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Review

An Overview of Non-Intrusive Load Monitoring Based on V-I Trajectory Signature

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Abstract: Non-intrusive load monitoring (NILM) can obtain fine-grained electricity consumption information of each appliance by analyzing the voltage and current data measured at a single point on the bus, which is of great significance for promoting and improving the efficiency and sustainability of the power grid and enhancing the energy efficiency of users. NILM mainly includes data collection and preprocessing, event detection, feature extraction, and appliance identification. One of the most critical steps in NILM is signature extraction, which is the basis for all algorithms to achieve good state detection and energy disaggregation. With the generalization of machine learning algorithms, different algorithms have also been used to extract unique signatures of appliances. Recently, the development and deployment of the voltage–current (V-I) trajectory signatures applied for appliance identification motivated us to present a comprehensive review in this domain. The V-I trajectory signatures have the potential to be an intermediate domain between computer vision and NILM. By identifying the V-I trajectory, we can detect the operating state of the appliance. We also summarize existing papers based on V-I trajectories and look forward to future research directions that help to promote the field's development.

Keywords: non-intrusive load monitoring; load identification; voltage–current trajectory; deep learning

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1. Introduction

Energy is the backbone of human civilization and an essential foundation for social development and progress. Secondary energy, dominated by electricity consumption, has gradually become the main form of energy consumption. Currently, electricity production mainly depends on the combustion of fossil fuels, which poses a considerable threat to the environment. In order to achieve carbon peaking and carbon neutrality, countries are accelerating the construction of new power systems with the theme of new energy. Demand-side energy management is an integral part of new power systems; however, due to the lack of fine-grained energy consumption information, it remains a challenge for individual consumers to participate in demand response. Reference [1,2] showed that fine-grained energy consumption information feedback to energy users can reduce energy by approximately 5–20%. Real-time load monitoring (LM) is considered as a good approach to obtaining valuable feedback information that helps to perform energy-saving measures and implement more effective energy management strategies, such as energy efficiency programs [3], demand side management, and peak load shedding [4].

Load monitoring includes intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM) [5,6]. ILM needs to install a sensor for each appliance, and the monitoring results of this method are relatively accurate. However, its cost is high, later maintenance is complex, and it is easy to violate consumers' privacy, making it difficult for users to accept. NILM only needs to install a sensor at the power supply entrance. The physical architecture of NILM can be seen in Figure 1. Fine-grained information about the user's power consumption can be obtained by analyzing the terminal voltage and current data. This method is low-cost, easy to implement, and easy for users to accept. Therefore, the NILM method has become a research hotspot for many researchers. NILM has two tasks: state detection, which detects changes in the electrical consumption signal due to on/off events of the concerned appliance, and energy disaggregation to estimate the energy consumption of the target appliance [7]. The performance of state detection and energy disaggregation mainly depends on the choice of appliance signatures.

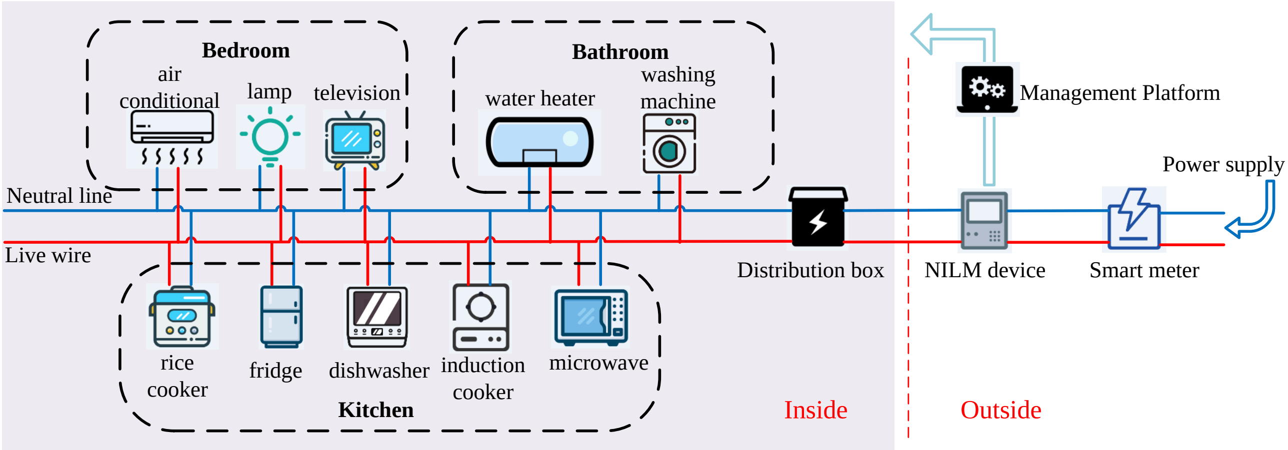


Figure 1. The physical architecture of non-intrusive load monitoring.

The algorithms of NILM are mainly divided into event-based and event-free-based [8]. Event-based methods first need to detect the switching state of the appliance and then extract the signatures of the appliance. On the other hand, event-free-based methods mainly disaggregate the total power data. Hidden Markov model (HMM)-based NILM methods are one kind of original event-free-based statistical NILM methods, which usually define multiple states for each appliance, where each state has its own probability distribution [9]. Furthermore, the formulated conditional factorial hidden semi-Markov model outperforms typical FHMMs, and the authors consider this method as a promising unsupervised approach for energy disaggregation [10]. Q. Liu et al. [11] described a low-complexity unsupervised solution inspired by a fuzzy clustering algorithm called entropy-constrained competitive clustering, and the demonstrated results show that the proposed method enables the generalization of the features and produces a set that can be considered for model learning. Recently, with the emergence of massive user data and the general improvement of hardware resources, deep learning has developed rapidly. Algorithms based on deep learning can automatically extract the signatures of appliances and classify them. Dandan Li et al. [12] propose a one-to-many model and a transfer one to-many model for multi-target energy disaggregation to improve the effectiveness and practicality of NILM. Reference [13] proposed an adaptive NILM based on feature fusion, and this paper used the V-I trajectories extracted from the BLUED dataset to train the autoencoder to extract features from the V-I trajectories of appliances. In the test, first of all, the fast Fourier transform (FFT) was used to extract the harmonic features of the appliance after dimensionality reduction in the V-I trajectory features. Then, the feature library was established by using the features of the known appliance. The distance between the samples and the templates in the feature library was calculated by the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) algorithm, and the distance was compared with the threshold to determine whether the appliance was unknown.

In recent years, with the widespread use of smart meters, the sampling frequency of data has gradually increased and the sensitivity to computing resources has decreased [14,15]. The V-I trajectory signatures are extracted based on events, and researchers are able to accurately detect appliance events from the data collected and extract the V-I trajectory signatures of appliances. Compared with other signatures, the V-I trajectory has a good discriminability. By identifying the appliances' V-I trajectory signature, the running state of the appliance can be accurately monitored, which has been widely used. Many methods based on V-I trajectory signatures have achieved great success in identifying appliance states, so researchers used different methods to construct the V-I trajectory of the appliance. With the excellent performance of machine learning in image processing results, the V-I trajectory signature has the potential to serve as the intermediate domain between computer vision and NILM. The main reason is that the V-I trajectory can be transferred to visual representation and then used in appliance recognition [16]. At the same time, using V-I trajectories can also detect unknown loads, which is of great significance to the integrity and practicability of the NILM framework. It has to be mentioned that, although the V-I trajectory signature can improve the performance in many NILM scenarios, there are some constraints for the application of the V-I trajectory signature. For example, the V-I trajectory signature requires a higher sampling frequency, which requires higher hardware conditions and data storage [17]. In addition, the extraction of V-I trajectory features depends on the detection of appliance switching events: if the event detection is not accurate, the methods will not be able to accurately identify the appliance's state [18].

The rest of this paper is arranged as follows. Section 2 mainly introduces the recent literature on NILM based on V-I trajectory. Datasets for acquiring V-I trajectories are described in Section 3. Section 4 introduces how to transfer the appliance V-I trajectory signature to visual representation. Performance metrics are listed in Section 5. Finally, Section 6 concludes this study and future work.

2. Literature Review of NILM Based on V-I Trajectory

Extracting the unique signatures of the appliance is the premise of realizing load disaggregation and identification. The load features can be divided into transient-state, steady-state, and non-traditional features [3]. Non-traditional features are often combined with traditional load features to improve the performance of load disaggregation and identification. The NILM algorithms based on steady-state analysis make use of steady-state signatures that are derived under the steady-state operation of the appliances. The transient behavior of major appliances is found to be distinct and their signatures are less overlapping in comparison with steady-state signatures; however, the major limitation is the high sampling rate requirement in order to capture the transient state [19]. These steady-state and transient-state signatures can be further subdivided, as shown in Figure 2. This section discusses the steady-state V-I trajectory signature used in the NILM system.

To comprehensively and systematically summarize the existing research on NILM based on V-I trajectory features, we searched the relevant literature on load identification based on V-I trajectory signatures in recent years. Next, we describe these literatures in detail.

H. Y. Lam et al. [20] first introduced the concept of a V-I trajectory signature, which was obtained by plotting the operating current of the appliance against the voltage. After that, the load signatures, such as the area, symmetry, and looping direction, were extracted from the V-I trajectory. After plotting the V-I trajectory, H. Y. Lam et al. [21] used the appliance signature in the form of a two-dimensional voltage–current (V-I) trajectory to characterize and classify the electrical loads. A hierarchical clustering method was employed to classify the appliances and construct the taxonomy of the appliances. The results show that the appliance classification method based on V-I trajectory shape signatures was effective for appliance classification and had engineering significance. Following this study, T.Hassan et al. [22] extended and evaluated appliance load signatures based on the V-I trajectory for the precision and robustness of prediction in classification algorithms. Nur Iksan et al. [23] identified the load by analyzing the shape of the V-I trajectory and using its characteristics. The simulation results show that using V-I trajectory signatures can assist in the identification of electrical appliances. Reference [17] presented an analysis of the performance of different appliance signatures on the classifier of the PLAID dataset. In addition, the accuracy under varying sampling rates using the V-I trajectory signatures with the same data-splitting strategy was discussed, and the results show sampling rates higher than 4 kHz provided relatively constant average accuracy results for most classifiers. Further, Liang Du et al. [24] first proposed mapping the V-I trajectories into a grid of cells with binary values. Graphical signatures can then be extracted for many appliances. This method improves the load classification performance and dramatically reduces computational costs compared to existing frequency-domain signature extraction algorithms.

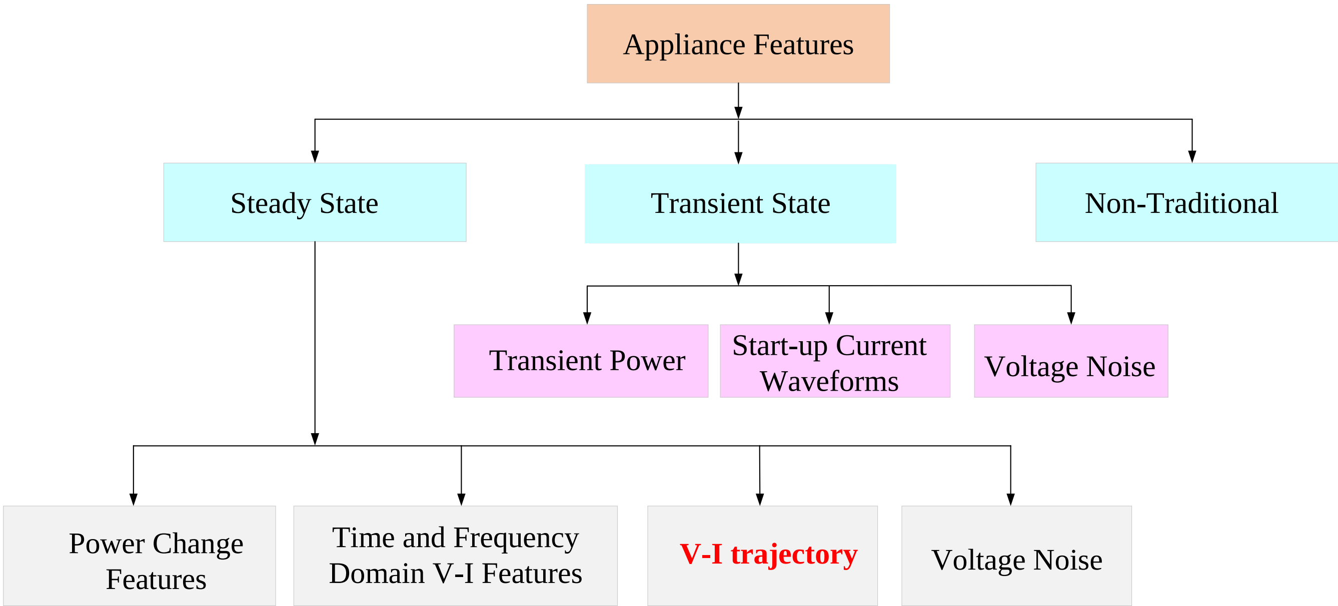


Figure 2. Taxonomy of appliance signatures for NILM.

Deep learning has been an active research field with abundant applications in pattern recognition, data mining, statistical learning, computer vision, natural language processing, etc. Many deep learning algorithms are also channeled into NILM for load identification and power disaggregation. Leen De Baets et al., in [25], used the contours of binary V-I trajectories to characterize appliances. From these contours, elliptic Fourier descriptors were computed and used as the input for neural networks outputting the appliance name. This method not only improves the prediction accuracy, but it also leads to significant storage savings compared to the original V-I trajectory image. In [26], a weighted pixelated image of the V-I trajectory was proposed as the input for a convolutional neural network that automatically extracts key features for load classification on the PLAID and WHITED datatset. The *F-measure* per appliance showed that the method give good results for a large number of appliances. Compared with the previous methods, which mainly focused on classifying the isolated V-I trajectory of a single appliance, Leen De Baets et al. [27] extracted the voltage and current data of a single appliance from the aggregated measurements by considering the difference in the current before and after the event, and validated that appliance classification using the extracted single appliance current and voltage works reasonably well. Reference [28] used a convolution neural network implemented on hardware to identify the appliance through the V-I trajectory. For the implementation on hardware, a field programmable gate array (FPGA) was used to exploit processing parallelism in order to achieve an optimal performance. Xiaomin Chen et al. [16] proposed an NILM method based on features of the V-I trajectory on the REDD dataset. First, the events were detected by the variation in the overall apparent power, and the V-I trajectory was extracted by smoothing and interpolation. Then, ten V-I trajectory signatures were quantified based on physical significance, and a support vector machine multi-classification algorithm was employed for load recognition.

Recently, with more researchers joining the research of NILM, more algorithms have been proposed to solve the problems faced by NILM. To detect unknown appliances, Leen

De Baets et al. proposed a Siamese network to map the V-I trajectories of loads to a newly learned feature space [29], and then used DBSCAN clustering to detect the V-I trajectories of unknown appliances. To further improve the identification accuracy and efficiency, reference [30] extended a set of new signatures for the V-I trajectory that was extracted in a steady and transient regime of an electrical appliance. The experimental results on the COOLL dataset show the effectiveness of the proposed features. In [31], a fast online appliance identification algorithm based on the V-I trajectory signature was proposed. A fast optimization model was established according to the similarity of appliance current waveforms. The appliance identification under the constraints of user operation and appliance signatures was realized by optimizing the switching coefficient of the template current in the library. Yanchi Liu et al. [32] proposed a transfer learning method based on the V-I trajectory to solve the problem of limited data label acquisition. Moreover, the V-I trajectory was also transferred to visual representation by color encoding, which enhanced the appliance signature's uniqueness and enabled the NILM implementation of transfer learning. Ref. [33] proposed adaptive weighted recurrence graphs blocks for appliance signature representation in event-based NILM. By transforming the activation current of one cycle into a weighted recursive graph to guarantee the uniqueness of the appliance signatures, the proposed method achieved better recognition results on LILACD and PLAID public datasets than traditional V-I-trajectory-based methods.

Lately, to solve the problem of the V-I trajectory signatures not being able to represent the energy information and the pixel utilization rate of the V-I trajectory image being low, Reference [34] added motion and momentum information to original V-I trajectory images through color encoding. Then, the active and reactive power information was discretized using the Chi2 method, and the result was added to the background's invalid pixels. Finally, the V-I trajectory was classified using a deep forest. A reconstructed V-I trajectory was proposed, and the PSO algorithm was introduced to determine the best threshold parameters to maximize the model's ability to classify, which can solve the problem of the existing V-I trajectory-based methods finding it difficult to identify similar appliances [35]. To ensure the identification accuracy of known appliances and realize the identification of unknown appliances, Zhao, Q et al. [36] proposed a V-I-trajectory-enabled deep pairwise-supervised hashing (DPSH) method for NILM. This method adopted a simple convolutional neural network for high-dimensional feature extraction. Then, to ensure the accuracy of identified appliance recognition and realize unknown appliance recognition, the method adopted a two-layer symmetric network structure and hash function learning to determine the coding rules. Therefore, the Hamming distance between the V-I trajectory codes of different known appliances was maximized to accurately recognize known appliances. This method can generate a new hash code for the unknown appliance when it appeared in the user environment. It can ensure the accuracy of the known appliance recognition while realizing the unknown appliance recognition. Yinghua Han et al. [37] proposed an asymmetric deep supervised hashing (ADSH) method based on the V-I trajectory signatures for NILM. This method used the V-I trajectory as the input for model, which solved the problems of the low calculation efficiency of massive data and low discrimination of manually extracted signatures. At the same time, hash code learning was performed with an asymmetric learning architecture; that is, for some training trajectories, high-dimensional feature extraction and hash function learning were used to determine the coding rules through a convolutional neural network model. For all training trajectories, the coding rules were directly learned to ensure that both codes were consistent in order to realize appliance recognition, which significantly improved the accuracy of appliance recognition while ensuring that the code length was small and the space complexity was reduced. To solve the problem of the label data being challenging to obtain and the V-I trajectory of the multi-state appliances being difficult to correctly identify, a semi-supervised learning method was proposed that was based on the semi-supervised teacher graph network [38]. This method made the feature distribution of the multi-state appliance more compact by constructing the teacher graph to improve the recognition results.

3. Datasets for the Study of V-I Trajectory Signature

The algorithm based on the V-I trajectory signature is mainly used to identify the switching events of the appliance correctly and, at the same time, detect the appliance's power according to the appliance's voltage and current. Therefore, the current literature predominantly uses public high-frequency datasets, mainly because the low-frequency data cannot capture the switching events of the appliance. Next, we will introduce some commonly used datasets for V-I trajectory extraction.

The REDD [39] dataset consists of whole-home and circuit/device-specific electricity consumption for seven real houses over a total period of 119 days from the US. The REDD dataset contains two main types of home electricity data: high-frequency current/voltage waveform data of the two power mains (as well as the voltage signal for a single phase) sampled at 15kHz from House3 and House5. The data are logged at a frequency of approximately once a second for the mains and once every three seconds for the circuits from House1 to House6. All file measurements are provided as generic data (DAT) files. The REDD dataset can be obtained from the website: http://redd.csail.mit.edu accessed on 23 November 2022. It can be downloaded upon requesting the logging credentials by email.

The PLAID [40–42] dataset includes current and voltage measurements for different residential appliances in Pittsburgh, Pennsylvania, USA. It has a 2014 release (PLAID 1), a 2017 release (PLAID 2), and a 2018 release. The 2014 release contains measurements for more than 200 different appliance instances representing 11 appliance types in 56 households, and a total of 1094 records collected at 30 kHz. The 2017 release contains measurements for more than 82 different appliance instances representing 11 appliance types in 9 households, and a total of 719 records collected at 30 kHz. The 2018 release contains measurements for more than 330 different appliance instances representing 17 appliance types in 65 households, and a total of 1876 records collected at 30 kHz. Additionally, 1314 records of the combined operation of 13 of these appliance types are contained in the PLAID. All file measurements are provided in CSV format. The PLAID dataset can be obtained from the website: http://www.plaidplug.com accessed on 23 November 2022.

The WHITED [43] dataset records the first 5 s of the appliances' voltage and current start-up measurements sampled at 44.1 kHz. WHITED comprises 1100 different records for 110 different appliances, which can be grouped into 47 different types (classes) in 6 different regions, and these single-phase measurements of households and industries are collected from Germany, Austria, Indonesia, and, recently, Canada. All data are saved as FLAC files. The WHITED dataset can be obtained from the website: https://www.in.tum.de/i13/resources/whited accessed on 23 November 2022.

The COOLL [44] dataset records 6 seconds of voltage and current measurements corresponding to 42 different appliances representing 12 appliance types' start-ups from a French University, where the sampling frequency is 100 kHz. Researchers performed measurements using an acquisition system coupled with an additional control system, allowing for the precise control of the turning on and turning off of appliances. As a result, 20 different energy consumption variations for each appliance were captured. The COOLL dataset contains 1680 ".flac" files (840 current and 840 voltage measurement instances) representing current and voltage measurements. All data are provided in FLAC format. The COOLL dataset can be obtained from the website: https://coolldataset.github.io accessed on 23 November 2022.

The LILACD [45] dataset measures the electricity consumption of three-phase and single-phase industrial appliances from Germany, where the voltage and current are sampled at 50 kHz. The dataset contains 15 different types of loads, resulting in a total of 1302 measurements: 381 for a single appliance, 864 for a combination of two appliances, and 56 for a combination of three appliances. All measurements are provided in TDMS format. The LILACD dataset can be obtained from the website: https://www.in.tum.de/i13/resources/lilacd accessed on 23 November 2022.

The BLUED [46] dataset collects single-phase voltage and current measurements at the main panel and separate appliance channels for a whole week in Pittsburgh, Pennsylvania. The sampling frequency of the collection system is 12 kHz, and there are approximately 50 appliances in the household. Once all of this was completed, there was a total of 2355 events labeled in the dataset. All data are provided in TXT and MAT formats. The BLUED dataset can be obtained from the website: http://nilm.cmubi.org accessed on 23 November 2022.

4. V-I Trajectory Extraction

The basic implementation framework of NILM is shown in Figure 3. First, NILM needs to obtain the user's terminal voltage and total current measurements or total power consumption data and extract the corresponding to signatures, and then detect the switching events of the appliance and extract appliances' signatures to train the NILM model, which establishes the mapping relationship between the signatures and the appliance operating state. Among them, the weather data and appliance signature libraries can help to improve the performance of the model. Appliance identification or energy disaggregation results could be communicated to grid companies and electricity consumers.

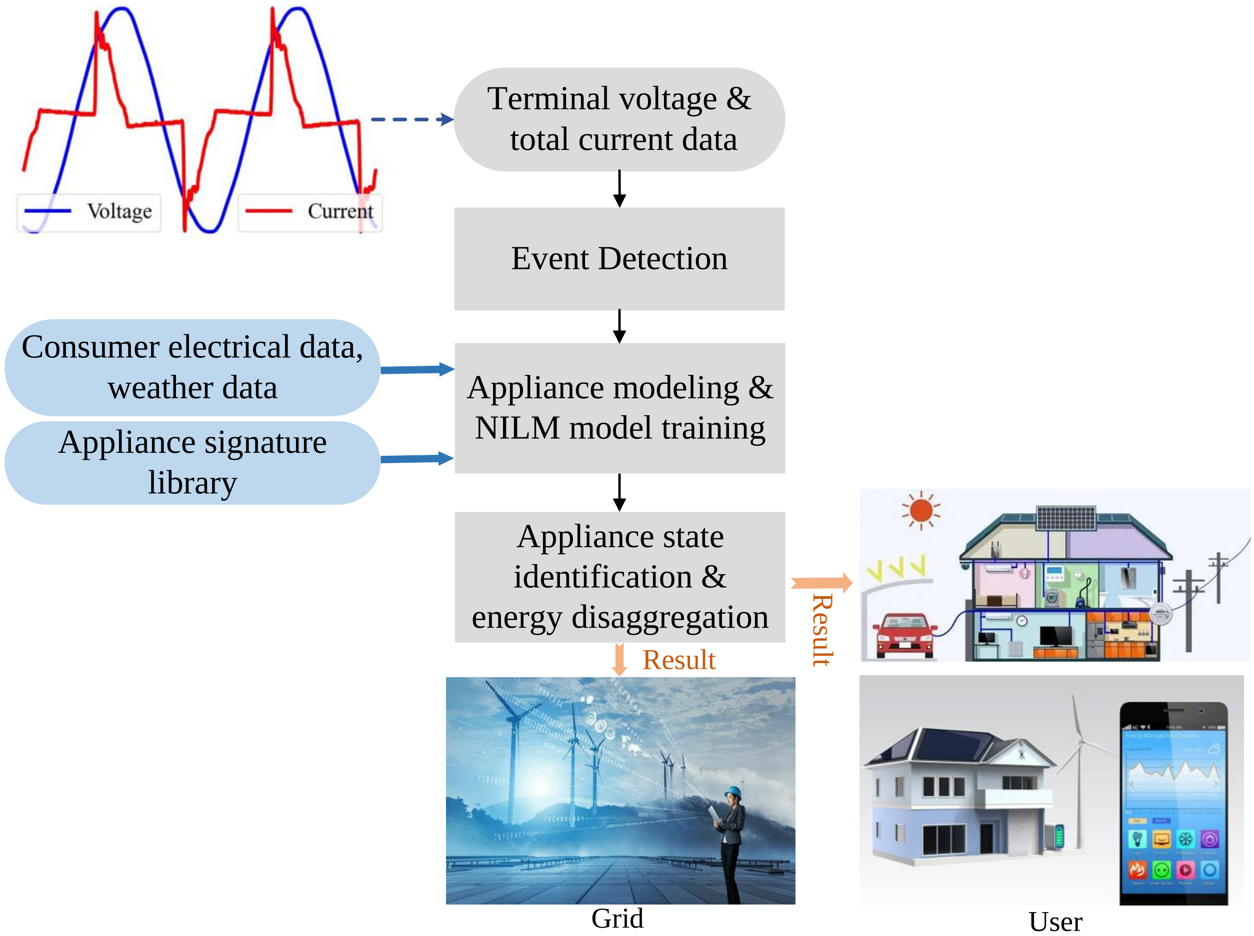


Figure 3. Typical event-based NILM framework.

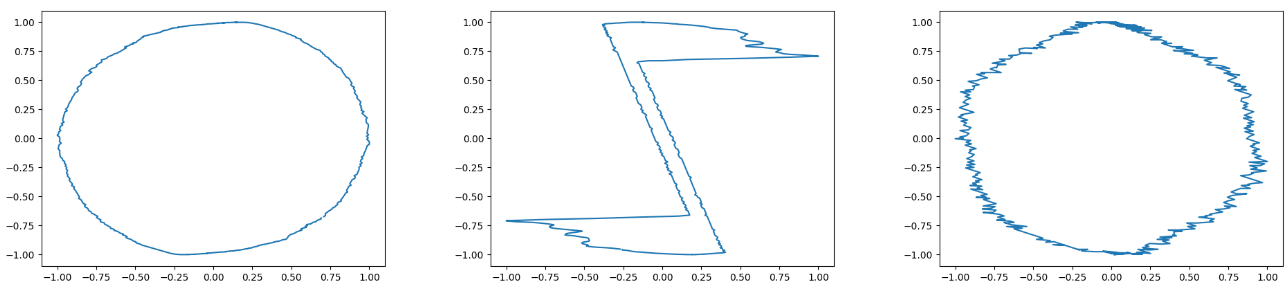
As described in the previous literature, the classification algorithm based on the V-I trajectory signatures can accurately detect the switching events of the appliance. To extract the V-I trajectory of each appliance, we assume that only one appliance switches state at one moment and extract the total voltage and current values before and after the event, marked as V_{on}, V_{off}, I_{on}, and I_{off}, respectively. Then, the steady state current and voltage values of the appliance where the switching event occurs can be calculated using the following formula [16,32]:

$$V = (V_{on} + V_{off})/2 \quad (1)$$

$$I = (I_{off} - I_{on}) \quad (2)$$

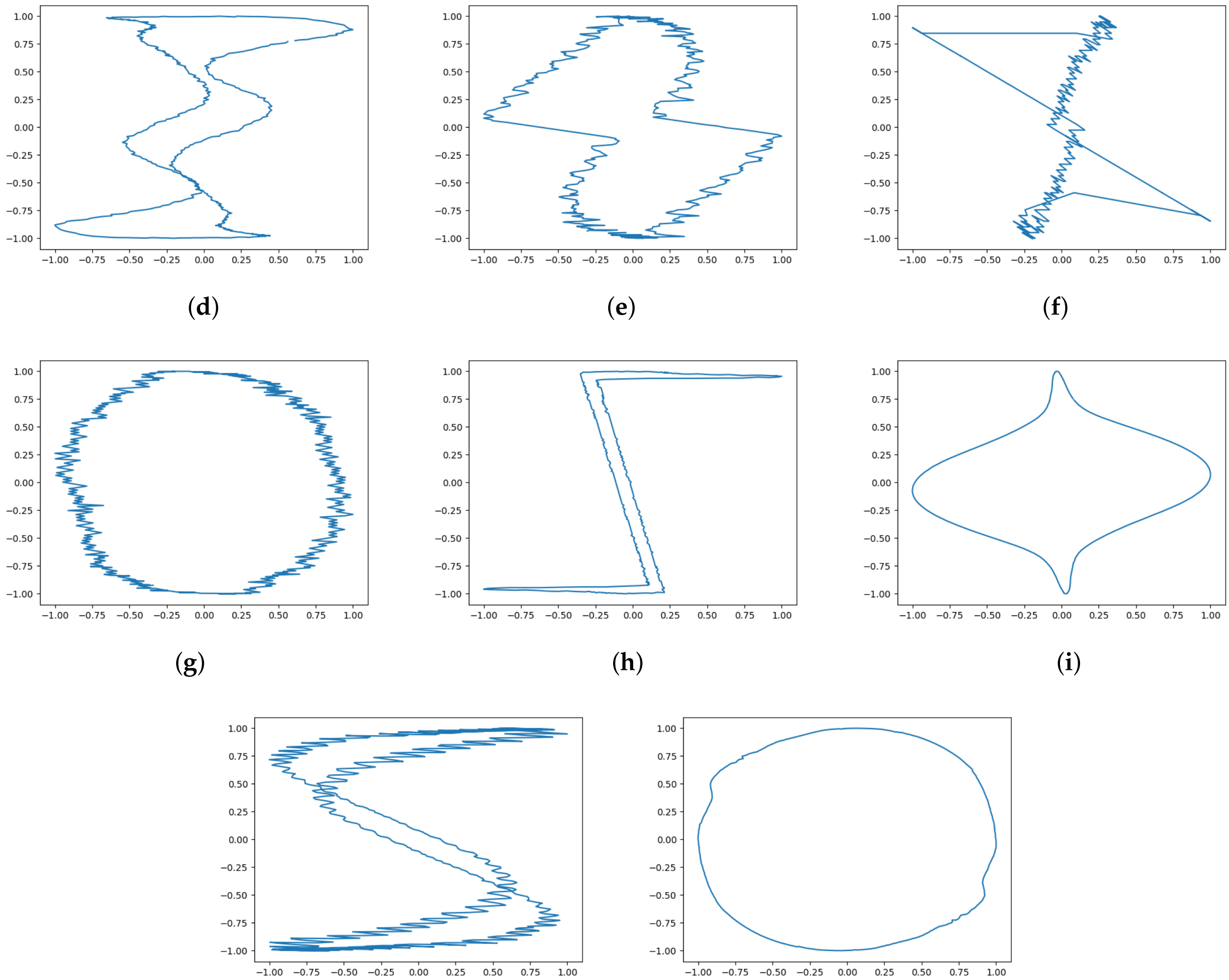
According to the voltage and current data of the load, a two-dimensional V-I trajectory image can be plotted.

The V-I trajectory features of loads can be visualized for an easy understanding. We draw some appliances' V-I trajectory images on the PLAID dataset, as shown in Figures 4–6. As we can see, Figure 4 shows the original V-I trajectory image. We normalize the voltage and current so that the trajectories of all appliances have the same scale. For each appliance, the one-cycle-long steady-state voltage and current are used to plot the V-I trajectory. The shape signatures can be preliminary defined to describe the shapes of the trajectories. The shape signatures contain asymmetry, the looping direction, the area, the curvature of the mean line, self-intersection, the slope of the middle segment, the area of the left and right segments, and the peak of the middle segment [16,21]. Figure 5 is a binary V-I trajectory image, which is one channel. We converted the amplitude-normalized V-I trajectories into binary images by setting up a $w \times w$ mesh on the raw V-I trajectories and making each cell 1 if there exist points within it, and 0 otherwise. In Figure 5, the w was set to 16, and the V-I trajectory mainly includes the appliances' shape signatures. Some researchers recently input binary V-I trajectories directly into deep neural networks, transformed the original data into higher-level and more abstract signature expressions through some simple nonlinearities, and then identified the appliance. The artificial neural network automatically extracts the signature extraction in the deep learning method. In contrast, the deep learning method not only has lower requirements for signature extraction and does not need the participation of experts but also has less human intervention, and the signature extraction itself is more comprehensive. To make the V-I trajectory image contain unique information about the appliance and facilitate the classification of the appliance [32], more appliance information is added to the V-I trajectory image to form three-channel V-I trajectory images, as shown in Figure 6. We calculated the pixel values of the three channels of the V-I trajectory according to the voltage and current values of different appliances, and then drew the color V-I trajectory images of different appliances, which were then identified by the deep learning algorithm. As a result, they are unique and can better identify appliances.



(**a**) (**b**) (**c**)

Figure 4. *Cont.*

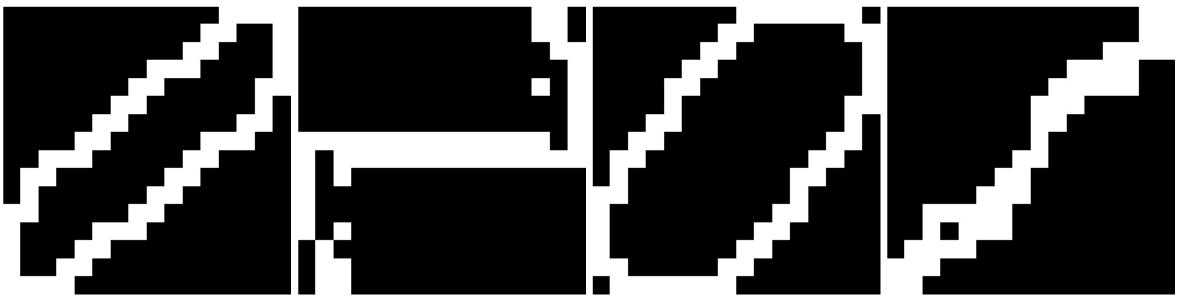


(**d**) (**e**) (**f**)

(**g**) (**h**) (**i**)

(**j**) (**k**)

Figure 4. The generated original images of (**a**) air conditioner, (**b**) compact fluorescent lamp, (**c**) fan, (**d**) fridge, (**e**) hairdryer, (**f**) heater, (**g**) incandescent light bulb, (**h**) laptop, (**i**) microwave, (**j**) vacuum, and (**k**) washing machine for PLAID dataset.



(**a**) (**b**) (**c**) (**d**)

Figure 5. *Cont.*

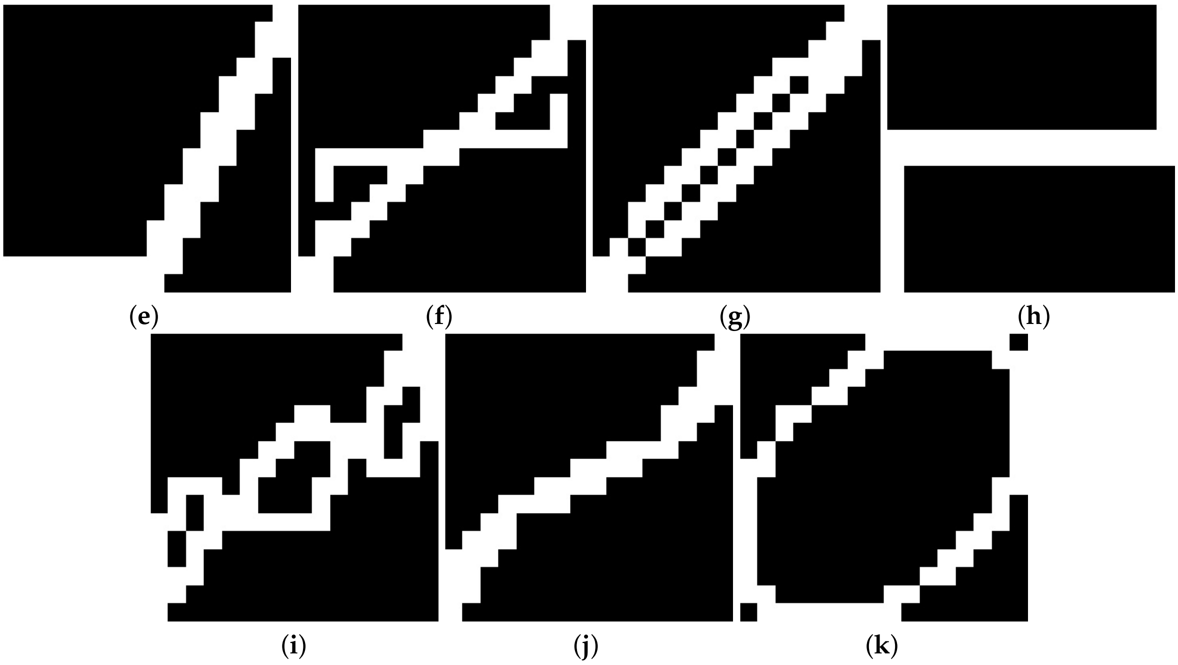


Figure 5. The generated binary images of (**a**) air conditioner, (**b**) compact fluorescent lamp, (**c**) fan, (**d**) fridge, (**e**) hairdryer, (**f**) heater, (**g**) incandescent light bulb, (**h**) laptop, (**i**) microwave, (**j**) vacuum, and (**k**) washing machine for PLAID dataset.

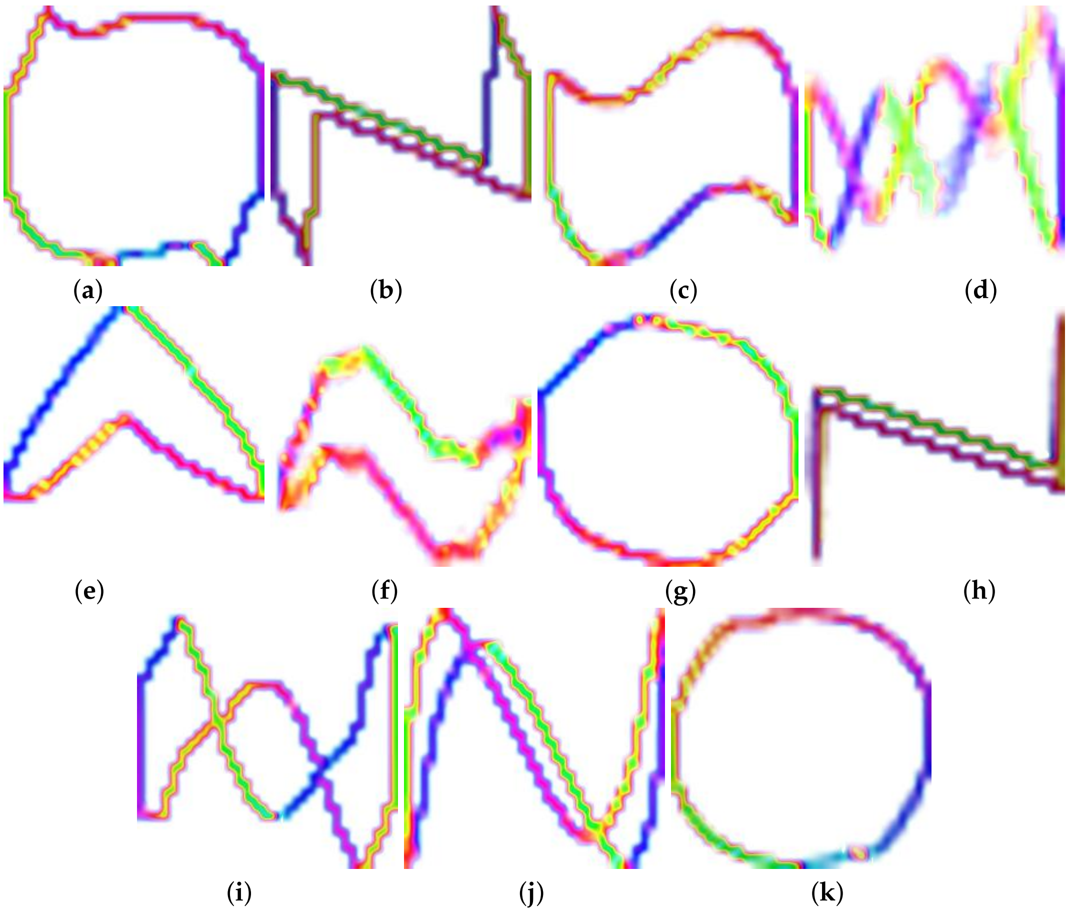


Figure 6. The generated color images of (**a**) air conditioner, (**b**) compact fluorescent lamp, (**c**) fan, (**d**) fridge, (**e**) hairdryer, (**f**) heater, (**g**) incandescent light bulb, (**h**) laptop, (**i**) microwave, (**j**) vacuum, and (**k**) washing machine for PLAID dataset.

5. Performance Metrics

The appliance identification of a specific V-I trajectory image is a binary classification problem. The classification prediction labels are divided into target appliance labels (correct prediction) and other appliance labels (prediction errors). The goal of load identification is to accurately identify more target load V-I trajectory images and avoid misjudging other appliance V-I trajectory images as target appliances as much as possible. The confusion matrix is a standard tool for the overall performance evaluation of binary classifier models. As shown in Table 1, the confusion matrix shows all possible classification results of the binary classifier, in which the row indicates the category that the V-I trajectory image belongs to, and the column indicates whether the V-I trajectory image predicted by the classifier belongs to the target appliance or other appliance.

Table 1. Confusion matrix applied in load identification.

Reference	**Prediction**	
	Positive	**Negative**
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

In the table, True Positive (TP) indicates the number of true classes. The real class of the sample is a positive class, and the result of model identification is also a positive class. False Negative (FN) indicates the number of false negative classes. The real class of the sample is positive, but the model identifies it as negative. False Positive (FP) indicates the number of false positive classes. The real class of the sample is negative, but the model identifies it as positive. True Negative (TN) indicates the number of true negative classes. The true class of the sample is negative, and the model identifies it as such.

According to the confusion matrix, multiple evaluation indicators can be deduced: *Precision*, *Recall*, and F1 score (*F*1-*score*). The details are as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1\text{-}score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{6}$$

The $F1$-*score* measures the overall *accuracy* of the load identification algorithm and is a weighted average of *Precision* and *Recall*. The larger the value of $F1$-*score*, the higher the identification accuracy of the appliance and the better the identification performance.

$$F_{macro} = \sum_{i=1}^{N} F_{1,i} \tag{7}$$

where F_{macro} is the average of $F1$-*score* scores of all of the appliances. N is the number of appliances in the dataset and $F_{1,i}$ is the $F1$-*score* score of the ith appliance.

We conclude the current algorithm for load identification based on V-I trajectory features in Table 2, where the publication year of the paper, the datasets used, the number of types of appliances, the frequency of datasets, and the evaluation metrics and performance are listed. It can be observed from Table 2 that the results of the load identification algorithm based on the V-I trajectory signatures are increasing, mainly because the V-I trajectory contains more and more appliances' signature information due to the application of machine learning algorithms on the V-I trajectory classification. These results can meet the needs of practical NILM.

Table 2. Existing methods for load identification based on V-I trajectory features.

Methods	Year of Publication	Dataset	Frequency	Number of Appliances	Metrics	Performance
[20]	2006	-	-	-	-	-
[21]	2007	-	-	-	-	-
[22]	2013	REDD	16.5 kHz	22	Precision	0.909
[17]	2015	PLAID	30 kHz	11	Accuracy	0.8603
[23]	2015	REDD	16.5 kHz	22	Accuracy	0.9134
[24]	2016	private	30.72 kHz	23	Accuracy	0.99
[25]	2017	PLAID	30 kHz	11	Accuracy	0.8175
[26]	2018	PLAID	30 kHz	11	F-measure	0.7760
[26]	2018	WHITED	44 kHz	22	F-measure	0.7546
[27]	2018	PLAID(2018)	30 kHz	12	F-measure	0.8795
[28]	2018	PLAID	30 kHz	11	F-measure	0.7816
[16]	2018	REDD	16.5 kHz	22	F-measure	0.9643
[29]	2018	PLAID	30 kHz	11	RI	0.996
[29]	2018	WHITED	44 kHz	22	RI	0.879
[30]	2019	COOLL	100 kHz	42	Accuracy	0.99
[31]	2019	BLUED	20 kHz	22	Accuracy	0.90
[31]	2019	Laboratory data	-	12	Accuracy	0.90
[32]	2019	PLAID	30 kHz	11	F-macro	0.9540
[32]	2019	WHITED	44 kHz	54	F-macro	0.9866
[33]	2020	PLAID	30 kHz	12	F-macro	0.9777
[33]	2020	LILACD	50 kHz	16	F-macro	0.9833
[34]	2021	PLAID	30 kHz	11	Accuracy	0.985
[35]	2021	PLAID	30 kHz	11	F-macro	0.9736
[35]	2021	IDOUC	30 kHz	23	F-macro	0.9878
[36]	2021	REDD	16.5 kHz	10	F-macro	0.984
[36]	2021	PLAID	30 kHz	6	F-macro	0.969
[37]	2021	REDD	16.5 kHz	10	F-macro	0.974
[37]	2021	PLAID	30 kHz	6	F-macro	0.961
[38]	2022	PLAID	30 kHz	11	F-macro	0.928
[38]	2022	WHITED	44 kHz	54	F-macro	0.9838

6. Conclusions

NILM can provide fine-grained data for appliances and is an effective means for power grid companies and users to obtain the appliance operating status and energy consumption information at a low cost. In this paper, these state-of-the-art load identification methods based on the V-I trajectory signature in NILM were analyzed and discussed in detail. First, the existing literature was surveyed and analyzed separately. Then, dataset selection, V-I trajectory signature extraction, and evaluation metrics based on the V-I trajectory were analyzed in detail.

Given the current analysis of V-I trajectory signature extraction and classification, these methods based on the V-I trajectory still have open work:

1. At present, the V-I trajectory is obtained by normalizing the voltage and current data, which leads to the lack of energy information.

2. An appliance with continuously varying power is difficult to be represented by the V-I trajectory; examples are dimmers and tools.
3. When a new appliance is added, or the appliance works abnormally, it is necessary to detect these abnormal V-I trajectories.
4. Due to the difficulty in obtaining high-frequency data and the expensive data storage, it is necessary to reduce the necessary number of training data.
5. How to obtain the power consumption information of an appliance through the identification of the V-I trajectory is still an open work.

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