Non-Invasive Load Recognition Model Based on CNN and Mixed Attention Mechanism

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Abstract: In recent years, deep learning has been widely applied in various fields, including the field of load recognition. Machine learning methods such as SVM and K-means, as well as various neural network approaches, have shown promising results. However, due to the significant differences among similar appliances and the existence of multiple operating states for each appliance, misjudgments often occur during load recognition. Therefore, this paper proposes a preprocessing method that transforms current-voltage data into V-If trajectories. Additionally, a non-intrusive load recognition algorithm is presented, which incorporates a self-designed convolutional neural network (CNN), a hybrid attention mechanism (ECA_NET and Spatial attention mechanism, ECA-SAM), and a hybrid loss function (Center Loss and ArcFace, CA). The effectiveness of this approach is demonstrated through simulation experiments conducted on the PLAID dataset, achieving a remarkable 98% accuracy in the identification of electrical appliances.

1 INTRODUCTION

The concept of Non-Intrusive Load Monitoring (NILM) was first proposed by Professor Hart from the Massachusetts Institute of Technology (Hart, 1992). It aims to identify and monitor various electrical appliances in households by analyzing the current and voltage waveforms in the power system. NILM technology can help households and businesses better understand their energy consumption, thereby improving energy efficiency and reducing energy costs. Additionally, NILM technology can be used in smart home systems and energy management systems to achieve smarter and more efficient energy management

The main focus of this study is the load recognition module in Non-Intrusive Load Monitoring (NILM), with an emphasis on load identification methods. By leveraging a series of deep learning techniques, the aim is to analyze the usage patterns of common household appliances and accurately identify the appliance categories. This assists home users in gaining a better understanding of their electricity consumption habits.

An algorithm for non-intrusive load recognition is proposed, incorporating a self-designed Convolutional Neural Network (CNN), a hybrid attention mechanism (ECA_NET and Spatial attention mechanism, ECA-SAM), and a hybrid loss function (Center Loss and ArcFace, CA). This algorithm aims to enhance the network's ability to extract load features, while promoting intra-class cohesion and inter-class dispersion, thereby improving load recognition capability.

2 RELATE WORK

Since the concept of non-intrusive load monitoring (NILM) was introduced, it has attracted significant attention from scholars both domestically and internationally. Researchers have been exploring various methods to improve the effectiveness and practicality of NILM.

In 1995, Leeb proposed an algorithm for transient event detection to identify loads (Leeb, 1995). In 2000, Cole et al. used current harmonics as load features and differentiated different loads by calculating the city-block distance and Hamming distance between harmonics, achieving load recognition (Cole, 2000). In 2008, Suzuki et al. introduced an NILM method based on integer programming, formulating the detection problem as an integer quadratic programming problem to achieve

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non-intrusive appliance load monitoring (Suzuki, 2008).

With the rapid development of deep learning, it has also been applied in the field of NILM. In 2015, Kelly et al. first applied denoising autoencoder (DAE) models to the NILM problem, showing that this model outperformed combinatorial optimization and factorial hidden Markov models (Kelly, 2015). In the same year, Lin et al. applied attention mechanisms to the NILM problem, proposing two networks: MA-net and MAED-net. The former is based on multi-head attention mechanisms, while the latter combines an encoder-decoder structure with multi-head attention mechanisms (Lin, 2020).

3 METHOD

This chapter uses a hybrid attention mechanism to improve the performance of convolutional neural networks. Different from the CBAM attention mechanism, a lighter ECA-Net channel attention mechanism is chosen to replace SE-Net to improve the performance of the network

3.1 Network Architecture

In this study, the channel attention mechanism ECA-Net and the spatial attention mechanism SAM are incorporated into the network to build a non-intrusive load recognition model based on CNN and hybrid attention mechanisms. The purpose is to enhance the network's ability to extract load features. The network architecture is illustrated in Figure 1.

From Figure 1, it is evident that both the channel attention mechanism and the spatial attention mechanism are added after the fourth and seventh convolutional layers, respectively. Additionally, the ECA-Net module is positioned before the SAM module. This configuration establishes the overall structure of the network model used in the experiment.

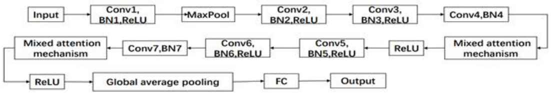

Figure 1: Network Architecture of Non-intrusive Load Recognition Model based on CNN and Hybrid Attention Mechanism.

3.2 Hybrid Attention Mechanism

ECA-Net, the channel attention mechanism: To address the issue of diminished details in image processing caused by the dimension reduction in SE-Net, researchers introduced ECA-Net (Zhu, 2020). ECA-Net effectively reduces the parameter requirement of the channel attention mechanism, while preserving the original channel dimension. As a result, ECA-Net offers a more lightweight solution that does not compromise on capturing intricate details in comparison to SE-Net.

The structure of ECA-Net is depicted in Figure 2:

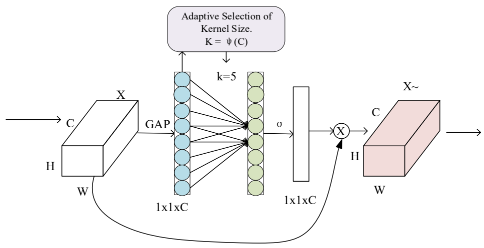

Figure 2: ECA-Net Architecture.

The role of the Spatial Attention Module (SAM) is to identify the most important parts within the network for processing. The structure of the Spatial Attention Module SAM is illustrated in Figure 3.

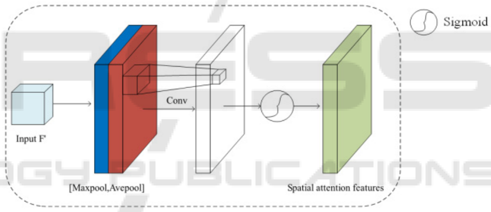

Figure 3: Spatial Attention SAM Architecture.

3.3 Constructing V-I Trajectory Diagram

The V-I trajectory is a widely-used load characteristic in load recognition applications. The main distinction of the V-I trajectory lies in the different current profiles. However, for resistive appliances such as heaters and hair dryers, the V-I trajectories are similar, making it difficult to differentiate between them. To address this, researchers proposed the application of Fryze power theory to decompose the reactive current, thereby enhancing the distinguishability of V-I trajectories.

The construction process of the V-I_f trajectory is depicted in Figure 4:

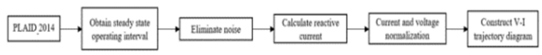

Figure 4: V-I_f trajectory construction flowchart.

The generated V-I track image and V-I_f track image are shown in FIG. 5, respectively, where each track image from left to right is: Air Conditioner, Fluorescent Lamp, Fan, Fridge, Hairdryer, Heater, Incandescent Light Bulb, Laptop, Microwave, Vacuum, Washing Machine.

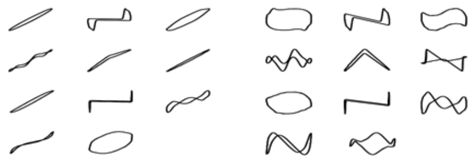

Figure 5: V-I and V-I_f trajectory diagrams.

It is evident from Figure 5 that the V-I_f trajectory image exhibits greater specificity as a load characteristic compared to the V-I trajectory image. This enhanced specificity is more advantageous for carrying out load recognition tasks.

3.4 Loss Function

Center Loss: center loss function was proposed in 2016(Wen, 2016). center loss function can narrow the intra-class distance and aggregate similar samples. The formula of center loss function is shown in (1) :

$$L_C = \frac{1}{2}\sum_{i=1}^{m} ||x_i - C_{y_i}||_2^2 \quad (1)$$

Where C_{y_i} represents the feature center of the y_ith class.

ArcFace Loss: The ArcFace loss function is an improvement upon the SoftMax loss function. It is a margin-based loss function that adds the margin m to the angle directly by normalizing the feature vectors and weights. This can be seen in (2):

$$L_A = -\frac{1}{N}\sum_{i=1}^{N} log \frac{e^{s(cos(\theta_{y_i}+m))}}{e^{s(cos(\theta_{y_i}+m))}+\sum_{j=1,j\neq y_i}^{n} e^{s\, cos\theta_j}} \quad (2)$$

Where θ_{y_i} the range of θ is shown in (3):

$$\theta_{y_i} \in [0, \pi - m] \quad (3)$$

Here, y_i represents the true class of sample i .

In this section, we attempt to combine the ArcFace loss function and the center loss function to create a hybrid loss function, which collectively guides the training of the network and improves the convergence speed of the model. The hybrid loss function (CA) used in this section is shown in equation (4):

$$L_{CA} = \lambda L_{\text{arcface}} + (1-\lambda) \text{L}_{\text{center}} \quad (4)$$

Here, λ represents the hyperparameter that balances the center loss function and the ArcFace loss function.

4 EXPERIMENT

4.1 DataSet

Due to the significant intra-class variations in PLAID and the presence of different brands and multiple operating conditions of loads, this section uses the PLAID dataset to construct V-I_f trajectory images for conducting experiments.

4.2 Evaluation Metrics

In this section, the accuracy metric ACC and the F1-macro are adopted to evaluate the proposed non-intrusive load identification method based on CNN_ECA-SAM_CA. A bar chart is used for comparison, providing a more intuitive representation of the model performance.

4.3 Experiment Settings

During training, the batch size is set to 10, with a total of 60 training iterations. The initial learning rate is set to 0.001 and it is decayed exponentially every 3 epochs with a decay rate of 0.9. The Adam algorithm is used as the training optimizer for the experiment. The hyperparameter λ is set to 0.95 (as defined in eq(4)).

5 RESULT

The accuracy and loss values of the proposed CNN_ECA-SAM_CA model on the validation set are shown in Figure 6 of this chapter. The horizontal axis represents the training epochs, while the left vertical axis represents the accuracy on the validation set and the right vertical axis represents the loss on the validation set. Both metrics tend to stabilize in the later stages of training.

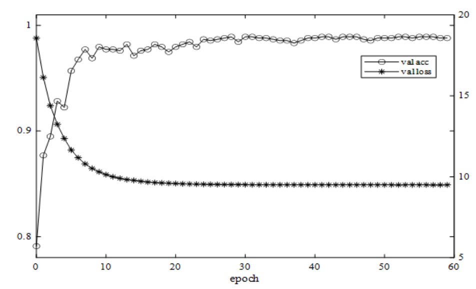

Figure 6: Validation training graph of the CNN_ECA-SAM_CA model.

In order to validate the effectiveness and feasibility of the proposed load identification algorithm based on CNN_ECA-SAM_CA, this chapter conducts ablation experiments including CNN_ECA-SAM_AL, CNN_CBAM_CA, and CNN_ECA-SAM_CA. Here, ECA-SAM represents a hybrid attention mechanism composed of ECA-Net and spatial attention mechanism, AL denotes the ArcFace loss function, CBAM represents the CBAM attention mechanism (Woo, 2018), and CA represents the hybrid loss function composed of the center loss function and ArcFace loss function. These experiments aim to demonstrate the effectiveness of the proposed hybrid attention mechanism and loss function. Additionally, a comparative experiment is designed to prove the effectiveness of V-I_f trajectory compared to V-I trajectory, as well as to compare with advanced load identification methods.

5.1 Experiment A

Conducting ablation experiments to validate the effectiveness of the designed hybrid attention mechanism and hybrid loss function

Table 1: Performance of three models on PLAID dataset-

Model	ACC	F1-macro
CNN_ECA-SAM_AL	0.9892	0.9824
CNN_CBAM_CA	0.9892	0.9828
CNN_ECA-SAM_CA	**0.9928**	**0.9890**

From Table 1, it can be seen that the comparative experiments based on the CNN_CBAM_CA and CNN_ECA-SAM_CA models are conducted to validate the effectiveness of the proposed hybrid attention mechanism. In terms of accuracy and F1-macro, the former achieves a slight decrease of 0.36% and 0.62% compared to the latter, demonstrating the effectiveness of the hybrid attention mechanism for non-intrusive load identification. Additionally, the experiments based on the CNN_ECA-SAM_AL and CNN_ECA-SAM_CA models aim to validate the effectiveness of the proposed hybrid loss function. It can be observed that, in terms of accuracy and F1-score, CNN_ECA-SAM_AL achieves a slight decrease of 0.36% and 0.66% compared to CNN_ECA-SAM_CA, indicating the effectiveness of the proposed hybrid loss function.

5.2 Experiment B

Conducting comparative experiments to validate the effectiveness of the proposed V-I_f trajectories relative to V-I trajectories.

Table 2: Results of V-If and V-I operations.

Load Features	ACC	F1-macro
V-I	0.9699	0.9530
V-I_f	0.9928	0.9890

Table 2 illustrates the accuracy and F1-macro scores of load identification based on CNN_ECA-SAM_CA in terms of V-I and V-I_f. It can be observed that load identification based on V-I_f trajectory images achieves higher accuracy and F1-macro scores compared to V-I trajectory images. This indicates that V-I_f trajectories are more suitable as features for load identification.

5.3 Experiment C

Table 3 presents a comparison of the results between the proposed model in this chapter and advanced load identification algorithms.

Table 3: Performance results of three models on PLAID dataset.

literature	methods	load feature	F1-macro
References (DE BAETS L, 2018)	CNN	Grey Verhulst-Integration (V-I) trajectory	0.7760
References (Faustine, 2020)	CNN	weighted recursive graph	0.8853
this paper	CNN_ECA-SAM_CA	V-I_f trajectory	0.9890

From Table 3, it can be observed that the proposed model in this chapter outperforms (DE BAETS, 2018) and (Faustine, 2020) in terms of the F1-macro performance metric, thus verifying the effectiveness of the proposed model.

6 CONCLUSION

In this paper, a non-intrusive load identification algorithm based on CNN_ECA-SAM_CA is proposed. It utilizes the ECA-Net attention mechanism and spatial attention mechanism, which are added to a self-designed convolutional neural network. The algorithm incorporates both the ArcFace and Center loss functions to achieve intra-class aggregation and inter-class dispersion. This solves the problem of significant intra-class variations in the load identification dataset. Through simulation experiments conducted on the PLAID dataset, it is demonstrated that this method effectively identifies appliances and performs well in identifying ambiguous appliances

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