 3.

In the proposed model, the Daubechies wavelets with six vanishing moments and three decomposition layers were adopted to process the training data. The original battery power data was divided into eight subseries, as shown in Figs 4–5.

4. Bidirectional long short-term memory

Recurrent neural networks (RNN) are developed for processing series, and have the ability to restore past sequential data. Long short-term memory (LSTM) is a representative RNN capable of effectively considering the long-term dependencies of a dataset. It introduces two concepts to achieve this goal: the memory cell and the cell state. Three gates, namely the input gate, the forgetting gate and the output gate, are applied to control the cell state. The forgetting gate can selectively discard information from the cell state; the input gate can absorb new information into the cell state; while the output gate determines the outgoing information from the cell. The LSTM model can better capture long-term dependencies because of the ability to learn what information to remember and what information to forget through the training process. The structure of LSTM is shown in Fig. 6. Its computational process can be illustrated by the following equations [9]:

\[
\begin{align*}
    f_t &= \sigma \left( W_{xf} x_t + W_{hf} h_{t-1} + B_f \right) \\
    i_t &= \sigma \left( W_{xi} x_t + W_{hi} h_{t-1} + B_i \right) \\
    C_t' &= \tanh \left( W_{xc} x_t + W_{hc} h_{t-1} + B_C \right) \\
    C_t &= f_t \ast C_{t-1} + i_t \ast C_t' \\
    o_t &= \sigma \left( W_{xo} x_t + W_{ho} h_{t-1} + B_o \right) \\
    h_t &= o_t \ast \tanh \left( C_t \right)
\end{align*}
\]

where \(i_t, f_t\) and \(o_t\) denote the input gate, forgetting gate and output gate, respectively; \(B\) denotes the bias vectors; \(W\) denotes the weight matrices; \(x_t\) denotes the layer input; \(h_t\) denotes the layer output; and \(C_t\) denotes the cell output state.

The LSTM structure in Fig. 6 can learn only the forward information flow of data. However, the backward information flow of sequential data may...
also help to improve forecasting accuracy. Inspired by this idea, BiLSTM connects two hidden layers in forward and backward directions to the same output. Fig. 7 shows the structure of BiLSTM unfolded along the time dimension, with the solid lines denoting the forward direction, while the dotted lines indicate the backward direction. The computational process is similar to LSTM, but the output is calculated by combining two hidden layers:

\[
y_t = \eta \left[ M \left( \overrightarrow{h_t}, \overleftarrow{h_t} \right) + b \right]
\]

where \( M \) is the corresponding method used to combine the outputs of the two hidden layers, which may be an average function, a summation function or a multiplication function [10].

5. Experiment and analysis

To demonstrate the effectiveness of the hybrid forecasting model, two sets of experimental robot power data are provided, for Robots 1 and 2. Figs 8–10 show the forecasting results for Robot 1 from one step to three steps ahead. The forecasting models included LSTM, BiLSTM and the proposed WPD-BiLSTM. The utilized LSTM models had the same parameters. The number of hidden units was 30; the Adam optimizer was adopted to train the network; and the maximum number of epochs was set at 100.
To evaluate the accuracy of the forecasting models, three commonly used indices were utilized, including mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE). The evaluation results of experiments on Robots 1 and 2 are listed in Tables 1 and 2, respectively.

From Figs 8–10 and Tables 1–2, it can be concluded that:

(a) The single LSTM model was barely capable of capturing the future tendency of the robot power voltage data. The MAPE, MAE and RMSE of the one-step forecasting results for Robot 1 were 0.3898%, 0.0472 V and 0.0584 V, respectively, which are the highest in the comparison results.

(b) The BiLSTM model obtained better forecasting results than the LSTM model due to its ability to learn forward and backward information at the same time. The variation trend of the forecasting results was similar to the actual measured data, and the forecasting error was also smaller than that of LSTM. The MAPE, MAE and RMSE of the one-step forecasting results for Robot 1 were 0.1732%, 0.0210 V and 0.0259 V, respectively.
Table 1. Accuracy evaluation of forecasting results (Robot 1)

| Algorithm | Horizon | MAPE (%) | MAE (V) | RMSE (V) |
|-----------|---------|----------|---------|----------|
| LSTM      | One-step| 0.3898   | 0.0472  | 0.0564   |
|           | Two-step| 0.3801   | 0.0460  | 0.0571   |
|           | Three-step| 0.3836  | 0.0464  | 0.0575   |
|           | One-step| 0.1732   | 0.0210  | 0.0259   |
| BiLSTM    | Two-step| 0.1797   | 0.0218  | 0.0270   |
|           | Three-step| 0.1838  | 0.0223  | 0.0276   |
|           | One-step| 0.0891   | 0.0108  | 0.0147   |
| WPD-BiLSTM| Two-step| 0.1013   | 0.0123  | 0.0166   |
|           | Three-step| 0.1201  | 0.0145  | 0.0204   |

Table 2. Accuracy evaluation of forecasting results (Robot 2)

| Algorithm | Horizon | MAPE (%) | MAE (V) | RMSE (V) |
|-----------|---------|----------|---------|----------|
| LSTM      | One-step| 0.3759   | 0.0493  | 0.0609   |
|           | Two-step| 0.3842   | 0.0504  | 0.0615   |
|           | Three-step| 0.3898  | 0.0511  | 0.0628   |
|           | One-step| 0.2598   | 0.0341  | 0.0442   |
| BiLSTM    | Two-step| 0.2617   | 0.0343  | 0.0434   |
|           | Three-step| 0.2667  | 0.0350  | 0.0442   |
|           | One-step| 0.1535   | 0.0201  | 0.0288   |
| WPD-BiLSTM| Two-step| 0.1430   | 0.0188  | 0.0261   |
|           | Three-step| 0.1481  | 0.0194  | 0.0265   |

(c) Wavelet-based decomposition was effective at reducing forecasting difficulty and improving forecasting accuracy. The original non-stationary series was decomposed into eight relatively stable subseries. The forecasted turning points and peak values were the closest to the actual power level.

(d) The proposed model showed the highest forecasting accuracy in all experiments. For example, the MAPE, MAE and RMSE of the three-step forecasting results for Robot 1 were 0.1201%, 0.0145 V and 0.0204 V, respectively. The MAPE, MAE and RMSE of the three-step forecasting results for Robot 2 are 0.1481%, 0.0194 V and 0.0265 V, respectively. The evaluation indices for Robot 1 and Robot 2 were the lowest of all the comparison models, regardless of the forecasting horizon.

6. Conclusions

In this paper, a data-driven model was proposed to forecast robot power voltage. The original non-stationary power voltage series was decomposed into eight subseries. For each subseries, a BiLSTM predictor was established. All forecasting results were integrated to obtain the final forecasting result. Three models – LSTM, BiLSTM and WPD-BiLSTM – were compared based on two sets of measured robot battery voltage data. The results showed that BiLSTM was able to make full use of forward and backward information, and therefore performed better than the LSTM model. The proposed WPD-BiLSTM model combined wavelet decomposition and deep learning, and showed the highest accuracy in all experiments and forecasting horizons. The model can therefore be applied in the management of on-board robot battery power and provide effective support for the safe use of transportation robots.

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Conflict of interest statement. None declared.

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