# A New Event Detection Technique for Residential Load Monitoring

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***Abstract*—In the process of non-intrusive load monitoring, the first step is to find the switching on/off events as accurate as possible. However, there are extensive disturbances in the recorded data, due to the voltage fluctuations, electrical noise and etc, resulting in either false detection or event missing. To solve this problem, a new event detection technique is proposed in this paper. This technique uses median filter algorithm and the proposed ripple mitigation algorithm to effectively remove the unexpected disturbances and extract the real signal of switching on/off events. The proposed algorithms are very easy to implement in the low cost devices. The lab data and BLUED data tests show more than 90% accurate rate of event detection.**

***Keywords*— Event detection, event pairing, home appliances, load monitoring, switching on/off.**

## I. Introduction

NILM is a brief of the Non-Intrusive Load Monitoring, which can provide detailed information of individual load operation in a group of loads supplied by one circuit, without access to each load. In 1980's, researchers from MIT originated the approach of NILM [1, 2]. Since then, extensive researches focus on this topic [1-8].

With many years of efforts, the NILM technology has been greatly improved [6-8]. The process of NILM normally consists of two steps, first, detection of the switching on/off events of each load or load group, second, classification of the loads. The accurate event detection is the prerequisite of accurate load classification. To this end, many methods are proposed, either using steady state or transient quantities [9, 10]. Reference [2] and [8] recommends the segment detection algorithm. Reference [11] proposes the wavelet transform detection algorithm. Reference [12-15] suggest the sequential probability test of the sliding window bilateral cumulative and transient event detection algorithm. To accomplish those algorithms, various electrical quantities, such as active power, reactive power and harmonics, as well as the high performance hardware are required [6]. With the help of these methods, the accuracy rate of event detection can reach about 95% [14, 15].

NILM aims at various types of electric power consumers, such as industrial, commercial, residential, and etc. Different types of consumers have different types of loads, which operate in different ways [6]. Therefore, the method of NILM should be developed upon the type of consumer. Among those, residences have obtained the most attractions, not only due to the large number of potential users, but also due to the technique challenges to face [15-19].

On one hand, it is well known that the loads owned by different residences vary from one to other. The habits of using home appliances in different residences are also diverse. The frequency of replacement of home appliances in residences is much higher than that of other type of power loads. With the electronics and intelligent development, More harmonic noise is generated in the power grid. Those characteristics require the highly robust techniques to accommodate the above mentioned diversities and variations.

On the other hand, because the residential power users are widely distributed and equipped with the low cost meters with single function only. From the practical point of view, the NILM method for residences should be able to implement through low cost devices. The transient quantities are not good choices for NILM in this case, as it needs high sampling rate. In the same way, the algorithms require complicated calculations are also not suitable for present residential applications.

This paper proposes easy to implement algorithms to conduct the detection of load switching on/off events, which can effectively remove power impulse noise and power ripple noise in the power grid. These algorithms can be embedded in single function meters, the most popular one in residences.

The load event detection process actually consists of two parts. One is to find the switching on/off events and the other one is to accurately pair one switching-on event with one switching-off event for the same load, so that the paired events can be sent to the next step to recognize its type. The rest of paper is organized as follows. Section II presents the method to find out the switching on/off events of loads. Section III introduces the method to make the correct switching on and off events in pair. Section IV verifies the proposed methods by both the lab data and the data published in BLUED (Building-Level fully-labeled Dataset for Electricity Disaggregation) database. Section V concludes this paper.

## II. Event Detection

It is the common sense that the switching on/off of load brings immediate power jumping up/down in the recorded power readings. This is the evidence of load switching on/off. If a proper threshold can be set to screen the power records, those load switching on/off events can be correctly detected.

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However, when those power records, measured at the real residence's power panel, are investigated, many unexpected signals are observed.

Figure. I shows the power records for a refrigerator. In this figure, there is an impulse at the starting instant and ripples during the operation of a load. The impulse is actually due to the motor starting in refrigerator, while the power ripples is due to the load characteristics, voltage fluctuation and measurement noises. The impulse signal is good for event detection but brings difficulty to the event pairing. The ripples will cause small-power event missing if the threshold is increased or false detection if the threshold remains in normal. It requires data processing algorithms to remove those impulses and ripples.

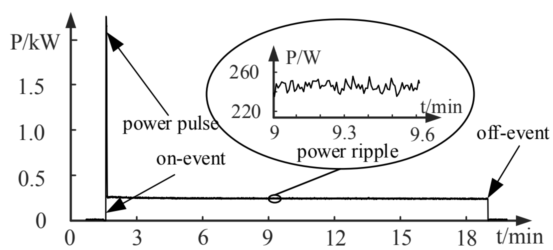


Figure. I Power impulse and ripples.

### A. *Median Filter Algorithm for Power Impulse Elimination*

The median filter is a nonlinear digital filtering technique, often used to remove noise from a signal. It is very suitable for this application, since it preserves edges while removing unwanted impulses [21].

The main idea of the median filter is to run through the signal record by record, replacing each record with the median of neighboring records. The pattern of neighbors is called the "window", which slides, record by record, over the entire signal. Since the event detection is a one-dimension problem, the window just covers several consecutive records. As an example, using a window size of three with one record immediately preceding and following each record, the process of the median filter applied to a power signal segment with 9 records is shown in Figure. II. In this figure, W1 to W2 indicate the window number. In the boundary cases, the first and the last records are repeated to fill the window. Each window covers three consecutive samples. The median value in each window is to replace the original sample value. The replaced signal, after median filter applied, is shown in the bottom figure in Figure. II.

With this process, the out-of-range record of the 4th sample in the power signal segment is eliminated from the signal. However, the power change event is still retained in the replaced signal.

It is obvious that if the window size is set as $2n+1$, the power impulse lasting less than $n$ records will be eliminated. Therefore, the window size selection becomes very important. This size should be set not too short to eliminate the unexpected power impulse, also not too long to miss the real appliance starting events.

To determine the correct window size, the starting durations of the home appliances and the operation time of short-term using appliances must be investigated first. After scanning massive measurements taken for various home appliances, it is found that the power impulse is always observed during the starting period of motor-based appliances and always lasts less than one second.

Some appliances have very short operation time, such as microwave ovens and induction cookers. Their different working conditions are achieved by adjusting the duty cycle. The test results suggest that in the lowest duty cycle, the operation duration is never less than five seconds.

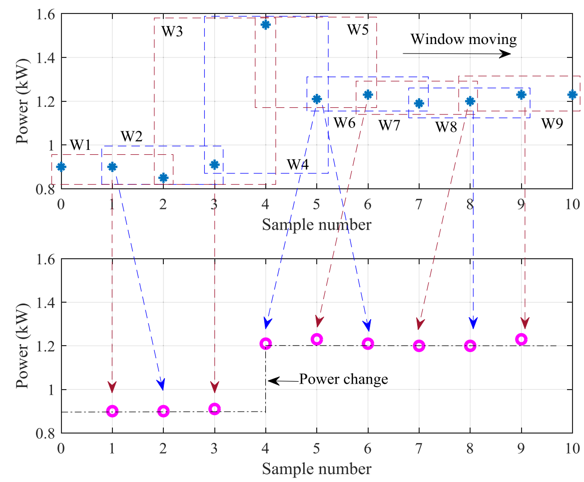


Figure. II Example of median filter application.

Based upon above investigation and considering some margin, the window size for median filter is suggested as nine with the sampling rate of 1 Hz, so that the power impulse can be effectively eliminated without missing real events.

Figure. III demonstrates a sample power signals before and after the median filter treatment. It can be seen that the median filter are capable to remove the power impulses without change of the real starting events. However, the ripple is still there in some extent.

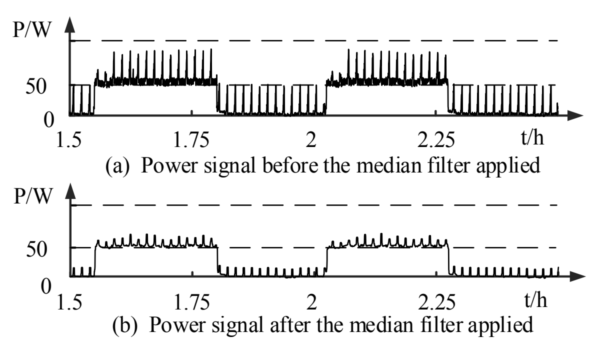


Figure. III Power signals before and after the median filter applied.

### B. *Power Ripple Mitigation Algorithm for Event Extraction*

The edges in power signal become much clearer after the median filter. The event detection is to extract the edges from the signal. However, the simple comparison between two records are still not available to accurately extract the edges because of the ripples. Figure.IV shows the absolute values of subtraction of each two records, $\Delta P_i$. It can be seen that the starting signal of the second event in the signal is blurred by the ripple noises.

$$\Delta P_i = P_{i+1} - P_i \qquad 1 < i < m \tag{1}$$

where, $P$ is the value of recorded power signal, $i$ is the number of the sampled power, and $m$ is the total number of records.

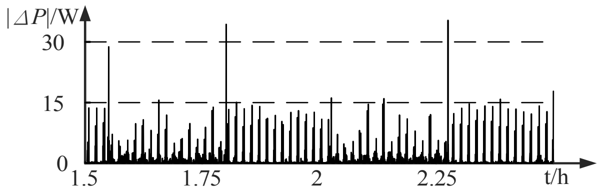


Figure. IV The absolute values of $\Delta P$.

To eliminate the impact of noise on the event extraction, the following algorithm is proposed.

The power ripple is caused by random fluctuated voltages, measurement noises and etc. With this notion in mind, the magnitudes of ripples should follow the normal distribution with the mean value of approximate zero. The algorithm is to reduce the ripples in $|\Delta P|$ signal as shown in Figure.IV and distinguish the switching on/off events from the signal.

For a data segment contains one signal and noises with normal distribution, the summation of all the data will return the original signal. Being inspired by this idea and considering that the investigated data segment may contain more than one signal. The ripple mitigation algorithm is proposed as follows.

Assuming that the window size is $2q+1$, the investigated data, $\Delta P_j$, is located at the middle of this data string as shown in Figure. V.

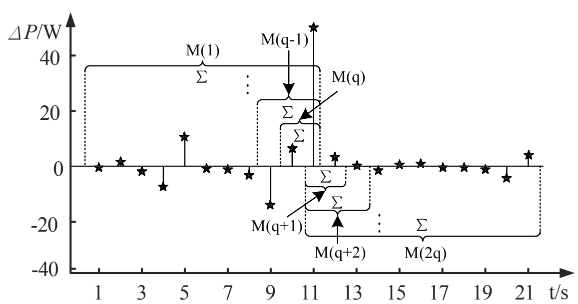


Figure. V Explanation of the ripple mitigation algorithm.

A series of M is calculated by

$$\begin{aligned} M(j-m) &= |\sum_{j-m}^{j} \Delta P_i|, \quad m = 1,2,3,\cdots q. \\ M(j+m) &= |\sum_{j}^{j+m} \Delta P_i|, \quad m = 1,2,3,\cdots q. \end{aligned} \tag{2}$$

A total of $2q$ values of M are obtained, then let

$$|\Delta P_j| = \min[M(1), \ \ldots, M(2q)] \tag{3}$$

In this way, the noises can be mitigated effectively, while the signal is retained. This algorithm is especially suitable for the conditions that two more signals are in one data segment. As to the window size, $q$=10 is selected in the proposed algorithm.

A resulted $|\Delta P|$ signal by applying the ripple mitigation algorithm is illustrated in Figure. VI. The load switching on/off events can be clearly distinguished from the signal.

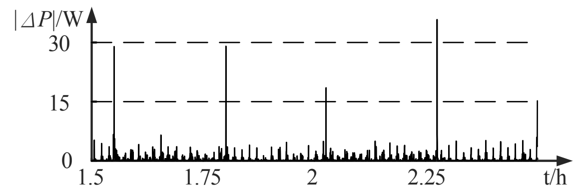


Figure. VI $\Delta P$ signal after the ripple mitigation algorithm applied

Therefore, it becomes easy to collect switching-on and switching-off events, separately, by setting up a threshold. In the example given in Figure. VI, the 10W threshold is sufficient to identify all events. In other words, the operation of small-wattage home appliances can be monitored by the proposed algorithms. However, if the threshold of 10W is applied to the signal shown in Figure.IV, a lot of false detection and some event missing will occur.

The operation durations of different loads are quite different, therefore, the switching-on and switching-off events should be correctly paired.

## III. EVENT PAIRING

The idea of the event-pairing algorithm is that the values of $\Delta P$ at on-event and off-event, caused by the same appliance, are similar, and the current waveforms extracted at on-event and off-event are also similar. The current waveform of event can be extracted by subtracting the current waveforms before and after the on- or off-events. The extracted current waveform data is stored together with the corresponding $\Delta P$.

The event pairing is accomplished by the procedure shown in Figure. VII, which is explained as follows.

- When an on-event is detected, the corresponding $\Delta P_{on}$ together with the one-cycle current waveform data $I_{on}$ will be stored in on-event set. This process keeps going.
- When an off-event is detected, the corresponding $\Delta P_{off}$ and one-cycle current waveform data $I_{off}$ is also extracted, and stored in off-event set.
- Comparison of $\Delta P$: the value of $\Delta P_{off}$ is compared with the values of $\Delta P_{on}$, detected before the off-event is detected, in on-event set. The judgement of paired is made by (4) holding. Otherwise, these two events are not considered from the same appliance. There may be more than one paired on-events or off-events.

$$\left|\Delta P_{on}+\Delta P_{off}\right|\le\left|\Delta P_{off}\right|\times 10\% \tag{4}$$

- Comparison of current waveforms [22]: the current waveforms of those paired on-events then are compared with that of the off-event, individually. The correlation coefficient $S$ is employed to quantify the similarity of two current waveforms. The judgement of paired is made by (5) holding. Otherwise, these two events are not considered from the same appliance. By this process. There may be more than one paired on-events or off-events.

$$S=\frac{\left|\sum_{i=1}^{n}\left(I_{on\_i}-I_{on-avg}\right)\left(I_{off\_i}-I_{off-avg}\right)\right|}{\sqrt{\sum_{i=1}^{n}\left(I_{on\_i}-I_{on-avg}\right)^{2}\times\sum_{i=1}^{n}\left(I_{off\_i}-I_{off-avg}\right)^{2}}}>0.8 \tag{5}$$

where, $S$ is the correlation coefficient between two current waveforms for on- and off-events, respectively. $I_{on\_i}$ and $I_{off\_i}$ are the $i^{th}$ sampling data for the two waveforms. $n$ is the total number of samples in one current cycle; $I_{on-avg}$ and $I_{off-avg}$ are average values of one cycle sampling data for on- and off-events, respectively.

If there is still more than one paired on-events, the on-event with bigger $S$ would be selected.

- If there is no on-event to pair after two-step comparison for single event, this off-event will be compared with the combined on-events that have not yet been paired. The unpaired on-events are combined in a way that their $\Delta P_{on}$ and $I_{on}$ are added up. If this pairing is success, it indicates that this off-event is actually multi-load switching off. If there is still no on-event to pair, this off-event will be stored in the off-event set for future use.

- If there is one more unpaired off-event, this event will be combined with other unpaired off-events by adding up their $\Delta P_{off}$ and $I_{off}$. The combined off-event is compared with the previous unpaired on-event. If this pairing is success, it suggests that the on-event is actually multi-load switching on.

- If the time of the data remaining in on-event or off-event set exceeds 15 hours or other durations, the data will be deleted for reducing the computing burden.

After this process, the following paring can be completed.

(1) One on-event v.s. one off-event,

(2) Multi-on-event v.s. one off-event,

(3) One on-event v.s. multi-off-event.

In the cases of (2) and (3), each pair of on-off event can also be recognized, since the multi-on or multi-off events are already recorded.

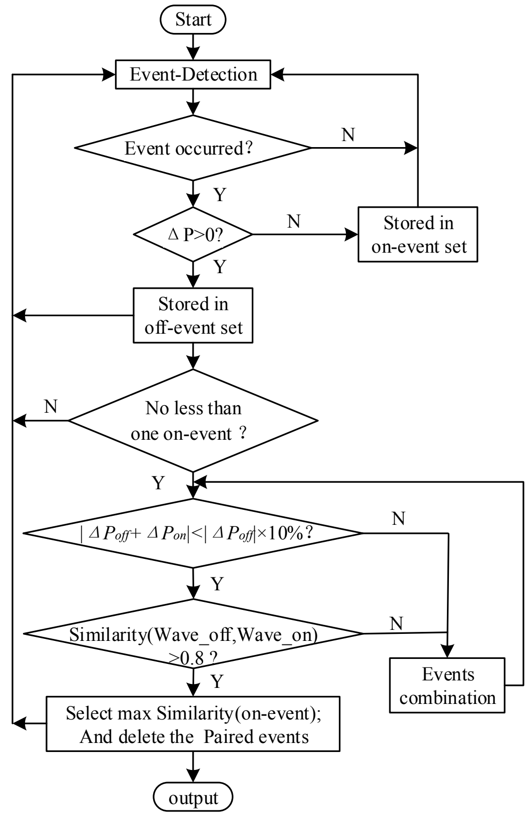


Figure. VII Flowchart of event pairing.

It should be noticed that the current waveform data should be aligned to the fundamental voltage.

In summary, the algorithms either for the event detection or for the event pairing do not require complicated calculation and high speed or high storage for hardware. They are very easy to implement in low cost devices.

## IV. VERIFICATIONS

The proposed method is verified by the experimental data taken in our lab and using data from BLUED database.

### A. BLUED Data Verification

Building-Level fully-labeled Dataset for Electricity Disaggregation (BLUED) was collected by Kyle Anderson, Adrian Filip Ocneanu, Diego Benitez, et al. In the BLUED dataset, the sampling rate of data is 12 kHz. The sampled voltage and current, as well as the time stamps for each switching on/off events of appliances are provided.

- **Case 1:**

The time duration of data segment: 18:30 to 20:00, 2011/10/20

Measured phase: phase A

The recorded switching on/off events are listed in Table I.

Table I. Event records

| Time | Event | Time | Event |
|---|---|---|---|
| 18:31 | on: Bedroom Lights | 18:54 | on: Backyard Lights |
| 18:37 | on: Refrigerator | 18:54 | off: Refrigerator |
| 18:46 | off: Bedroom Lights | 19:36 | on: Refrigerator |

| | | | |
|---|---|---|---|
| 18:52 | on: Washroom Lights | 19:52 | off: Backyard Lights |
| 18:53 | off: Washroom Lights | 19:53 | off: Refrigerator |

By applying the proposed algorithms to the data, the events are found out as marked in Figure. VIII. The results perfectly match the event records in Table I.

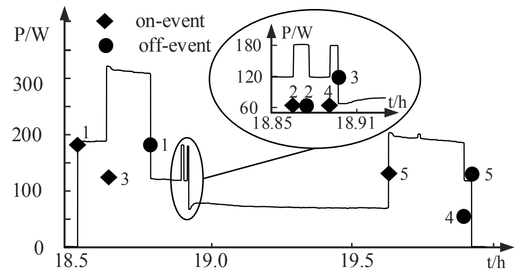


Figure. VIII: Event detection results for Case 1.

- **Case 2:**

A data segment for more complicated case in BLUED is also employed to verify the proposed algorithm.

The time duration of data segment: 11:58:32, 2011/10/20 to 03:28:41, 10/23/2011.

Measured phase: phase A

Location: 001

Dataset: 001

Total of 115 pairs of events are involved in this time segment. The results are concluded in Table II, respectively. More than 99% of switching on/off events are detected and more than 92% events are successfully paired.

Table II. The results for Case 2

| **Statistics items** | | **percentage** |
|---|---|---|
| ***Detection succeeded*** | on-events: 114 | 99.13% |
| | off-events:114 | |
| ***Detection failed*** | on-events: 1 | 0.87% |
| | off-events: 1 | |
| ***Pairing succeeded*** | 106 pairs | 92.17% |
| ***Pairing failed*** | 2 pairs | 1.74% |
| ***Pairing error*** | 6 pairs | 5.22% |

Because of some data download issue, only these two data segments are available. To further verify the proposed algorithms, the experiments are designed and conducted as presented in the following subsection.

*B. Experimental Data Verification*

The following tests are conducted in the laboratory to verify the proposed algorithms in the complicated load operation conditions.

In the laboratory, the sockets with power record function is used to record the power of each appliance by sampling rate 1 Hz, and the National Instruments data acquisition system is used to collect the voltage and current data at supply circuit by sampling rate 12.8 kHz.

1) Case 1: Appliances with similar powers but different current waveforms.

The kettle and the microwave oven have similar power, different current waveforms. In the experiments, the following actions were performed.

- Two appliances were turned on at the same instant, turned off at different instants;
- Two appliances were turned on at different instants, turned off at the same instant.

The proposed algorithms successfully completed the event detection and pairing process for above cases.

2) Case 2: Appliances with similar current waveforms but different powers.

Kettle, electric heater and incandescent lamp are all of resistive characteristics and similar current waveforms, but different power levels. In the experiments, the following actions were performed.

- Appliances were turned on at the same instant, turned off at different instants;
- Appliances were turned on at different instants, turned off at the same instant;
- Appliances were turned on at the same instant and turned off at the other instant.

The proposed algorithms also work very well to detect and pair the events.

3) Cases 3: Appliances with a variety of working states

Microwave oven has heating, thawing, barbecue and other working states. The water dispenser has heating, cooling, warming states. In the different working states of these appliances, the proposed algorithms can accurately achieve the event detection and pairing.

4) Case 4: A variety of appliances

In the lab, the complicated appliances use environments are constructed by TV, compact fluorescent lamps (CFLs), incandescent lamps (ILs), fridge, kettle, Oven, etc. to simulate the real home situations. In the 50-minute duration, 39 pairs of switch on-off events were conducted manually, the voltage and current at supply circuit were recorded. The overall scenario of the experiments is illustrated in Figure. 9.

By applying the proposed algorithm to these data, the results are

- 39 pairs of events were detected
- 36 pairs of events were paired correctly
- One pair of event was wrong paired
- Two pair of events were not paired.

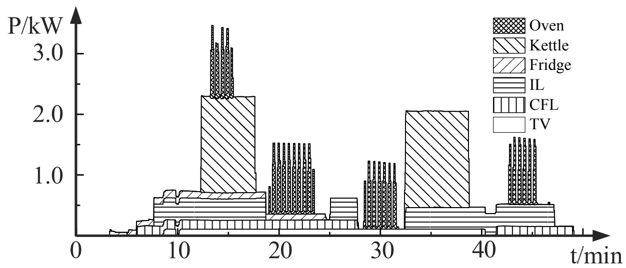

Figure.9: The power curve of the experiment

It can be seen that even though in the complicated situation, the proposed algorithms still has 100% of the event detection rate and more than 92% of the event paring rate.

## V. CONCLUSIONS

The proposed algorithms for load event detection have high success rate in various home appliances applications. They do not require high sampling rate and high speed computing hardware and therefore are very suitable for low cost devices, similar to the home meters. In comparison with existing event detection method with low sampling and computing burden, the proposed algorithms greatly improve the success rate of event detection.

## REFERENCES

[1] Hart G W. Prototype "Nonintrusive appliance load monitor," *MIT Energy Laboratory Technical Report, and Electric Power Research Institute Technical Repoert.* 1985.

[2] G. W. Hart. "Nonintrusive appliance load monitoring," *Procedings of IEEE, 80(12)*, pp. 1870-1891,1992.

[3] Michael Zeifman. "Nonintrusive appliance load monitoring review and outlook," *IEEE Transactions on Consumer Electronics. 57(1)*, pp. 76-84, 2011.

[4] Michael Zeifman, Kurt Roth. "Non - intrusive appliance load monitoring (NIALM): promise and practice," *IEEE Transactions on Consumer Electronics. 57(1)*, pp. 76-84, 2011.

[5] Huang Yicheng Yang Honggeng. "A Method based on K-Means and fuzzy algorithm for industrial load identification," *Power and Energy Engineering Conference (APPEEC), Asia-Pacific*, pp. 1-4, 2012.

[6] Zhenyu Wang, Guilin Zheng. "Residential appliances identification and monitoring by a nonintrusive method," *IEEE Transaction on smart grid. 3(1)*, pp. 80-92, 2012.

[7] Cheng Xiang, Li Linzhi, "Wu Hao, et al. A survey of the research on non-intrusive load monitoring and disaggregation, " *Power System Technology. 40(10)*, pp. 3108-3117, 2016.

[8] Seyed Mostafa Tabatabaei, Scott Dick. "Toward non-intrusive load monitoring via multi-Label classification," *IEEE Transactions on smart grid. 8(1)*, pp. 26-40, 2017.

[9] Jian liang Simon K.K.Ng, John W.M.Chen. "Load signature study—part I: basic concept, structure, and methodology, " *IEEE Transactions on Power Delivery. 2(2)*, pp. 551-560, 2010,

[10] Jian liang Simon K.K.Ng, John W.M.Chen. "Load signature study—Part II disaggregation, " *IEEE Transactions on Power Delivery. 25(2)*, pp. 561-569, 2010.

[11] Hsueh-Hsien Chang, Kun-Long Chen, Yuan-Pin Tsai, et al. "A New measurement method for pPower signatures of nonintrusive demand monitoring and load identification," *IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS. 48(2)*, pp. 764-771, 2012.

[12] Niu Lulu, Jia Hongjie. "Transient event detection algorithm for non-intrusive load monitoring," *Automation of Electric Power Systems. 35(9)*, pp. 30-35, 2011.

[13] Ling Yuan, Fei Wang. "Real-Time analysis and event detection of power load based on spark," *Wuhan: Huazhong University of Science & Technology*, 2015.

[14] Ding Shijing, Wang Xiaojing, Yongjing et al. "Research on event-based non-intrusive load monitoring method," *Building Electricity, 36(07)*, pp. 57-64, 2017.

[15] Ding Shijing, Wang Xiaojing, "The Research on non-intrusive residential load monitoring based on event detection," *Chongqing: Chongqing University*, 2017.

[16] Lei Dongmei Yong Jing. "The Research on algorithm of the NILM in circuit fault detection and household appliances power consumption monitoring ," *Chongqing: Chongqing University*, 2012.

[17] Wang Zhichao, Yong Jing. "The Research on algorithm of the NIALM of residential appliances," *Chongqing: Chongqing University*, 2015.

[18] K Chahine, KEK Drissi , C Pasquier, et al. "Electric load disaggregation in smart metering using a novel feature extraction method and supervised classification," *Energy Procedia. 6(1)*, pp. 627-632, 2011.

[19] Li Tan, Yang Honggeng, Gao Yun. "Oview of exploration on house load identification of intelligent metering," *Distribution & Utilization, 28(6)*, pp. 39-42, 2011.

[20] Anderson.K, Ocneanu A F, Benitez D, et al. "BLUED: A fully labeled public dataset for event-based non-intrusive load monitoring research," *Anderson K,Ocneanu A F,Benitez D,et al. KDD Workshop on Data Mining Applications in Sustainability*, 2012.

[21] Wang Min, Zhao Jingyu, Chen Tao, et al. "Extremum median filter map denoising algorithm based on energy function, " *Journal of Electronics & Information Technology, 39(6)*, pp. 1387-1393, Jun, 2017.

[22] Xiaojing wang, Dongmei Lei, Jing Yong, et al. "An online load identification algorithm for non-intrusive load monitoring in homes," *IEEE Eighth International Conference on Intelligent Sensors*, pp. 1-6, 2013.