Multi-state household appliance identification based on neural network

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Abstract. In the current non-intrusive load monitoring process, the states switching of some multi-state appliances is difficult to be correctly identified by the switch event detection method, and the energy consumption statistics due to poor multi-state identification of the electrical appliances are not accurate. This paper proposes a multi-state household appliance load identification method based on convolutional neural network and clustering model. First, a convolutional neural network is used to construct an appliance type identification model. Then, a multi-state identification model is established to identify the state of different multi-state appliances. The experimental results show that the proposed method achieves multi-state identification of electrical appliances and has good engineering and practical value.

1. Introduction

Traditional intrusive load monitoring relies on the installation of monitoring devices on a single device to monitor the energy consumption of each device. Therefore, there are some disadvantages such as high cost and complicated installation\cite{1}. With the development of smart homes, non-intrusive load monitoring (NILM) is getting more and more attention. Non-intrusive load monitoring only requires the installation of a monitoring device at the power inlet to obtain household energy consumption aggregate data\cite{2}. The development of non-intrusive load monitoring overcomes the shortcomings of intrusive load monitoring, reduces hardware costs and installation complexity, enables residents to effectively manage household energy consumption. Power companies can obtain specific power data at lower cost and allocate power resources for users reasonably and guide the users to use resources reasonably.

At present, the common method of non-intrusive load monitoring is to decompose the obtained aggregate data into single device, and then perform device identification by decomposing single device signal\cite{3}. The non-intrusive load identification method is mainly divided into load recognition based on mathematical optimization and load recognition based on pattern recognition. The load recognition algorithm based on mathematical optimization mainly includes the recognition method based on snapshot type load signatures and the recognition method based on incremental load signatures. The load recognition method based on pattern recognition mainly includes the methods of supervised learning\cite{4,5} and unsupervised learning\cite{6}. At present, the research on non-intrusive load identification mainly focuses on the feature recognition of single-state electrical appliances. However, there are relatively few studies on electrical identification in different operating states. this paper proposes a multi-state household appliance load identification method based on clustering and
convolutional neural network, which reduces the complexity of work and improves the recognition accuracy.

The structure of this paper is as follows. The second part is a brief introduction to the research work of single-state electrical appliances and multi-state electrical appliances. The third part elaborates the relevant theoretical knowledge involved in the article. The fourth part introduces the experimental process, analyzes the experimental results, and finally gives the conclusion of this paper.

2. Related work
The research on non-intrusive load monitoring is mainly divided into load identification for single-state appliances and load identification for multi-state appliances. In 2016, Liang Du proposed a load recognition method based on image features. The VI trajectory is mapped to a cell with a binary value. The cell through which the trajectory passes is marked as 1, and the cell whose trajectory has not passed is marked as 0. The recognition average accuracy rate reached 99%[7]. In 2018, Leen De Baets et al. proposed another feature extraction method, which maps VI trajectories into n × n grids, and calculates the number of trajectory points in each grid. The VI image was trained and tested with convolutional neural networks. The macro-average F-measure is 77.6% for the PLAID dataset and 75.46% for the WHITED dataset[8]. However, the resistive appliances were still not well recognized. These methods are mainly focused on the identification of single-state appliances, but there is no identification of multi-state appliances.

In recent years, researchers have made great contributions to the identification of single-states appliances, and the recognition accuracy has been continuously improved. However, most of the research has focused on the identification methods of single-state appliances, but the research on the identification of multi-state electrical appliances is rare. Kushan Ajay Choksi et al. constructed the power matrix with power time series, and then realized the recognition of multi-state appliances by machine learning. The average recognition accuracy was about 89.9%[9,10]. However, the form conversion usually reduces the recognition accuracy. In order to get better results, this paper proposes a multi-state appliances identification method, which has achieved good results.

3. Theory
3.1. The construction of Convolutional neural network model
In this paper, the one-dimensional convolutional neural network is used to process the power time series. The model mainly includes three units. The first unit includes two layers of convolution and one layer of pooling. Here, the maximum pooling is adopted. The second unit also includes two layers of convolution and one layer of pooling. The global average pooling is used here. The last unit includes the Dropout and the full connection layer and the output layer. The model structure is shown in Figure 1. The first unit is convolved with 100 convolution kernels of size 10×1. The max pooling window is set to 2. The second unit is convolved with 150 convolution kernels of the same size. Average pooling does not set up a pooling window. Since the neural network training is prone to over-fitting problems, in order to prevent over-fitting, we set the dropout layer in the network.

Figure 1. Model structure.
3.2. The construction of cluster model

The k-means clustering algorithm is used to determine the different states, as shown in the following figure. The horizontal axis represents time, the vertical axis represents power, and different colors represent different states. Since the time point of collecting data is relatively tight, we set the time interval display of the horizontal axis of the image. Different electrical data collection time points are different. We set different intervals for different electrical appliances. For example, the dishwasher displays one every 30 time points, the microwave oven displays one every one time. We can clearly see from the figure which state the appliance is in, and we can know which time the appliance has switched state.

![Dishwasher status switching diagram.](image1)

**Figure 2.** Dishwasher status switching diagram.

![Microwave status switching diagram.](image2)

**Figure 3.** Microwave status switching diagram.

4. Experiment

In order to prove the effectiveness of the proposed method, the following experiments were carried out to verify the proposed method.

4.1. Model training

In this paper, the dataset is divided into training set, validation set and test set according to the ratio of 6:2:2 to train the model. We need assign different electrical labels to different electrical data. In this paper, different electrical labels are encoded by means of One-Hot Encoding.

Since the computer is only extremely sensitive to binary counting, this article sets the batch to 64. By reducing the value of the loss function and reducing the loss value to achieve the minimum cost, the classification cross entropy loss function is used in this paper.

The classification cross entropy loss function is defined as follows:

$$\text{loss} = -\sum_{i=1}^{n} \hat{y}_{i1} \log y_{i1} + \hat{y}_{i2} \log y_{i2} + ... + \hat{y}_{im} \log y_{im}$$

(1)

Where n is the number of samples and m is the number of categories. The Adam optimizer is used to solve for the minimum loss.

4.2. Experiment result

The model uses the validation set to determine the hyperparameters, uses the training set to adjust the parameters, and finally uses the test set to determine the actual effect of the model.

4.2.1. Appliances type identification result. According to the above evaluation criteria, the experimental results obtained are shown in Table 1, which proves the robustness of the proposed
Table 1. Experimental results table.

| Appliance       | Recall | Precision | F1-score measure |
|-----------------|--------|-----------|------------------|
| Bathroom gfi    | 98%    | 98%       | 98%              |
| Dish washer     | 90%    | 93%       | 92%              |
| Electric heater | 100%   | 38%       | 55%              |
| Fridge          | 97%    | 99%       | 98%              |
| Kitchen outlets | 100%   | 100%      | 100%             |
| Light           | 98%    | 99%       | 99%              |
| Microwave       | 100%   | 100%      | 100%             |
| Oven            | 100%   | 50%       | 67%              |

4.2.2. Appliances states identification result. We compare the state identification results of electrical appliances by manual sampling, and randomly select different examples of different electrical appliances for comparison. The results are shown in Table 2.

Table 2. Status recognition accuracy.

| Appliance       | Accuracy |
|-----------------|----------|
| Oven            | 78%      |
| Microwave       | 98%      |
| Light           | 74%      |
| Kitchen outlets | 62%      |
| Fridge          | 81%      |
| Electric heater | 100%     |
| Dish washer     | 96%      |
| Bathroom gfi    | 96%      |

5. Conclusion

This paper introduces a novel multi-state appliances identification method based on k-means clustering and neural network. The accuracy rate of load identification reaches 99%, loss value is 0.1. The average accuracy of state recognition reaches 85.6%. With the development of technology, the identification of electrical appliances in any state is crucial to the development of smart homes, which will become one of the problems we need to solve in the future.

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