A Triple-threshold-based Load Event Detection Algorithm for Non-intrusive Load Monitoring

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Abstract. Event detection is an important foundation of non-intrusive load monitoring algorithm. In this paper, the common household appliance load events are classified, and a new triple-threshold event detection algorithm is proposed aimed at solving the problems of false detection and missing detection in the practical application. Firstly, a low power threshold is used to realize high-sensitive detection of the load events, and secondly the detected events are spliced according to the time threshold to get the complete events. Thirdly, the high threshold is used to discriminate the complete event set to filter out the disturbance caused by load fluctuation. Finally, the results are modified with a correction logic. The test results carried with static data show that, the algorithm proposed in this paper is more accurate for positioning the time of putting into and cutting off load, which is conducive to improve the accuracy of transient interval interception of load events, and has advantages in detecting slow rising load events. In addition, the algorithm proposed in this paper has a small amount of calculation, which can meet the requirements of application in the hardware of smart meter.

1. Introduction

Non-intrusive load monitoring (NILM) is a new technique to obtain residential power consumption details. This technique uses smart meter sampling data, applies signal analysis and machine learning algorithm, so that it can obtain some information such as start-up and stop time, energy consumption and usage rule of electrical appliances[1,2]. The implementation steps of NILM generally include data acquisition, data processing, event detection, feature extraction, and load classification[3]. The specific details of each step are as follows: a) data acquisition is used for digital sampling of analog voltage and current signal; b) data processing is used to calculate root mean square (RMS), power, harmonic and other electrical parameters; c) event detection is used to detect electrical switch or state switching events from data sequence; d) feature extraction and load classification have a strong correlation and are used to assign categories to the detected electrical appliances. In the above steps, event detection is the most important. Almost all NILM algorithms need to distinguish the steady-state and transient sections before and after load switching by event detection. On this basis, the subsequent calculation is performed. Event detection algorithm has a great influence on the performance of NILM algorithm, even determines the success or failure of the design of NILM algorithm.

There are many research results about load event detection algorithm. In the Ref. [4], a sliding window based cumulative sum (CUSUM) algorithm is proposed, which can effectively detect load switching events. In the Ref. [5], the research results of load event detection algorithm , including multi
decision fusion [6], pattern recognition [7], improved Canny algorithm [8], wavelet transform [9], etc, are fully summarized. On this basis, a method combining adaptive Gaussian filter with CUSUM is designed, which is called improved CUSUM algorithm. By introducing Gaussian filter, the value of $\beta$ in the Ref. [4] is reduced, so as to improve the detection accuracy. In the Ref. [10], a sliding window event detection algorithm based on power variance judgment, called two-step variance method, is proposed. This algorithm can determine the switching time of electrical appliances and avoid the interference of system noise and small power fluctuation. The above algorithms have follow problems in practical application: a) The detection rate of bilateral CUSUM for slow varying load events is low, and its anti-noise performance is insufficient; b) The improved CUSUM improves the noise immunity, but it has no obvious effect on the detection of slow varying load. Moreover, if the value of $h$ in the Ref. [5] is increased, the transient process interception time error will be increased; c) The two-step variance method is not suitable for complex appliance load mode transformation, and it can not detect slow varying load events. In practical application, there are many slow varying loads, and the typical load is variable frequency air condition. The existing event detection algorithms have the problem of missing detection when dealing with variable frequency air condition.

In order to solve some problems of event detection algorithm in practical application, this paper proposes a new idea of load event detection. Firstly, low threshold is used to detect load events with high sensitivity, and then load events are spliced according to time threshold. Finally, high threshold is used to screen effective load events, which can ensure the detection performance of conventional load events and detect slow varying load events accurately. Simulation results show that, compared with the existing algorithms, the proposed method improves the detection accuracy of conventional load events, and significantly improves the detection accuracy of slow varying and impact events.

2. Classification of residential load events

Residential power load event detection is essentially the problem of data sequence change point detection. In this paper, the power sequence is used as the object of load event detection. With the development of economy and technology, there are many kinds of household appliances, and their working characteristics and start stop characteristics are very different. In this paper, the different load events are classified firstly.

2.1 Step-type load event

This kind of event is mainly caused by the switching of pure resistive electrical appliances in the family, and the power curve is similar to the step function, such as electric kettle, electric water heater, electric rice cooker, electric radiator, etc. The Fig.1 shows the measured power curve when the electric kettle is turned on.

![Power curve of the electric kettle](image)

Figure 1: Power curve of the electric kettle

It can be seen from the Fig.1 that the step-type load event has two main characteristics: a) the power fluctuation before and after load event is small, generally less than 10W; b) the transient time of switching on and off is very short, which generally does not exceed 60ms.
2.2 Impact load event
This kind of event is mainly caused by electrical appliances with compressor or motor, such as air conditioner, vacuum cleaner, refrigerator, etc. The Fig.2 shows the measured power curve when the vacuum cleaner is turned on.

![Figure 2: Power curve of the vacuum cleaner](image)

It can be seen from the Fig.2 that the impact load event has two main characteristics: a) there is a large impulse after the load is put into operation, and the peak power is usually several times or even tens of times of the steady-state power; b) the impact time is short, and the time width of the impact peak is about 0.2S to 0.6s.

2.3 Slow rising load event
This kind of event is mainly caused by electrical appliances with inverter components, such as induction cooker and variable frequency air conditioner. The starting is a long-lasting power rising process, and the duration is related to the control strategy. The measured starting power curves of induction cooker and variable frequency air conditioner are respectively shown in the Fig.3 and Fig.4.

![Figure 3: Power curve of the electromagnetic furnace](image)

![Figure 4: Power curve of the inverter air conditioner](image)

It can be seen from the Fig.3 and the Fig.4 that the duration of slow rising load events is generally several seconds or even minutes, and it is accompanied by a small amplitude of power fluctuation in the process of power rising, showing a saw-tooth shape.
3. Principle of triple-threshold load event detection algorithm

In view of the shortcomings of the existing algorithms for load event detection, the basic idea of the triple-threshold algorithm proposed in this paper is to divide event detection into three steps: a) detect mutation events using low threshold, and consider the small load fluctuation as a part of load events; b) splice the abrupt events according to the time threshold, that is, the load events in a short time are considered to be a transient process; c) pick up the effective load events using high threshold, so as to filter out the disturbance caused by load fluctuation. Taking the event of putting load into operation as an example, the algorithm implementation steps are described in detail.

3.1 S1: detecting mutation point using low threshold

According to the sampling data of current and voltage, the power value is calculated and the power sequences are obtained. The sliding window sequence located at power point \( i_P \) is notated as

\[
SW_i = \{SW^\text{pre}_i, P_i, SW^\text{post}_i\}
\]

(1)

Where, \( SW^\text{pre}_i \) is defined as forward window, and \( SW^\text{post}_i \) is defined as backward window, which represent the power sequence with width \( w \) before and after \( P_i \) respectively. \( SW^\text{pre}_i \) and \( SW^\text{post}_i \) are defined as

\[
\begin{align*}
SW^\text{pre}_i &= \{P_{i-w}, P_{i-w+1}, \ldots, P_{i-1}\} \\
SW^\text{post}_i &= \{P_{i+1}, P_{i+2}, \ldots, P_{i+w}\}
\end{align*}
\]

(2)

The low threshold \( LOW_{\text{thr}} \) is used to detect whether \( i_P \) is a mutation point. The discriminant is

\[
\Delta P = \mu(SW^\text{post}_i) - \mu(SW^\text{pre}_i)
\]

(3)

Where, \( \mu(\cdot) \) represents the mean function. If \( \Delta P > LOW_{\text{thr}} \), then \( P_i \) is considered as a mutation point. Assuming that the power point \( P_i \) is a mutation point, the close set composed of the index of the power sequence number of the sliding window is

\[
D_{up}(i) = [i-w, i+w]
\]

(4)

In the first step, setting a low threshold can help to improve the sensitivity of event detection and minimize missed detection, but it will inevitably lead to the problem of detecting additional events, which need to be solved by event splicing.

3.2 S2: splicing events using time threshold

For a slow rising load event, the transient process will last for a long time. Because of the low threshold, more than one event are inevitably detected out. Therefore, it is necessary to splice these events into one event according to the time threshold. As shown in the Fig.5, in the whole start-up process of a variable frequency air conditioner, several mutation points will be detected out in multiple sliding windows. That is to say, more than one event will be detected out in the start-up process. In the second step, these additional events will be spliced into one event.

**Figure 5** Power curve of the inverter air conditioner

In the Fig.5, the ith and jth sliding windows are taken as examples to illustrate the load event splicing process. The set formed by the index of the ith sliding window is denoted as \( D_{up}(i) \). If
upDi D j \neq \varnothing$, then it is considered that the ith and jth sliding windows are in the transient process of the same load event. The discriminant is as follows

$$\Delta T = j - i - 2w$$  \hspace{1cm} (5)

The time threshold is set to $TIME_{thr}$. If $\Delta T \leq TIME_{thr}$, then the load mutation points detected in the two sliding windows are considered to belong to the transient process of the same event. Merge $D_{up}(i)$ and $D_{up}(j)$ into a closed set:

$$D_{event}(i) = [L(i), R(i)]$$ \hspace{1cm} (6)

Where, $D_{event}(i)$ is the ith load event, $L(i)$ and $R(i)$ are

$$\begin{align*}
L(i) &= i - w \\
R(i) &= j + w
\end{align*}$$ \hspace{1cm} (7)

After the step of event splicing, all power mutation points detected in the same long transient process will be spliced into the same event. Finally, the sequence of events obtained is $(D_{event}(1), D_{event}(2), ..., D_{event}(N))$.

3.3 S3: filtering load events using high threshold

High sensitivity detection and time-domain splicing, which can detect slow rising events, but can not overcome the problem of false detection caused by load fluctuation. Therefore, a high threshold $THR_{HIGH}$ shall be used to filter the event sequence obtained in the second step. To determine whether $D_{event}(i)$ is an event, the discriminant is defined as follow

$$\bar{\Delta P} = \frac{1}{w} \sum_{k=L(i)}^{L(i)+w} P_k - \frac{1}{w} \sum_{k=R(i)-w}^{R(i)} P_k$$ \hspace{1cm} (8)

Where, if $\bar{\Delta P} > THR_{HIGH}$, then $D_{event}(i)$ is considered to be a real load event rather than a fluctuation disturbance.

4. Experimental test and analysis

In order to verify the effectiveness of the detection algorithm proposed in this paper, the improved CUSUM algorithm and two-step variance detection method are selected as the comparison objects, and the three algorithms are tested and compared by using the actual electrical load static data. This test method has the convenience of simulation, and can reflect the actual performance. The relevant parameters are set as follows: $LOW_{thr} = 5W$, $TIME_{thr} = 0.8s$, $HIGH_{thr} = 20W$, $w = 0.4s$, the sliding window distance is the same as $w$, other parameters are consistent with those in the comparative references.

4.1 Example 1: step-type load event detection

In this example, the electric kettle is used as the tested electrical appliance of which the nominal power is 1800W. The electric kettle is controlled to start and stop for many times. The detection results of step load events with three detection algorithms are shown in the Fig.6, Fig.7 and Fig.8. The red dot indicates the active power curve segment of load events detected by the algorithm.

![Figure.6 Detection results of two-step variance method](image)
Comparing with the Fig.6, Fig.7 and Fig.8, it can be seen that: a) The two-step variance method can detect the beginning position of the event in advance, but loss a segment at the end of the event; b) The improved CUSUM algorithm can detect the start position of the event accurately, but the delay of the end position of the event is large; c) The algorithm proposed in this paper can accurately detect the starting position of the event.

4.2 Example 2: impact load event detection

In this example, the fixed frequency air conditioner is used as the tested electrical appliance. The results of the three detection algorithms are shown in the Fig.9, Fig.10 and Fig.11. The red dot indicates the active power curve segment of load event detected by the algorithm.
Comparing with the Fig.9, Fig.10 and Fig.11, it can be seen that: a) Two-step variance method has a good detection effect, but it still has the problem of large position error; b) A turning-off event will be detected in the descending section of the peak since the improved CUSUM algorithm is a bilateral cumulative calculation.

4.3 Example 3: slow rising event detection
Variable frequency air conditioner is a typical slow rising load, and its slow rising time varies from a few seconds to a few minutes, which is a great challenge to the detection algorithm. In this example, the inverter air conditioner is used as the tested electrical appliance. The input power of refrigeration is 1068w, the heating power is 1120w, and the maximum current is 12.2A.

The first two detection algorithms can not detect the load event during the slow rising process of the air conditioner. The detection results of the proposed algorithm are shown in the Fig.12.

As it can be seen from the Fig.12, the duration of the tested variable frequency air conditioner from start to steady state is about 40 seconds. Due to the slow rising speed of power, the variance value and cumulative value in the short-term sliding window are very small, so the first two algorithms can not detect the start of variable frequency air conditioner, which will directly lead to the failure of NILM algorithm based on event detection to identify the variable frequency air conditioner. The algorithm proposed in this paper first detects a series of continuous events in the slow rise section with low threshold, and then splices the events with time threshold. The power change of the slow rising event
formed by splicing is about 600W, which obviously can pass the high threshold screening, and finally detects turning-on event of the frequency conversion air conditioning.

5. Conclusions

NILM algorithm is highly dependent on event detection. In this paper, a new idea of event detection algorithm is proposed based on engineering practice. The algorithm has good performance in practice through combining detecting, splicing and filtering according different thresholds.

In this paper, the detection performance is tested with the actual static data. The results show that the algorithm has more advantages than the existing algorithms in the detection of slow rising load events, and has been applied in a large-scale pilot project in Jiangsu Province.

The algorithm proposed in this paper also inevitably has false detection and missed detection, and there is still space for optimization of multi threshold cooperation. Taking the detection accuracy, recall rate and other parameters as the optimization objectives, multi threshold combination optimization can be carried out, which has not been discussed in this paper.

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