A Novel Approach for Event Detection in Non-intrusive Load Monitoring

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***Abstract*—Monitoring household electricity consumption is important to help reduce energy usage. To improve the detecting accuracy of switch on and off events, this paper proposed a new improved event monitoring method based on CUSUM, which aims for better detection performance particularly in terms of low power appliances. Furthermore, introducing confidence level as the criteria and the bootstrapping algorithm effectively reduce detection errors and missed detections. The experiment results show that the new approach achieves higher accuracy compared to the traditional method of non-intrusive load monitoring (NILM).**

Keywords—bootstrapping; CUSUM; event detection; non-intrusive load monitoring(NILM)

I. INTRODUCTION

Reducing energy consumption becomes the trend prevailing the present society, but it remains a challenging problem faced by people around the world [1]. The major reason behind that difficulty is that customers are not fully aware of how their energy is used. Therefore, being fully informed of how resource is used as the very first step of energy conservation is badly needed to improve among the public. With the improvement of people's living standard, household electricity consumption increases rapidly, leading to the greater peak-valley difference of electric network load and enormous energy waste. Thus how to manage household electricity usage is of great significance to address those problems. Not only does home electricity monitoring system allow customers to have a better understanding of their electricity usage, but also helps them reduce energy consumption to a great extent [2-3].

Non-intrusive load monitoring (NILM) has been regarded as the most promising and scalable solution to obtain specific information of household appliances. This method only need to set up sensors on the entrance side of users to collect voltage and current data in real time and then analyze through software in order to calculate the electricity usage of each appliance. As a result, NILM is cost-efficient and is applied online to constantly capture the changing power load.

The first problem NILM needs to address is how to observe precisely switch on and off events. Several different NILM techniques have been proposed in the literature. In 1992, Hart in his classical document adopts the sectional detection method where the active power (or apparent power) is collected and is then categorized by power difference into two stages: the stable stage and transient stage [3]. Reference [4] shows the wavelet algorithm is employed to detect events by decomposing the acquired open signal into multiple signals including event edge, conversion process and duration. Reference [5] uses the transient event detection algorithm based on sequential probability ratio test, which features simple operation and better anti-interference performance. In [6], both the forward counter and backward counter are added to monitor the CUSUM in order to reduce detection errors caused by mistaking continuous fluctuation of load power for another switch on event, and this method proves to effective in addressing the above-mentioned problem.

In this study, some typical techniques of change-point analysis are combined with bootstrapping to create a new detection method based on CUSUM. This newly proposed method therefore effectively reduces the detection errors and missed detections in comparison with the traditional method of NILM.

II. EVENT DETECTION

The core of event detection method is to use a combination of cumulative sum charts (CUSUM) and bootstrapping to monitor power changes iteratively. This method consists of four steps: 1) Calculate and plot a cumulative sum based on the power data. 2) Performer the bootstrapping analysis. 3) Record confidence level 4) Determine the occurrence of the switch on and off events and their locations.

A. CUSUM

CUSUM is commonly used in the statistical process of change point detecting algorithm, which was first proposed by E. S. Page in 1954 [7]. Since then, many scholars have conducted in-depth research on this algorithm and have expanded its content. The theoretical foundation of CUSUM is the sequential probability ratio test that accumulates the sample data information to amplify the small deviations in the process, leading to higher response rate. A brief introduction to the algorithm flow is presented as following.

Suppose in the time sequences of power $P = \{p_i\}_{i=1}^{\infty}$, the length of a sliding window W_n is defined as n, first calculate the power mean $\overline{W_n}$ as in (1).

$$\overline{W_n} = \frac{\sum_{i}^{i+n-1} p(i)}{n} \tag{1}$$

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Next, after initializing the cumulative sum at zero by setting $S_0 = 0$, the difference between power value and mean value is added up to the previous sum and then the other cumulative sums within the window can be obtained, as in (2).

$$S_i = S_{i-1} + (p_i - \overline{W_n}) \tag{2}$$

In this way, we get the power CUSUM chart, which shows how the data deviate from the mean value. As in Fig.1, this is the power waveform that we have collected when the 1800W kettle is turned on for three consecutive times. The procedure of CUSUM is illustrated in Fig. 2. By comparing Fig. 1 with Fig. 2, it is obvious that the trend shown in CUSUM chart coincides with the power data waveform's rise and fall.

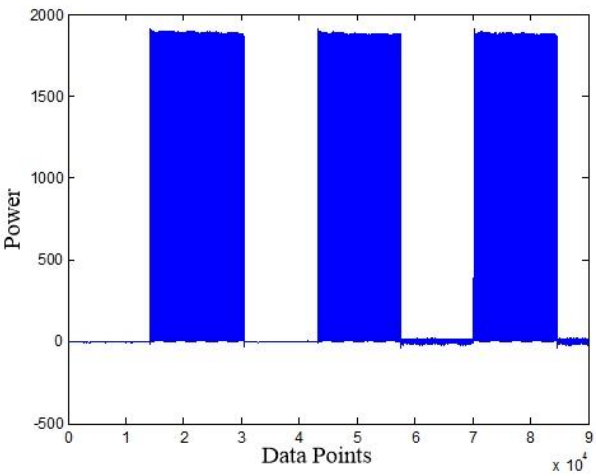

Fig. 1. Power waveform of kettle.

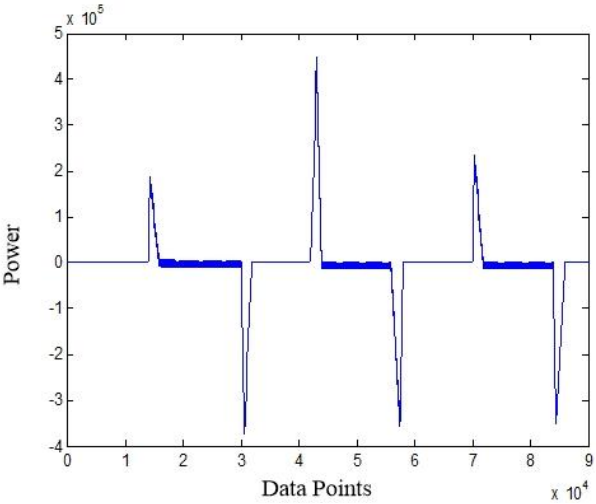

Fig. 2. CUSUM chart of kettle.

But in our study, we place more emphasis on variation range of CUSUM in the window, which is represented by S_{diff}. It helps us determine whether there is a switch on event and S_{diff} is easy to get by using (3).

$$S_{diff} = S_{max} - S_{min} \quad \text{where} \tag{3}$$

$$S_{max} = \max_{i=0.....n} S_i$$

$$S_{min} = \min_{i=0.....n} S_i$$

B. Bootstrapping

Through the analysis of the real power data of households, we find that there is a significant fluctuation in the voltage on the daily basis. Electricity consumption peaks during the evenings and working hours in the mornings, which makes the voltage become significantly lower than the normal value. This posts a big challenge for NILM because voltage fluctuations lead to different characteristic curves of appliance's electrical voltage, current, and power, having a huge impact on setting thresholds to determine switch on and off events. To this end, this study introduces the repetitive random experiment mechanism of bootstrapping, a statistical method, to minimize the above-mentioned effects [8]. The detailed steps of a single bootstrapping are as follow:

1) The original power time sequences in the window are randomly disturbed to get the new sequences are $P_1^0, P_2^0, \dots, P_n^0$. Based on the new random sequences, calculate the bootstrap CUSUM, denoted $S_1^0, S_2^0, \dots, S_n^0$.

2) Calculate the maximum and minimum values of bootstrap CUSUM, and then get the magnitude of the change by using (3), denoted S_{diff}^0.

3) Repeat experimenting step 1 through step 3 for *K* times to realize the idea of sampling without replacement in bootstrapping and at the same time to make preparations for calculating confidence level.

C. Confidence Level

After several iterations, we get the sequence $\mathrm{S}_{\mathrm{diff}}^0, \mathrm{S}_{\mathrm{diff}}^1, \dots, \mathrm{S}_{\mathrm{diff}}^{\mathrm{k}}$ which best represents bootstrap CUSUM variations. Next, we compare it with the original $\mathrm{S}_{\mathrm{diff}}$ and let *X* be the number of bootstraps for which $\mathrm{S}_{\mathrm{diff}}^0 < \mathrm{S}_{\mathrm{diff}}$, so the confidence level of switch on and off events can be gained by using (4).

$$Confidence\ Level = 100\frac{X}{K}\% \tag{4}$$

D. Detect On-Off Event

Compared to the method that determines the switch event by setting a threshold, confidence level through the Bootstrapping more accurately reflect those changes of appliances at working state. Based on a series of experiments, we found that the confidence level at between 95% and 98% can effectively capture minimal power variations when appliances are switched on and off.

Finally, we use the mean square error (MSE) estimate where the switch on and off events take place. We define an MSE-based estimator as in (5).

$$\mathrm{MSE(j)} = \sum_{i=1}^{j}(p_i - \overline{W_{n1}})^2 + \sum_{i=j+1}^{n}(p_i - \overline{W_{n2}})^2 \tag{5}$$

Where $\overline{W_{n1}} = \frac{\sum_{i=1}^{j} p_i}{j}$ and $\overline{W_{n1}} = \frac{\sum_{i=j+1}^{n} p_i}{n-j}$

The specific method is to divide the data within the window into two segments: *1* to *j* and *j+1* to *n*, and calculate the mean of two segments respectively. Analyzing the fitting of the data of two segments and their respective mean value helps we identify power variations. The result shows that when the MSE of estimator is minimized, the value of *j* is the best estimate of switch on and off events.

Then, we test the 1800W kettle that was previously used, employing confidence level and MSE estimator to monitor switch on and off events. The results are illustrated in Fig. 3. When the confidence level reaches more than 98%, we believe that a switch on or off event occurs and the red square boxes indicate that an event is detected. The experimental results show that the confidence levels in six experiments all reach 100%, which are consistent with the kettle's real working states. The method therefore proves feasible and effective in detecting switch on and off events.

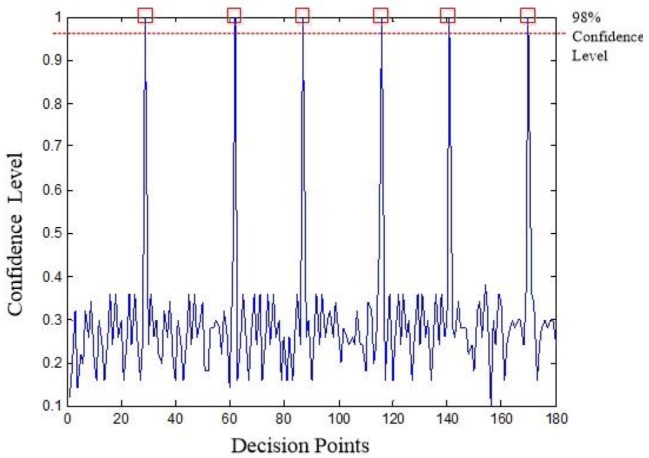

Fig. 3. Detected and labeled events by the improved event detecting method based on CUSUM (denoted by red ⊡).

At this point, the discussion of the improved event detecting method based on CUSUM comes to an end. In the next chapter, we will verify the effectiveness of the algorithm by means of multiple experiments.

III. Experimental Results

In this section, we investigate the performance of the proposed On-Off event detection method for detecting different types of household appliances. We select six typical appliances including kettle, television, fan, microwave oven, oxygen generator, and desktop computer, with rated power ranging from 60W to 1800W.

We built an experimental platform in the laboratory to simulate the real household electoral environment. Then, the high precision data acquisition module is adopted, and the sampling frequency reaches 10 kHz. Finally, we use MATLAB to make an off-line analysis of experiment data.

A. Detection of Small Power Appliances among Multiple Superposed Electrical Appliances

In the system with few loads, it is easy to capture the changes occurred in the working state of both the high power and low power appliances. By analyzing the line characteristics, we can easily find out when the switch on and off events happen. However, when many electrical appliances are working at the same time, the current and power waveform reflect the superposition of multiple features, even including noise interference that has an impact on the final detection results. In order to solve this problem, this paper proposes the improved event detecting method based on CUSUM to enhance the detection accuracy of small increments in power data.

We designed the experiment in which a variety of electrical appliances are switched on in turn and are working at the same time. Fig. 4 depicts a snapshot of power data with labeled appliance On-Off events over about a 45 second period. The labels IDs for the appliance events (ID 1~10) are summarized in Table Ⅰ.

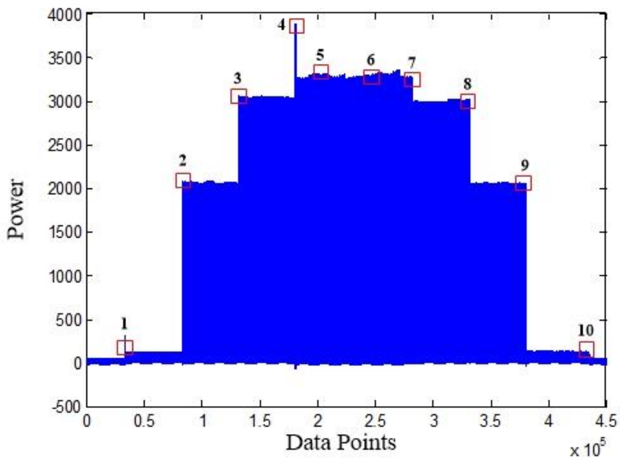

Fig. 4. Power waveform of multiple appliances with labeled On-Off events.

TABLE I. Labeled Appliance Events

ID	Appliance Event Description
1	Fan went to On
2	Kettle went to On
3	Microwave went to On
4	Television went to On
5	Desktop computer went to On
6	Desktop computer wen to Off
7	Television wen to Off
8	Microwave wen to Off
9	Kettle wen to Off
10	Fan wen to Off

As Fig. 4 shows, we can see that when the desktop computer (ID 5) is turned on, its rated power is only about 80W and the current characteristics are very unstable compared to those of resistive apparatus, which makes its switch on and off events hard to capture. Thus, we apply our new event detecting method to tackle the multi-appliance stacking problem. As we did before, the confidence level threshold is set as 98%, and bootstrapping iteration times $K = 100$, and the test results are illustrated in Fig. 5. It can be seen that all of ten switch on and off events are correctly detected, the algorithm therefore is also effective in identifying On-Off events of low power appliances.

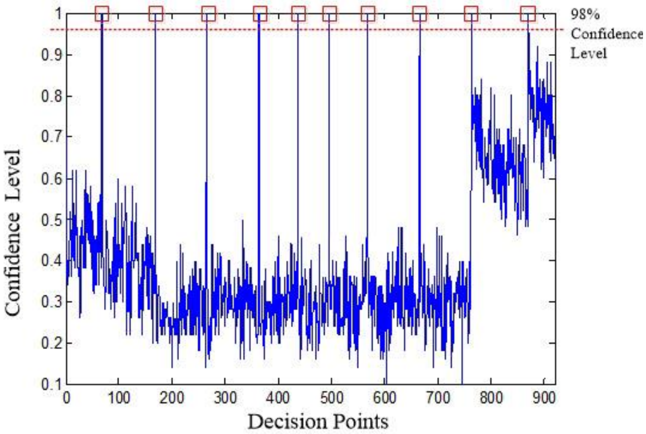

Fig. 5. Detected and labeled events by the improved event detecting method based on CUSUM (denoted by red ⊡).

B. Comparison of Three Event Detection Algorithms

We compare the improved event detecting method based on CUSUM with another two traditional methods, the method of mean deviation of current and the method based on average power, to analyze their advantages and disadvantages, with detection probability as the major performance metric.

The algorithm based on average power is simple to implement and has high detection probability for high power devices under stable working conditions, but its disadvantage is that the threshold is generally set on the basis of experience, which is prone to produce false alarm in the electrical environment with a high level of noise.

Reference [9] proposes an event detecting method based on the mean deviation of current, which calculates the current intensity in a window by using (6).

$$I_{intensity} = \frac{\sum_{j=1}^{N} |i(j) - mean(i)|}{N} \tag{6}$$

When the variation of the current intensity calculated from (7) is greater than a pre-assigned threshold α, the On-Off event of an appliance is detected.

$$\Delta I_{intensity} = (I_{intensity})_{s+1} - (I_{intensity})_s \tag{7}$$

In order to compare the performance of three algorithms, we conduct the switch on and off event detection test on the above-mentioned six electrical appliances, with turning on and off each appliance for 100 times. Confidence levels and Bootstrapping iterations are consistent with previous experiment results, and thresholds for the other two algorithms are set as the ideal value after pre-experiment. The experiment result is illustrated in Table Ⅱ.

TABLE II. THE DETECTION PROBABILITY OF THREE ALOGITHMS

Appliance	***Rated Power***	***Average Power***	***Mean Deviation of Current***	***CUSUM***
Kettle	1800W	100%	100%	100%
Microwave	950W	98.5%	97%	99%
Television	210W	95%	99.5%	100%
Desktop computer	78W	81.5%	78%	91%
Oxygen Generator	600W	93.5%	97%	100%
Fan	60W	89.5%	84%	92.5%

Traditional NILM technology has been very high detection probability for resistive load. Electrical characteristics of microwave oven, oxygen generator and television are quite noticeable when those appliances are turned on or off, and they quickly restore the stable working conditions, so the three algorithms have also achieved good results. However, rated powers of the desktop computer and fan are low, and are susceptible to noise interference, resulting in false detection and missed inspection. The overall recognition rate is therefore lower. Thanks to CUSUM in timely response to the small changes, the proposed event detection algorithm is superior to the other two conventional algorithms.

IV. CONCLUSION

In this paper we propose an improved event detecting method based on CUSUM in NILM system, which can be used to accurately capture changes in load power. A series of experimental results show that the detection probability is highly accurate (over 91% in general), proving the feasibility and effectiveness of the new method. Further research work may include optimization of algorithm operation efficiency and further improve the detection rate for low-power electrical appliances.

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