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Non-intrusive load monitoring algorithm based on features of V–I trajectory

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ABSTRACT

Non-intrusive load monitoring (NILM) can monitor the status of electrical appliances on-line and provide detailed power consumption data, which is the basis for customers to perform energy usage analyses and electricity management. The voltage–current (V–I) trajectory can be used as a load signature to represent the electrical characteristics of appliances with different statuses. Therefore, this paper proposes an NILM algorithm based on features of the V–I trajectory. The variation in the overall apparent power was used as the criterion of event detection, and the delta of the V–I trajectory was extracted by smoothing and interpolation. Then, ten V–I trajectory features were quantified based on physical significance, which accurately represented those appliances that had multiple built-in modes with distinct power consumption profiles. Finally, the support vector machine multi-classification algorithm was employed for load recognition. We tested the proposed algorithm on both the REDD database and laboratory data. The numerical results demonstrate that the algorithm has higher accuracy than the algorithm using other load features.

1. Introduction

The advanced metering infrastructure (AMI) [1] is a comprehensive system for measuring, collecting, storing, analyzing and using customer information. A smart meter is used in the AMI to obtain customers' electricity consumption information and upload it to the data center via the communication network. This allows customers to view their own real-time electrical situation and enables two-way information flow between the power grid and users. Load monitoring is one component of the AMI. This technology disaggregates the aggregated electricity consumption data into the power consumption of individual appliances, and analyzes the corresponding electricity data, which can be applied to electricity management, energy saving, equipment fault diagnosis, and power demand response [2–4].

Intrusive load monitoring requires the installation of sensors on each appliance to measure electricity consumption. Although it can perform high-precision monitoring, it also leads to high installation costs [5,6]. Non-intrusive load monitoring (NILM) [7] offers detailed electrical information of individual appliances without changing the customer's existing circuit structure. This method has the advantages of low installation cost, little interference with users, and flexible application, and therefore, the method can be widely used in various fields.

Load signatures are the electrical behavior of an individual appliance when it is in operation. The NILM algorithm uses different load signatures to extract features for load recognition. Hart [6] first proposed using the variation of power as load features. The features were easy to extract, and the accuracy could reach 80%; however, the recognition accuracy will be greatly reduced for appliances with similar power consumptions. Furthermore, the steady-state load features, such as current harmonics [8], power harmonics [9,10] and current waveforms [11–13], are employed in NILM. In Ref. [13], the author transformed the steady-state current waveform via stationary wavelet transformation (SWT) and then used the Burg spectrum to identify the maxima at each level of the spectrum of the SWT decomposition to obtain the features of the current waveform. In Ref. [14], the authors used higher-order statistics combined with Fisher's discriminated analysis and genetic algorithms to extract a low-dimensional, representative feature vector from the load current signal. Steady-state load signatures are less disturbed by noise, but the similarity of load signatures increases with the expansion of load types. The wavelet transform [15] and S-transform [16] were employed to extract the transient load signatures, such as the transient voltage [17] and transient current [18]. Ref. [19] additionally obtained more load information by extracting the power spectrum of the transient current waveform to increase the difference among the load features. The use of transient signatures

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can improve the accuracy of load recognition because transient signatures have a shorter duration and differ for every appliance. However, the transient load signature extraction requires a high sampling frequency and large data storage capacity, resulting in an increased cost of hardware equipment. Moreover, the transient process of an appliance is affected by voltage fluctuations in the power grid and the aging of the appliance, leading to fluctuations in the transient signatures. The NILM algorithm for load recognition using a single power feature has also been studied. For example, Ref. [20] used active power to represent the load features, and the factor hidden Markov model (FHMM) was used to construct the household power consumption model. Disaggregated power was evaluated using the particle filter method. In Ref. [21], the author proposed the method of graph signal processing using the amount of change in active power for event classification and the features in the database to identify and label the event. More importantly, the development of AMI allows users to participate in NILM, providing appliance information and gradually forming a common database. Therefore, that appliance feature can be directly obtained through the smart meter from the existing database for modeling and training appliances. In Ref. [22], the author applied NILM to the household based on the smart meter infrastructure. The user sends the appliance information (active power in different states, etc.) and registers it to the database in the service provider via the smart meter. The service provider then establishes the hidden Markov model (HMM) for that household.

The voltage–current (V–I) trajectory is plotted based on the steady-state voltage and current, and it is used to express appliances' electrical characteristics. High-order harmonic characteristics, the phase angle difference between voltage and current, and the electronic appliance conduction characteristics can be obtained by calculating the V–I trajectory features, as detailed in Refs. [23–25]. In Ref. [23], the authors selected the multi-classifier parameters by using an enhanced variant of the differential evolution and compared the disaggregation accuracy with the different classifier selections. In Ref. [24], the authors selected eight trajectory characteristics and used hierarchical clustering for the load classification. The results demonstrated that trajectory features yielded higher classification accuracy than the traditional current eigenvector approach. The physical meanings of the trajectory have been illustrated in the literature; however, an approach to quantifying the trajectory features has not been defined. Therefore, this paper extracts the V–I trajectory of individual appliances based on the event. According to the analysis of the physical meaning of the trajectory features, an approach to quantifying ten trajectory features is proposed, and support vector machine (SVM) multi-classification algorithm is adopted for load recognition.

The main aspects of this paper are as follows: (1) proposing a V–I trajectory extraction approach based on the steady-state data before and after an event. The number of trajectory features is expanded, and ten trajectory feature quantization approaches are presented. (2) The algorithm is tested with the data in both the REDD database and laboratory data, and the results are compared with other algorithms that select the transient waveform and variation of the active power and the active and reactive power (PQ) in both the time and wavelet domains as load features.

The remainder of this paper is organized as follows. In Section 2, the NILM framework is reviewed. Section 3 introduces the event detection process. The V–I trajectory and its feature extraction approach are defined in Section 4. Section 5 describes the SVM multi-classification algorithm used for load recognition. Experimental studies are reported in Section 6. Finally, the conclusions are given in Section 7.

2. NILM framework

The basic steps in NILM are as follows (as shown in Fig. 1):

1) Data acquisition and processing: electrical data, including current, voltage, and power data, are obtained from a smart meter, and then, the raw data are de-noised.
2) Event detection: The state-switching process of an appliance over a certain period of time is an event. The occurrence of an event is accompanied by variations in power and current, and it is typically detected by comparing the variation in the electrical data during that duration with a predetermined threshold.
3) Feature extraction: The load features can be extracted based on the load signatures using different algorithms (e.g., Fourier transform). The load features provide load signature information from a numerical perspective to distinguish different appliances and are typically expressed in the form of vectors, the dimensions of which are determined by the number of features.
4) Load recognition: The load recognition process matches the load features with the features in the database and then obtains the appliance switching mode in the database corresponding to the current event.

3. Event detection

The apparent power continues to change during the appliance state transition. Fig. 2 illustrates the apparent power change while an appliance is started. The main part of that appliance is a motor, which starts with the impulse current. Take Fig. 2 as an example to illustrate the method of event detection. The step size is set to R ($R = 1$ s in this paper), and the apparent power at t s is S_t. If $\Delta S_t > S_{\mathrm{on1}}$ (at 4 s in Fig. 2), where $\Delta S_t = S_{t+1} - S_t$, the event detection begins and continues to calculate $\Delta S_{t+1}, \Delta S_{t+2} \ldots$, until $\Delta S_{t+d} < S_{\mathrm{on2}}$. If $S_{t+d} - S_t < S_{\mathrm{on2}}$, it is assumed that the device has a state transition at $t \sim t+d$ s where the event process start time t_{on} is t s, and the event process end time t_{off} is t + d s. d represents the duration of the event. The event detection is summarized by (1). t_{on} and t_{off} determine the sampling time of the voltage and current waveform for extracting the V–I trajectory in next section, so event detection is an indispensable step for V–I trajectory extraction.

$$\begin{aligned} &|\Delta S_t| \geq S_{\mathrm{on1}} \&\& |\Delta S_{t+1}| \geq S_{\mathrm{on1}} \&\& \ldots \&\& |\Delta S_{t+TR-1}| \geq S_{\mathrm{on1}} \\ &\&\& |\Delta S_{t+TR}| < S_{\mathrm{on1}} \&\& |\Delta S_{t+TR+1}| < S_{\mathrm{on1}} \&\& |S_{t+TR} - S_t| \geq S_{\mathrm{on2}} \end{aligned} \tag{1}$$

4. V–I trajectory features

4.1. Trajectory extraction

The quantization process of trajectory features is a numerical operation of the points on the trajectory; thus, the accuracy of the trajectory data will have a direct effect on the feature extraction and load recognition process. The existing literature does not discuss the trajectory extraction approach. However, in cases in which the meter sampling frequency is limited and the raw data contain noise, it is necessary to process the voltage and the current data before plotting the trajectory.

Consider a cycle of voltage and current waveform data per second during T seconds before t_{on} and T seconds after t_{off}. VV_{on}, VV_{off}, II_{on}, and II_{off} represent the voltage and current data sets in T cycles (seconds) before and after the event, respectively. Since the extraction of the V–I trajectory needs to operate on different cycles of voltage and current waveforms, the initial phase angle of VV_{on}, VV_{off}, II_{on}, and II_{off} in each cycle must be the same. In this paper, the fundamental voltage phase angle is taken as the reference to ensure that. Taking a cycle of voltage waveform data per second for