Identification of electrical equipment based on two-dimensional time series characteristics of power

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Abstract. Non-intrusive load monitoring provides real-time monitoring of the operational status of individual devices in the home and provides detailed power usage data. In this paper, a deep neural network structure with residual module and Batch Normalization layer is proposed for the problem that it is difficult to extract complete features. The new method of converting power data into two-dimensional image is used to identify electricity device. Finally, the accuracy rate of the test in the data set containing 21 kinds of electrical equipment is 97.2\%. The experimental results show that the method has high recognition for a large number of household electrical equipment, especially for appliances with multiple states and fewer samples rate.

1. Introduction

In recent years, global energy consumption has increased. Household electricity consumption occupies a larger proportion in the total energy consumption, and in the household electricity consumption, household appliances equipment consumption proportion is the largest. Therefore, to reduce energy consumption, we should start from reasonably reducing household electricity consumption and improving household electricity efficiency. In order to solve this problem, a method, called NILM, which integrates all load profile information with intelligent electricity meter is proposed. In the existing electrical equipment monitoring technology, this method only needs to monitor the total power consumption through the smart meter, and then decompose the monitored total power state into the power of each individual appliance.

The focus of this work is that, first, in data preprocessing, a resampling method is used to balance the number of samples for the data imbalance that occurs in the power data set. Then, a new method of converting one-dimensional time series into two-dimensional image is adopted. After the power time series data in the electricity data is converted into a two-dimensional image by GADF algorithm, the...
obtained two-dimensional image is input as a model. Finally, when constructing the model, this paper adds residual module and BN layer to the traditional two-dimensional convolution network to solve the gradient disappearance problem.

The structure of this paper is as follows. The second part gives the problem statement and solution in related work. The third part describes the methods used in this article, including the GADF algorithm and the overall network architecture. In the fourth part, the paper tests the overall performance of the proposed model. In the last part, a conclusion is given.

2. Related Work

The non-invasive load monitoring (NILM) method allows for the identification of aggregated data from a single measurement point[1]. In 1992, Hart proposed a preliminary concept of residential load decomposition, which explained how different electrical appliances could generate different power signals and showed how equipment usage could be represented by switching events[2]. There are also some novel methods that can be applied to NILM research, such as hidden markov model[3], deep neural network[4], etc. Using high-frequency data from PLAID[5] and WHITED[6] data sets, Lam et al.[7] proposed a classification method for electrical equipment based on v-i track shape. In their review, A.Ruano et al.[8] describe important approaches to solving NILM problems in recent years.

Wang et al.[9] proposed a new method for converting time series into images. They extracted features using a tiled neural network and classified them using a de-noising automatic encoder. Lamprini k. et al.[10] used the Gramian Angular Field Matrices (GAF) algorithm to convert the power data into images, then used the convolutional neural network Vgg16 for migration learning, and finally used the classification algorithm for training to identify the switching state of the device. The final accuracy on the REDD low-frequency dataset was less than 70%. The disadvantage of this method is that the method of migration learning increases the time complexity and the classification algorithm is not configured in the best way.

3. Implementation

In this paper, a coding method that converts time series into two-dimensional images is used. Converting power time series data into two-dimensional image representation preserves power time data time dependence, and GAF algorithm can save static in current sequence time domain information. Based on the traditional convolutional neural network, the network structure of this paper uses a network model with residual modules.

In this section, three main parts are introduced: 1. A new method of encoding power timing data into a two-dimensional image and retaining its time-frequency characteristics. 2. A solution to the problem of sample imbalance in power data collection. 3. The overall network architecture.

3.1. Data pre-processing

3.1.1. Gramian Angular Difference Field. In this process, a new method of converting time series into images proposed by Wang et al was used in this paper to conduct two-dimensional coding of power sequences, which could make full use of the advantages of computer vision in load identification. There are two coding frameworks for encoding time series into images, Gramian Angular Field (GAF) and Markov Transition Field (MTF). According to the different coding Angle selected in GAF, it is divided into Gramian Angular Difference Field (GADF) and Gramian Angular
Summation Field (GASF). GADF is more suitable than the other two methods for constructing two-dimensional images with power timing data. It can extract more information into the feature space, so only GADF is used in this paper. The GADF coding process is shown in figure 1.

![GADF coding flowchart.](image)

**Figure 1.** GADF coding flowchart.

### 3.1.2. Imbalance class.

In traditional machine learning algorithms, there is a basic assumption that the data distribution is uniform, that is to say, the number of training samples is the same, but the actual problems encountered in real scenarios often do not conform to this assumption. Unbalanced samples can cause the training model to focus on categories with a larger number of samples, resulting in lower accuracy for a few sample categories. In NILM, the number of samples varies from device to device in the collected data set because of the different usage rates of different appliances in the home.

![Statistical results of the sample number of 21 kinds of electrical appliances in the experimental data set.](image)

**Figure 2.** Statistical results of the sample number of 21 kinds of electrical appliances in the experimental data set.

As can be seen from figure 2, the number of samples of some devices is even more than 3 times, which leads to the problem of unbalanced samples in classification. The model trained with unbalanced samples may be more inclined to the majority of samples, resulting in a decrease in the accuracy of a few samples. Therefore, in this experiment, the combination of oversampling and under-sampling is chosen to balance the sample. First, use the smooth method to oversample. After a few classes are oversampled to 1.5 times the number of samples of the majority, then under-sampled to the same number of samples. Under-sampling adopts a strategy of selecting mid-point under-sampling, that is, if the original data length is $n_1$ and the under-sampling is required to be $n_2$, then...
then the original data is equally divided into n1-n2, respectively. The midpoint is discarded. This strategy preserves the distribution characteristics of the original data while under-sampling.

3.2. Overall network architecture

The network structure proposed in this paper (as shown in figure 3) is a two-dimensional convolution model combines the residual network. In the two-dimensional convolution part, a five-layer two-dimensional convolution extraction feature is used, and a convolution kernel of size 3 and a step size of 1 is used, and the number of convolution kernels is sequentially increased. In the entire network architecture, each layer has a Batch Normalization layer and a pooling layer after convolution. In addition, the global connection pool is used in front of the full connection layer to reduce the parameter amount. These are not marked in the figure, using relu as per layer's activation function, and placed after the BN layer, in addition to using the BN layer, the dropout layer is used to overcome the overfitting problem.

![Figure 3. Model Structure.](image)

In the training process of the neural network, if you want to further improve the load identification capability, you need to deepen the network hierarchy. As the network layer deepens, the gradient disappears. The performance on the recognition rate is first to rise and then drop rapidly. In order to avoid this problem, residual network appears. Residual network has a lot of advantages. It can control the number of parameters by reducing the network layer, and it has obvious hierarchy. The number of feature maps is increasing layer by layer, so as to ensure the expression ability of output features. Moreover, And in the absence of dropout, regularization and global average pooling can reduce parameters and increase training speed.

4. Experiment

4.1. Data pre-processing

The data set used in this paper is the power identification data set of ocean university of China. The sampling rate of current and voltage in the data was 4kHZ, that is, 80 data points were collected within a period of 0.02s. The experimental data included 21 electrical appliances and transient data in no-load condition, each of which was switched on and off at least 100 times.
4.2. Model Training

The parameters of each layer of the network model in this paper are shown in table 1 below. The input data of the model is a two-dimensional image with a size of 64*64 converted from the original data. The final output layer has 21 nodes, which is determined by the number of types of devices. In the training process, the initial learning rate was set as 0.01, and the learning rate attenuation strategy was adopted to reduce the learning rate to 0.1 times of the original in the 15th round and the 80th round, and 0.5 times of the original in the 40th round, for a total of 100 iterations.

4.3. Result

4.3.1. Evaluation Standard. For classification problems, there are two methods of calculating accuracy. Calculating the accuracy of category prediction without classification is called micro-averaging. Another method is to calculate the prediction accuracy of each category first, and then get the prediction accuracy through arithmetic average, which is called macro-average. In this paper, macro average is selected as the evaluation index, and the equation obtained is:

$$F_{macro} = \frac{2 \times P_{macro} \times R_{macro}}{P_{macro} + R_{macro}}$$

Where $P_{macro}$, $R_{macro}$, $P_i = \frac{TP_i}{TP_i + FP_i}$, $R_i = \frac{TP_i}{TP_i + FN}$ represent the number of samples that predict the positive class as the positive class, and $FP_i$ represents the number of samples that predict the negative class as the positive class.

4.3.2. Result on the datasets. After the experiment, the evaluation index can be obtained. As shown in figure 4, the smallest value comes from the refrigerator. Figure 4 is the model training result represented by confusion matrix. It is found that when the compressor of the refrigerator is working, the power waveform generated will be confused with the freezer and the small refrigerator, and when the temperature in the refrigerator reaches the set value, the refrigerator will enter the standby state, and the power waveform generated at this time will be confused with the small power appliance, resulting in a decrease in the recognition rate.

![Figure 4. The confusion matrix of model training results.](image-url)
5. Conclusion and Future Work

In this paper, a resampling method is used to balance the number of samples. For the balanced data, a new method is adopted to transform the one-dimensional time series into two-dimensional images as the input of the model, and the residual module and BN layer are added into the traditional two-dimensional convolutional network to solve the gradient disappearance problem. In the experiment, the method was applied to the data set containing 21 kinds of electrical equipment for testing, and the accuracy rate reached 97.2%. For a large number of household electrical equipment, especially for multi-state and small sample number of electrical appliances has a high identification rate.

In addition, the method of converting power data into a two-dimensional image can be further improved, thereby improving the classification performance of the electric equipment, and the method can also be applied to load decomposition of the electric equipment.

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