Real-time identification of residential appliance events based on power monitoring

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Abstract. Energy monitoring for specific home appliances has been regarded as the pre-requisite for reducing residential energy consumption. To enhance the accuracy of identifying operation status of household appliances and to keep pace with the development of smart power grid, this paper puts forward the integration of electric current and power data on the basis of existing algorithm. If average power difference of several adjacent cycles varies from the baseline and goes beyond the pre-assigned threshold value, the event will be flagged. Based on MATLAB platform and domestic appliances simulations, the results of tested data and verified algorithm indicate that the power method has accomplished desired results of appliance identification.

1. Introduction
Nowadays, with the rapid development of smart grid and smart home, intelligent appliances put more emphasis on the humanized design, and the power grid and consumers also tend to the two-way interaction. On family power consumption issues, on one hand, users not only need to know how many total watts their home have consume, but also they prefer to know per watt come from what kinds of appliances. On the other hand, the grid needs to adjust the power supply strategy and formulate reasonable electricity price mechanism according to feedback information of users, aiming to promote energy saving and emission reduction [1]. Many advanced technology continuously applied to household load identification field, and the non-intrusive load monitoring analyzes the condition of electric consumption of users through collecting the signals at the entrance of electricity, which can meet the need of low cost and easy installation better.

In the early 1990s, Professor G.W. Hart from the MIT has proposed NIALM. He put forward the most primitive MIT method with the support of Electric Power Research Institute (EPRI), using the cluster analysis algorithm to monitor the active power and reactive power, but it is difficult to identify appliance load with similar power [2]. Since then, L.K. Norfold increased the transient features to improve the MIT method [3]. Laughman used harmonic to recognize load, making the calculation simplified [4]. Leeb established the relationship between harmonic and the active power, the reactive power, and classified the appliance load based on the principle of minimum distance [5]. Lin employed genetic programming and pattern recognition technology to NIALM [6]. Recently, more and more techniques including FFT, wavelet transform, were applied to load identification.
2. The event detection algorithm and power calculation

Measurement of power parameters serves as the prerequisite for calculating energy consumption of household appliances. Serious errors in a certain power parameter would result in inaccurate identification of device types. The paper adopts voltage and current sensors to take accurate measurements and calculates power of each household device through MATLAB platform. Algorithms based on statistics have been put forward to recognize the switch-on and switch off events of domestic appliances, among which methods based on generalized likelihood ratio (GLR) and mean-difference are widely used. Those methods are mainly employed in an offline manner and allow data flow to spread the whole algorithm, which is quite different from online event detection algorithm where the power data is passed to the algorithm one after another. In this paper, the algorithm tracks the power difference of various periods. Given that the power difference in the samples exceeds the fixed threshold value, the event would be marked.

Current Harmonic which is well-recognized in alternating current power system refers to the spectral component in the waveform of voltage or current. Its frequency is integral multiple of fundamental frequency of voltage, which is 60 Hz in the United States. Generally, instantaneous voltage and current are defined by (1).

\[
\begin{align*}
v(t) &= V_0 + \sum_{k=1}^{\infty} V_k \cos(k\omega t + \phi v_k) \\
i(t) &= I_0 + \sum_{k=1}^{\infty} I_k \cos(k\omega t + \phi i_k)
\end{align*}
\]

In (1), \(V_0, I_0\) are averages; \(V_k, I_k\) are respectively harmonic amplitudes of \(K\)’s voltage and current. Measured current and voltage signals over time are showed in Fig. 1, which clearly indicates that there is a direct current named \(V_0\) and the first harmonic component called \(V_1\) which is dominant in the voltage signals.

![Figure 1. Measured current and voltage signals over time.](image)

Within the window period \(T\), instantaneous power is calculated through \(p(t) = v(t)i(t)\) (where \(T\) usually refers to one or several periods of fundamental frequency of voltage waveform). The average power derives from (2).

\[
P_a(t) = \frac{1}{T} \int_{t-T}^{t} p(\tau) \, d\tau = V_0 I_0 + \frac{1}{2} \sum_{k=1}^{\infty} V_k I_k \cos(\phi v_k - \phi i_k)
\]
3. Event detection algorithm

3.1. Establishment of experimental platform

In accordance with variations of the whole electricity consumption, recognition technology based on power variation decides the operation status (switch on or off) of a certain device. Power algorithm identifies whether an appliance is turned on or off by observing load curves. Occasionally, different devices may create the same result (for example, the computer’s power is 150 W, which is the same as the television’s), and the only difference between them is the timing.

3.2. Experimental principles

When the power variation (among the observed samples) differs from the baseline and exceeds the assigned threshold value, the event will be marked. In this algorithm, two parameters need to be set up: sample numbers of each period and an assigned power threshold value $H$. The algorithm principle is as follows: $N$ represents the number of energy signal received as time passes by, so the power average of each period can be calculated. Next Subtraction is done between two power averages of neighboring periods, whose result will be compared with the assigned threshold value $H$. The decision vector consists of TRUE and FLASE (ON would be activated when the difference exceeds the fixed threshold value; otherwise, OFF would be activated.) When the result of decision vector is ON and no more repeated detection is allowed within 50 periods, a switch-on event is identified. When the result of decision vector is off, a switch-off event is recognized. Information on event location and power mean difference is saved in event queue. Take the switch on and off events of 280W water fountain for example, the Fig. 2 illustrates how the power difference respond to power variations.

\[
\Delta P_{diff} = (P_{diff})_s - (P_{diff})_{s-1}
\]

Where \( \frac{\sum_{k=1}^{N}|p(k) - mean(p)|}{N} \)

Figure 2. Power variations and power difference of a water fountain.

Fig. 2 demonstrates the power differences of a water fountain within several periods. In accordance with (3), the power difference is calculated. Suppose there’s no more repetitive detection of On/off status events within fixed periods and the power waveform is marked at the MATLAB platform, the operation status of household appliance at certain moment would be identified by comparing the power difference and pre-assigned threshold value.

\[
\Delta P_{diff} = (P_{diff})_s - (P_{diff})_{s-1}
\]

Where \( \frac{\sum_{k=1}^{N}|p(k) - mean(p)|}{N} \)
4. Experimental process and analysis
In the process of real-time monitoring, samples would be affected by the outside environment and varied load attributes of appliances, which result in the errors in identifying operation status of appliances. On one hand, the moment a device’s plug is pulled out of a socket, the electrical current is relatively larger and creates electric arc. The soaring power affects the accuracy of switch-off status identification. On another hand, when starting a device, its power goes far beyond the rated power, bringing an inrush current which is $2\sqrt{2}$ times larger than the rated power. The load power goes back to the rated level after the electrical current returns to the fixed level. Thus, there is a peak power at the time of starting household appliance.

4.1. Simulation experiment of individual appliance
Among all the appliances with high, medium or low level of power, the set of typical household appliance is selected as the subjects of study, including air-conditioner, fluorescent light, fan, and computer.

Voltage and current samples measured from sensors are simulated at the MATLAB platform and are calculated through the improved algorithms of power difference. The above-mentioned process concludes instantaneous power waveforms of four appliances and identification results of on/off operation status. The results are showed in Table 1.

| Appliance       | Starting times | Closing times | Accuracy | Error  |
|-----------------|----------------|---------------|----------|--------|
| Computer        | 50             | 50            | 99%      | 1.2%   |
| Fluorescent light| 50             | 50            | 100%     | 0%     |
| Fan             | 50             | 50            | 99%      | 2.5%   |
| Air conditioner | 50             | 50            | 75%      | 5.22%  |

As Table 1 illustrates, the improved average power difference algorithm of identifying switch-on/off events is verified and its results demonstrate its feasibility in household appliance identification.

4.2. Simulation experiment of multiple appliances
After the above-mentioned individual load on/off status identification is analyzed, multiple loads identification experiment is conducted. The data sampling frequency is set to 10 kHz, and data acquired is sent to MATLAB for processing.

As Fig. 3 shows, ◯ represents switch-on event and ◌ denotes switch-off event. Such appliances as television, water fountain, refrigerator, kettle, electric radiator are turned on successively in 10th second, 30th second, 40th second, 70th second, and 110th second. The water dispenser is switched on again in the 150th second, and so is the refrigerator in the 210th second. Then the water dispenser, refrigerator, kettle, television, electric radiator, water dispenser are turned off one by one. In the above-mentioned process, refrigerator and water fountain are turned on and off two times respectively.
From the point of view of the type of electrical appliances, refrigerator is a motor device, which creates peak waveform when it is switched on, while water fountain and kettle are resistive load appliances that trigger little change in both current and power. The transient waveforms of the above-mentioned five devices are captured at the time of turning on and off, which are applied to the improved average power difference algorithm. All the identification results of on-status events are accurate, and most of off-status events detections are correct. One thing that needs to be pointed out is that pre-assigned specific threshold value would clearly enhance the identification accuracy of switch-off events. The identification accuracy rate of operation status of various appliances is shown in Table 2.

| Electric radiator | Kettle | Refrigerator | Water fountain | Television |
|-------------------|--------|--------------|---------------|------------|
| Switch-on event   | 100%   | 100%         | 100%          | 100%       |
| Switch-off event  | 99.5%  | 100%         | 94.5%         | 100%       | 98%        |

5. Conclusion
This paper improves the transient event detection algorithm based on the average power difference. With the help of the MATLAB platform, the simulation experiment is established and different events identifications are flagged successfully. The results show that the improved algorithm effectively recognizes the on/off status of various appliances in the power load, with the identification accuracy reaching above 95%. What the algorithm accomplished in the experiment demonstrates its high performance and efficiency. However, it has limited capacity of recognizing the appliances with the same power, which still needs efforts made to improve in future research.

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