Y. Jin, E. Tebekaemi, M. Berges, and L. Soibelman, "A time-frequency approach for event detection in non-intrusive load monitoring," in *Proceedings of the Signal Processing, Sensor Fusion, and Target Recognition XX*, Orlando, Florida, USA, 2011, p. 80501u-80501u.

http://dx.doi.org/10.1117/12.884385

A Time-Frequency Approach for Event Detection in Non-Intrusive Load Monitoring

Yuanwei Jin*, Eniye Telebakemi*, Mario Berges†, and Lucio Soibelman†

*Department of Engineering and Aviation Sciences, University of Maryland Eastern Shore, Princess Anne, MD 21853

†Department of Civil and Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA 15213

ABSTRACT

Non-intrusive load monitoring is an emerging signal processing and analysis technology that aims to identify individual appliance in residential or commercial buildings or to diagnose shipboard electro-mechanical systems through continuous monitoring of the change of On and Off status of various loads. In this paper, we develop a joint time-frequency approach for appliance event detection based on the time varying power signals obtained from the measured aggregated current and voltage waveforms. The short-time Fourier transform is performed to obtain the spectral components of the non-stationary aggregated power signals of appliances. The proposed event detector utilizes a goodness-of-fit Chi-squared test for detecting load activities using the calculated average power followed by a change point detector for estimating the change point of the transient signals using the first harmonic component of the power signals. Unlike the conventional detectors such as the generalized likelihood ratio test, the proposed event detector allows a closed form calculation of the decision threshold and provides a guideline for choosing the size of the detection data window, thus eliminating the need for extensive training for determining the detection threshold while providing robust detection performance against dynamic load activities. Using the real-world power data collected in two residential building testbeds, we demonstrate the superior performance of the proposed algorithm compared to the conventional generalized likelihood ratio detector.

Keywords: E vent Detection, Goodness-of-Fit, Short Time Fourier Transform, Non-intrusive Load Monitoring

1. INTRODUCTION

Statistics on residential and commercial building energy consumption show that buildings account for almost 40% of U.S. primary energy consumption.[1] Among all the energy sources for building such as natural gas, renewable, and petroleum, electricity accounts for about 70% of building energy consumption.[1] Thus, energy management and control of appliances for residential and commercial buildings become increasingly important. Nonintrusive load monitoring (NILM) is an emerging technology that can disaggregate individual electrical loads due to various household appliances in individual buildings from measurements made at a centralized location, such as the electric utility service entry.[2,3] Another important application for NILM is to monitor the operating schedule and the health of the major loads on shipboard electro-mechanical systems using only the measurements of the input voltage and aggregate current.[4,5] With the advancement of sensor technology, modern ships such as naval vessels have developed a strong need for devices capable of monitoring numerous electrical loads on board. An NILM is an ideal tool for the task of automating the analysis of sensor data while minimizing the number of required sensors.

Contact information: Dr. Yuanwei Jin; phone: (410) 621-3410, fax: (410) 651-6486, e-mail: `yjin@umes.edu`.

Signal Processing, Sensor Fusion, and Target Recognition XX, edited by Ivan Kadar,
Proc. of SPIE Vol. 8050, 80501U · © 2011 SPIE · CCC code: 0277-786X/11/$18 · doi: 10.1117/12.884385

In a utility application, an NILM system connects with the total load using pluggable meters or contactless electromagnetic field sensors to gather data such as current, voltage, and power. It uses simple hardware but complex software for signal processing and analysis. Only a single point in the circuit is instrumented, but mathematical algorithms must separate the measured load into separate component. In commercial applications, knowledge of electricity consumption and time of use in individual buildings is vital to consumers and utility companies. For utility service providers, this information provides the basis for billing and payments, while for consumers, the utilities information helps monitor and reduce energy consumption in buildings. Furthermore, the electrical load usage due to appliances can be related to the aggregated behavior of individual person, which typically exhibits a periodicity in time on a number of scales (daily, weekly, etc) that reflects the rhythms of the underlying human activity. Hence, NILM is an ideal platform for extracting useful information about electricity usage, daily human activity, and thus in turn enables potential changes of consumer behavior.[6,7,8]

Load monitoring normally consists of a sequence of signal processing and analysis steps in order to achieve the goal of event detection, appliance event classification, appliance activity tracking, and energy consumption estimation. Event detection, also called load detection in this paper, refers to the detection of the change of On and Off status of the loads in buildings or shipboard electro-mechanical systems. The goal of event detection is to raise an alarm after the onset of an event (i.e., On or Off status of an appliance or the appliance state-transitions), which would enable identification of the time-instant when the On or Off event occurs. We should note that many appliances contain several individual loads as building blocks. For example, an electric clothes dryer may contain a 120 V motor and 240 V thermostatically switched hearting element, controlled so that the motor may be on while the heating element if off, but not vice versa. Hence, load detection may result in detecting multiple loads' On and Off status of a single appliance. These detected load activities will be classified into corresponding appliances in the event classification stage. Furthermore conventional event detector often time requires periodic training to adjust the detection threshold due to the dynamics of electrical loads in order to achieve a high detection probability and a low false alarm rate. This condition imposes severe limits on the achievable accuracy of the event detector, thus reducing the practical usage of a NILM system.

This paper focuses on event detection based upon the continuous power data stream collected from whole-house power meters. The goal of event detection is 1) to raise a flag after the onset of an event (i.e., on or off status of an appliance or other appliance state-transitions), and 2) to identify the time-instant where the change of appliance status occurs. The proposed event detection consists of two steps: 1) to detect an event within each data block (or window) and 2) to locate the time-instant of change for the event. This is often called change point detection in time series data analysis.[9,10] This paper extends our previously developed time-domain event detection algorithm that utilizes goodness-of-fit (GOF) test for identifying the load activities.[11] The GOF test allows a simple method for deciding the detection decision threshold which depends on the data window size. Compared with the conventional generalized likelihood ratio test, the proposed GOF method achieves high correct detection rates and low false alarm rates while avoiding expensive training for obtaining the detection thresholds.[11] The main reason for the success of the GOF test is that this method does not pre-assume specific statistical distribution models of the sensor data. Instead, it compares the difference of the two unknown distributions, i.e., the distribution of the data in the pre-event window and the distribution of the data in the test window, to determine whether significant changes have occurred within the data in the statistical sense. A significant change of data distribution indicates that an event has taken place. In this paper, we introduce a joint time-frequency approach for event detection and change-point estimation. The data stream is recorded and divided into blocks (or windows) of finite number of samples. Using a properly chosen windowed short time Fourier transform, the proposed algorithm enjoys a simple yet effective method for obtaining the change point using the first harmonic component the power signals. The proposed algorithm is tested using voltage and current data collected by inexpensive contactless electromagnetic field sensors deployed in a residential building testbed. The detection performance in terms of the correct detection rate and the false alarm rate are calculated.

The results showed that the proposed time-frequency event detector is robust and yields superior performance compared to the conventional generalized likelihood ratio test.

The remainder of this paper is organized as follows. Section 2 presents the methodology and method of the proposed algorithm. Section 3 conducts experimental test of the detection algorithm using power data streams collected at two residential building testbeds. The conclusion is presented in Section 4.

2. DESCRIPTION OF THE EVENT DETECTION METHODOLOGY AND METHOD

2.1 Power Calculation and Representation

Current or voltage changes associated with appliances can be measured using conventional pluggable or in-line meters or emerging low-cost easy-to-deploy contactless electromagnetic field (EMF) sensors. From the measured instantaneous voltage $v(t)$ and current $i(t)$, one can calculate the instantaneous power

$$p(t) = v(t) \times i(t). \tag{1}$$

Since one of the goals of an NILM system is to estimate the total power consumption of all the appliances deployed in buildings, the average power need to be calculated by

$$P_{ave}(t) \quad = \quad \frac{1}{T}\int_{t-T}^{t} p(\tau)d\tau, \tag{2}$$

where T is the period of the processing window. In the U.S., the utility fundamental frequency is 60 Hz, thus, the window period T typically is over one or a few cycles of $1/60$ seconds. In an AC electric power system, harmonics have always been presented. Harmonics refer to spectral components present in a voltage or current waveform, whose frequencies are integer multiples of fundamental frequency (i.e., 60 Hz in the US) of the voltage form. Harmonic currents are created by nonlinear loads, such as variable speed drives (VSDs), electronic ballasts for fluorescent lighting, switching power supplies, and rectifiers. In general, we may decompose the instantaneous voltage and current waveforms as a Fourier series,

$$v(t) \quad = \quad V_0 + \sum_{k=1}^{\infty} V_k \cos(k\omega t + \phi_{v_k}) \tag{3}$$

$$i(t) \quad = \quad I_0 + \sum_{k=1}^{\infty} I_k \cos(k\omega t + \phi_{i_k}) \tag{4}$$

where V_0, I_0 is the average value. V_k, I_k is the amplitude of the k-th harmonic of voltage and current, respectively. By (2) we obtain the average power

$$P_{ave}(t) \quad = \quad V_0 I_0 + \frac{1}{2}\sum_{k=1}^{\infty} V_k I_k \cos(\phi_{v_k} - \phi_{i_k}) \tag{5}$$

Similarly, we can also define the reactive power by decomposing the current and voltage in another format as follows:

$$Q_{ave}(t) \quad = \quad \tilde{V}_0 \tilde{I}_0 + \frac{1}{2}\sum_{k=1}^{\infty} \tilde{V}_k \tilde{I}_k \sin(\phi_{\tilde{v}_k} - \phi_{\tilde{i}_k}) \tag{6}$$

Note that the average power calculation given in (5) is consistent with the commonly used *active power* in the power industry. Furthermore, we should note that in a practical NILM system, $P_{ave}(t)$ or $Q_{ave}(t)$ varies over time t because of the continuous changes in the appliance operation status.

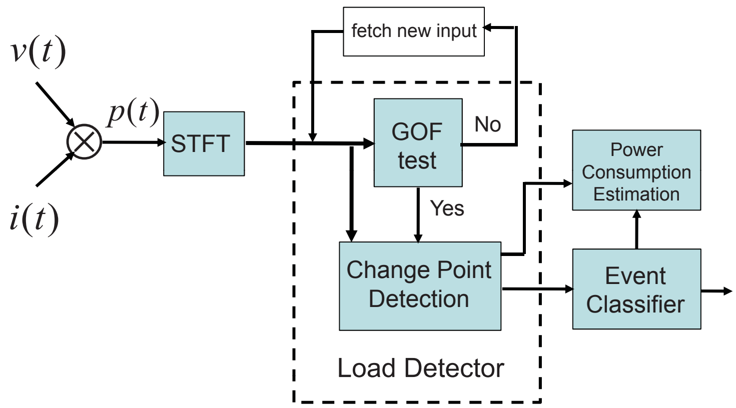


Figure 1. Illustration of the proposed load detector using goodness-of-fit (GOF) and change point detection. The instantaneous power signal $p(t)$ is computed from the measured voltage $v(t)$ and current $i(t)$. A short-time Fourier transform (STFT) is performed on the $p(t)$. The resulting signals are fed into the load detector. The output of the load detector will be fed into a classifier for the identification of appliance event. Eventually the disaggregated power consumption of all the appliances on the network is estimated.

2.2 Short-Time Fourier Transform

The concepts of short-time Fourier analysis are fundamental for describing any quasi-stationary (slowly time varying) signals such as speech.[12] It is well known that the discrete Short Time Fourier Transform (STFT) can be considered from the perspective of a Discrete Fourier Transform (DFT) taken over short time sections of the signal (the window is fixed) or from the perspective of a filtering operation at a given frequency (the frequency is fixed). The usual mathematical definition of the Short-Time Fourier Transform (STFT) is given by[13]

$$P_n(e^{j\omega}) = \sum_{m=-\infty}^{\infty} p(n-m)w(m)e^{-j\omega m} \tag{7}$$

where $p(n)$ is the input signal (i.e., power signal) at time n; $w(n)$ is the suitably chosen window sequence; $P_n(e^{j\omega})$ is the STFT of windowed data centered about time n. $|P_n(e^{j\omega})|^2$ is commonly called "spectrogram" which is used to illustrate that time-frequency distribution of the non-stationary signal $p(n)$.[14] Furthermore, we note that the short time Fourier transform can be interpreted as a filter-bank analysis of the signal $p(n)$.[12] In fact, we can show that

$$\begin{aligned} P_n^*(e^{j\omega}) &= \sum_{m=-\infty}^{\infty} p(n-m)w(m)e^{j\omega m} && (8)\\ &= \left(\sum_{m=-\infty}^{\infty} p(n-m)w(m)e^{-j\omega(n-m)}\right)e^{j\omega n} && (9)\\ &= \left[\left(p(n)e^{-j\omega n}\right) * w(n)\right] e^{j\omega n} && (10) \end{aligned}$$

Let

$$\overline{P}_n(e^{j\omega_k}) \triangleq \left(p(n)e^{-j\omega_k n}\right) * w(n) \tag{11}$$

where $\overline{P}_n(e^{j\omega})$ is written as the linear convolution of the signal $p(n)e^{-j\omega n}$ with the impulse response of the filter $w(n)$. The symbol $*$ denotes the linear convolution. $w(n)$ is a low-pass filter being applied to the signal

$p(n)e^{-j\omega n}$. The modulation of $p(n)$ by $e^{-j\omega n}$ servers to shift the frequency spectrum of $p(n)$ at frequency ω to 0 frequency. Thus the short-time Fourier transform can be thought of as filtering the shifted spectrum of $p(n)$ in the region of frequency ω_k by the low-pass filter $w(n)$. Furthermore, note that

$$|P_n(e^{j\omega})|^2 = |\overline{P}_n(e^{j\omega})|^2 = |\left(p(n)e^{-j\omega n}\right) * w(n)|^2 \tag{12}$$

Eqn. (12) shows that the spectrogram of $p(n)$, i.e., $P_n(e^{j\omega})$ is viewed as a function of n for a fixed ω. In practice, the STFT is computed at a finite set of discrete values of ω.[12,14] Let the window be of length M, defined in the range $0 \leq m \leq M-1$. We sample $P_n(e^{j\omega})$ at K equally spaced frequencies $\omega_k = 2\pi k/K$, with $K \geq M$ as indicated in the following:

$$\begin{aligned} P_n(e^{j\omega_k}) &= \sum_{m=0}^{M-1} p(n-m)w(m)e^{-j\omega_k m} && (13)\\ &= \sum_{m=0}^{M-1} p(n-m)w(m)e^{-j2\pi km/K}, \;\; 0 \leq k \leq K-1 && (14) \end{aligned}$$

We should note that the spectrogram can be used to study the behavior of time properties at a particular frequency. If we fix ω_k, $P_n(e^{j\omega_k})$ characterizes the time variation of the spectrum at ω_k. This information will be utilized in section 2.3.3 to estimate the change point of the detected event. When implementing the STFT with window size K, we examine the following two scenarios: (1) At $k = 0$ (i.e., the zeroth order harmonic component), we obtain $P_n(e^{j0}) = \sum_{m=0}^{M-1} p(n-m)w(m)$, which essentially is the average power and thus can be represented by (5). This data stream will be fed to the GOF detector. (2) At $k = 1$ (i.e., the first-order harmonic component) of the instantaneous power signal at the normalized frequency $\omega_1 = 2\pi\frac{1}{K}$. If we choose $K = 300$, sampling interval $T_s = 1.11 \times 10^{-4}$, and note that the fundamental frequency for current or voltage in a power system is $f_0 = 60$ Hz, we have $\omega_1 = \Omega_0/2$, where $\Omega_0 = 2\pi f_0 T_s = \frac{2\pi}{150}$ is the normalized fundamental frequency. Thus, the spectrogram $|P_n(e^{j\omega_1})|^2$ characterizes the time behavior of the discrete-time power signal $p(n)$ at half of the normalized fundamental frequency Ω_0. This data stream will be used to identify the change point of the transient signals of the load.

2.3 The Load Detector

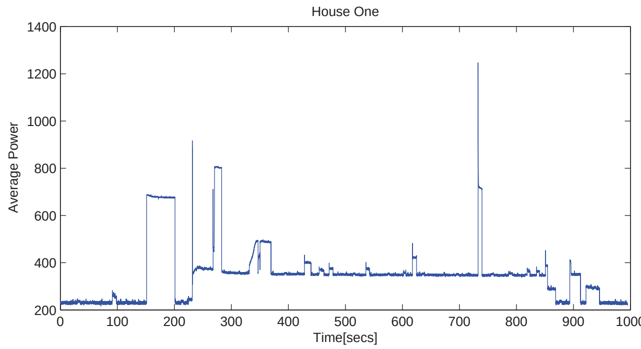
The load detector detects the change of On and Off status of a load and identifies the point of change, i.e., the time stamp. The detection is carried out in two steps sequentially. The first step is the goodness-of-fit (GOF) test by which the status change of a load is detected. The second step is the change point detection by which the time-stamp is identified. The GOF test has been developed in our previous paper.[11] However, the change point of the previously developed algorithm uses a simple threshold using the time domain average power data. Here we will use the frequency domain spectral component to identify the change point and to achieve a reduced the false alarm rate. Next we briefly review the signal data model and the GOF test following by a description of the change point detection method.

2.3.1 Signal Data Model

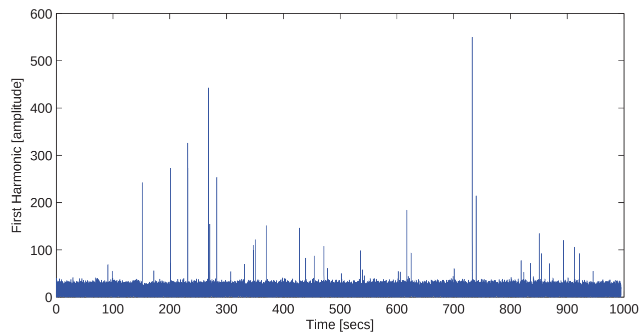
From the calculated power data given in (5), we model the discrete average power signal calculated as

$$p_i = e_i + v_i, i = 1, 2, \cdots, n \tag{15}$$

where v_i is the disturbance in power measurement and is assumed to be distributed as a white Gaussian process. The symbol e_i is considered as an indication that the data sample belongs to an appliance transition power



(a)



(b)

Figure 2. Plots of the output of the short-time Fourier transforms. (a) The average power data, i.e, zero-th order harmonic of the power signal ($k = 0$). Transitions of events are clearly visible. (b) The first-order harmonic of the power signal ($k = 1$). The signals are very spiky. The noise floor is high.

signature. n is size of the observation window of the sampled power data. We should note that at a high sampling rate, the event signature signal e_i consists of the static state, transient state, and oftentimes a bursty period due to nonlinearities of the appliance load condition. Thus, the overall power signal behavior p_i is complicated and must be processed using statistical means. If there is no event, only white noise exists, which can be represented as $p_i = v_i$, $i = 1, \cdots, n$. The event detector operates on two sliding data windows defined as follows:

Pre-event window. The pre-event window is used as the reference for upcoming events. The pre-event window is defined as

$$W_{i,k} = \{p_n | i \leq n \leq k\} \tag{16}$$

Detection window. This is the window preceding the pre-event window. This is the working window of the GOF test. It is in this window we intend to detect the occurrence of an event, i.e., on or off of an appliance. The detection window is defined as

$$W_{l,m} = \{q_n | l \leq n \leq m\} \tag{17}$$

where $l = i + n$, and $m = k + n$. Next, we develop a framework for event detection based on the χ^2 test for goodness-of-fit. The parameters of detectors of the detection window are compared to the pre-event window, and a decision is reached based on the outcome of a event detector.

2.3.2 Goodness-of-Fit (GOF) test

The goodness-of-fit test seeks to determine whether a set of data could reasonably have originated from some given probability distribution. Assume that we have n independent and identically distributed (iid) random samples p_i, $i = 1, 2, \cdots, n$, drawn from a distribution $G(p)$, which is *a priori* unknown. We have a supposed distribution function $F(p)$. The problem can be formulated as the binary hypothesis testing problem

$$\begin{aligned} \mathbb{H}_1 : \quad G(p) &\neq F(p) \\ \mathbb{H}_0 : \quad G(p) &= F(p) \end{aligned} \tag{18}$$

GOF tests will allow deciding between the two hypotheses in (18). In event detection, we will explain the GOF problem differently: There exist two sets of iid samples. The reference set (i.e., the pre-event window data set) consists of n samples p_i, $i = 1, \cdots, n$, with the distribution $G(p)$. The test set (i.e., the detection window data set) consists of n samples q_i, $i = 1, \cdots, n$ with distribution $F(q)$. Both $G(p)$ and $F(q)$ are unknown. The goal of GoF tests is to decide between the two hypotheses of (18). If the null hypothesis $\mathbb{H}_0$ is rejected, we claim that an appliance event occurs. Various goodness-of-fit tests have been developed in statistics literature. The χ^2 goodness-of-fit test for event detection is given by[11]

$$\ell_{\text{GOF}} = \sum_{i=1}^{n} \frac{(q_i - p_i)^2}{p_i} \tag{19}$$

We would reject the $\mathbb{H}_0$ hypothesis that the distribution of the population is the hypothesized distribution if the calculated value of the test statistic[15]

$$\ell_{\text{GOF}} > \chi^2_{\alpha, n-1} \tag{20}$$

with $100(1-\alpha)\%$ confidence interval and $n-1$ degrees of freedom. We should note that $\chi^2_{\alpha,n-1}$ is the decision threshold that depends on the window size n and the detection confidence level α. The expression (20) reveals two important features of the proposed GOF test for event detection:

1) The threshold for the GOF test in a function of window size n and can be conveniently calculated, thus eliminating the need for periodic training.

2) A guideline for choosing the suitable window size is given as follows.[11]

$$n_0 < n < n_1 \tag{21}$$

where n_0 is the minimum sample size given by[11, 16]

$$n_0 = \left(\frac{z_{\alpha/2} \hat{\sigma}_p}{E} \right)^2 \tag{22}$$

where $z_{\alpha/2}$ is the upper $100\alpha/2$ percentage point of the standard normal distribution. $E = |\bar{p} - \mu_p|$ is the allowable difference or change in the power signal that would be detected. Note that the signal p_i in (15) is assumed to be a random process with mean μ_p and variance σ_p^2. If we use the sample mean $\bar{p}$ and sample variance $\hat{\sigma}_p$ to estimate μ_v and σ, respectively using n samples, we can be $100(1-\alpha)\%$ confident that the error $|\bar{p} - \mu_p|$ will not exceed a specified amount E when the minimum sample size is given in (22). The quantity E can be pre-determined by users, for example, at 30 Watts. Furthermore, the maximum window size, n_1, of the detection window should be limited by the maximum length of the state-transient of the appliance signatures.

The importance of Eqns. (20) or (21) in GOF event detection is that they provide a guideline for choosing the window size, and then the decision threshold, based on training data. Once the window size is chosen, repeated training or a data-dependent threshold becomes unnecessary. This is a significant advantage compared with the conventional generalized likelihood ratio test.

2.3.3 Change Point Detection

The change point detector will be activated when the GOF detector produces a positive detection. The change point, i.e., the time stamp, indicates the starting point of the transient signal of an event. Identifying this transient point is important because 1) it is needed to classify the detected appliance if the shape and the length of the appliance signature waveform are used by the classifier and 2) it is needed to calculate the aggregated energy consumption including the transient signals. In our previous work, the change point detection is performed by searching the starting point of the transient of the average power signal using a threshold in the time domain. The threshold was chosen properly through training. In general, given the spectrogram obtained by the short time Fourier transform, the change point can be identified by searching the maximum value of the Euclidean distance between the spectrogram at time n and $n-1$, respectively,

$$d(n) = \sum_{k=0}^{K/2-1} \left(|P_n(e^{j\omega_k})| - |P_{n-1}(e^{j\omega_k})|\right)^2 \tag{23}$$

This method, among others, is commonly used in speech processing for onset detection.[17,18] In this paper we propose to use the first (or the first a few) harmonic of the instantaneous power signal to search for the transient point of a detected event. Fig. 2(a) and (b) show the zero-th order harmonic component ($k = 0$), i.e., the average power, and the first order harmonic component ($k = 1$) of the instantaneous power signal, respectively. The two data sets are obtained by performing a windowed short time Fourier transform of the power signal with a period of 1000 seconds. In section 2.2 we show that the short time Fourier transform can be interpreted as a filter-bank analysis of the power signal $p(n)$. The spikes appear in the data window after the GOF test declares a detection would be a good indicator of the change point of the event transient. Figs. 3-4 depict the signature waveforms of a total of eight appliances collected from a residential building testbed. The zero-th order (i.e., the average power signal) and the first-order harmonic signal are plotted. A careful examination of the first harmonic component of the power signal reveals that the dominant peak of the spectrogram is a good indicator of the change point of the event with the signature of duration 2.50 seconds. The estimation error is within the range of 33.3 ms, which is very small compared with the transient length.

3. EXPERIMENTAL RESULTS

A series of experimental week-long data-sets were collected in two residential building testbeds. Contactless electromagnetic field (EMF) sensors were used to collect instantaneous voltage and current signals about the operation of the appliances during the period of study. The sampling period is $T_s = 1.11 \times 10^{-4}$ seconds. From the measured voltage and current signals, we performed the discrete-time short time Fourier transform to obtain the average power and the first-order harmonic component. The FFT data window size is chosen at 300 points with 50% overlap. We then conducted experiments on these power data using the developed event detector (i.e. GOF) for performance evaluation relative to the conventional generalized likelihood ratio test (GLRT).[11] Next we consider two testing scenarios to examine the performance of the proposed GOF detector relative to the GLRT detector.

1. Testing appliances with complex signatures

The first test utilizes data collected from the residential building testbed $\#1$ that different appliances are manually switched on and off to examine the signatures of the each appliance. Some of the signatures of the appliances are complicated and appear to have a multi-stage transition, for example, the hair iron, microwave, and oven, etc. Figs. 5(a)(b) depict the snapshots of power data with labeled appliance events over about a 2000-second period. The appliance events are labeled (ID $1 \sim 38$). The detection results by the GOF and GLR[11] detectors

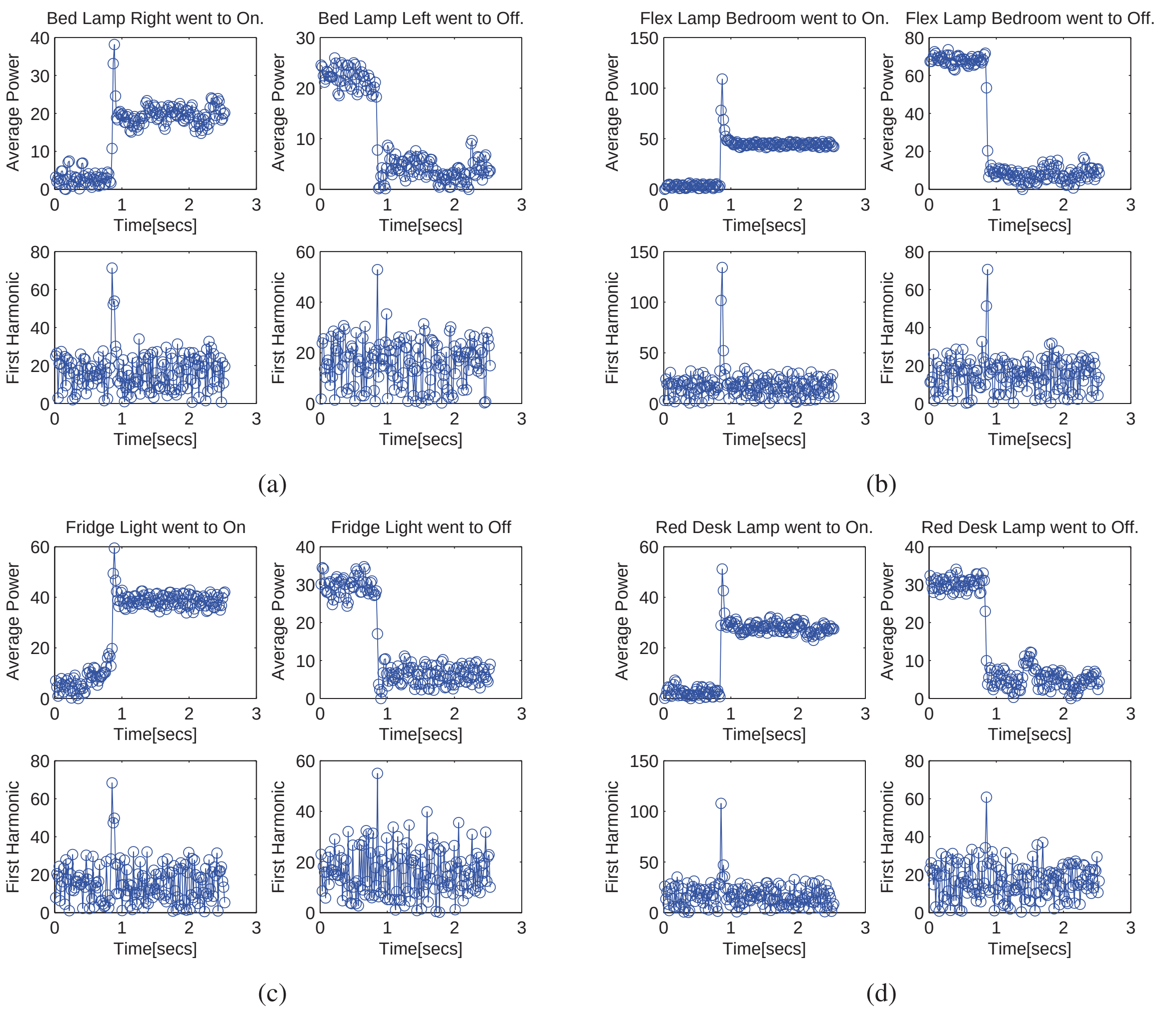


Figure 3. The signature of appliances characterized by the average power and first harmonic component of the power. (a) The On and Off signature waveform of a bed lamp. (b) The On and Off signature waveform of a flex lamp. (c) The On and Off signature waveform of a fridge light. (d) The On and Off signature waveform of a desk lamp.

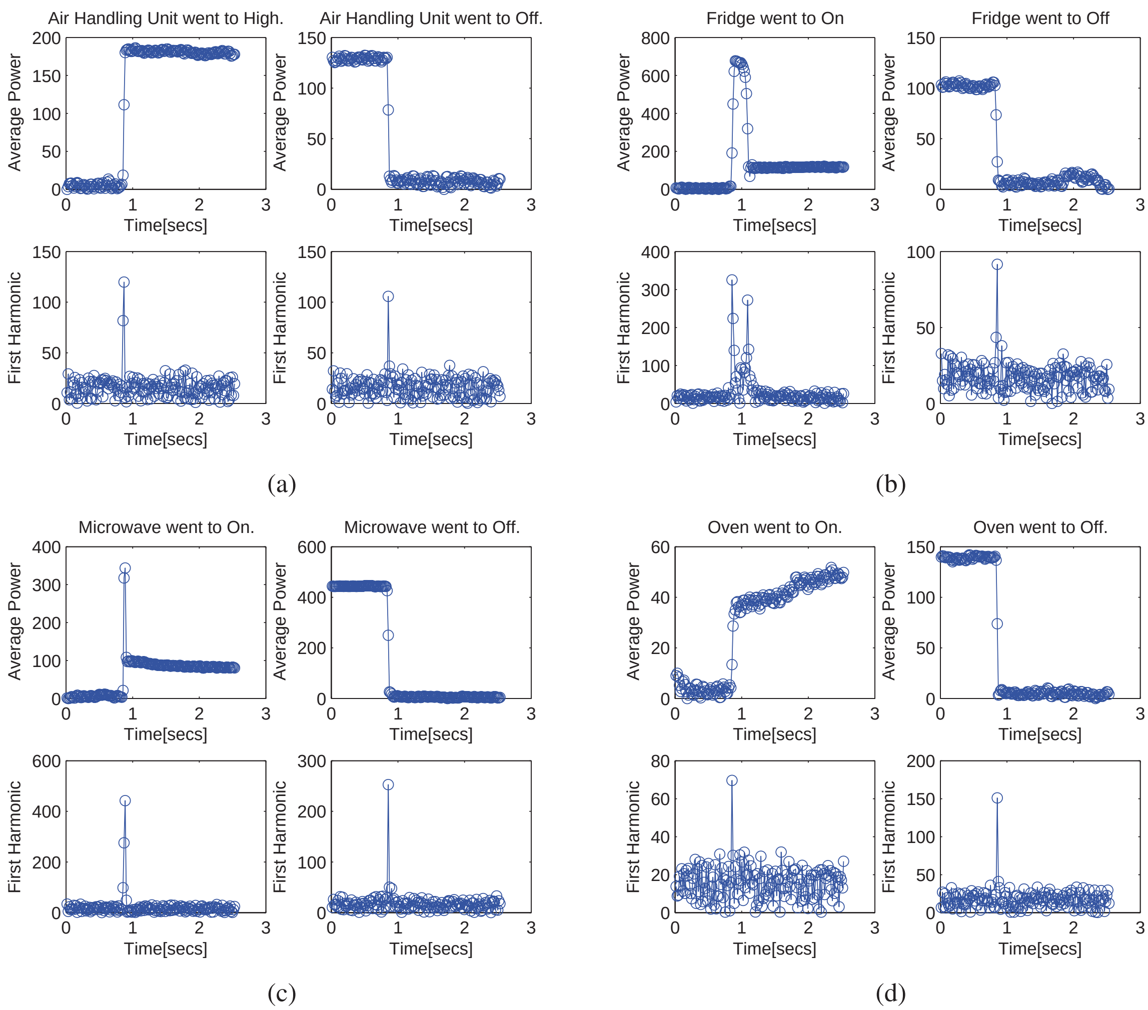
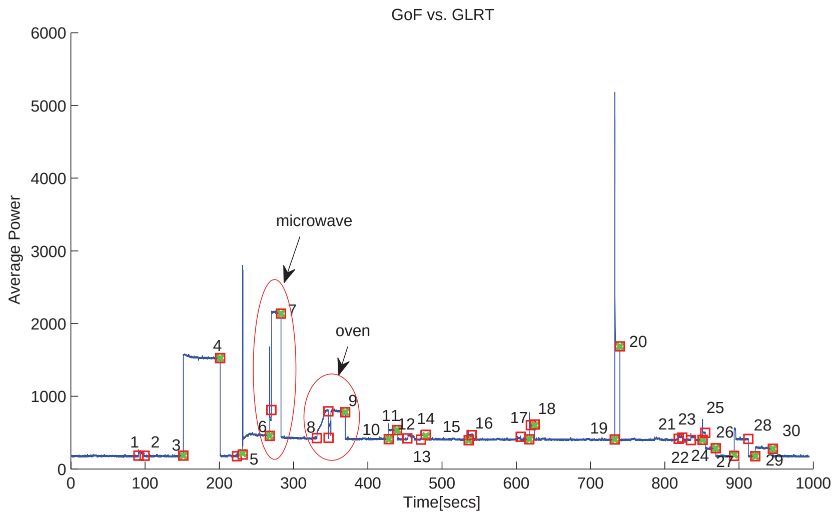
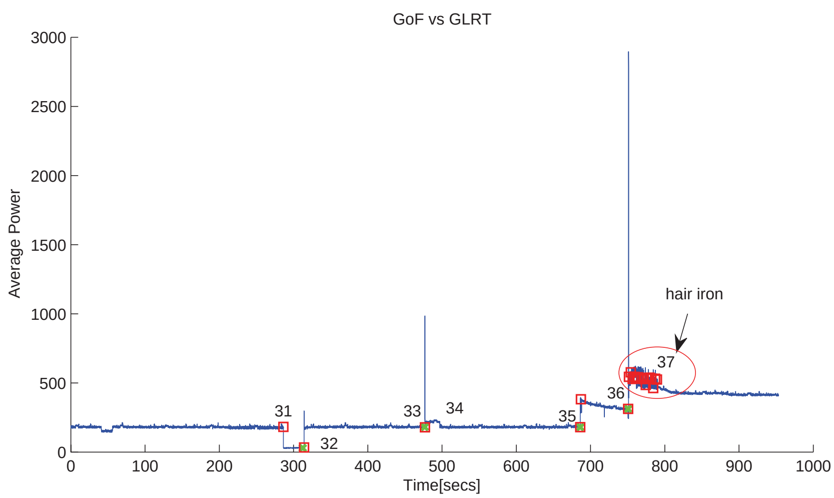


Figure 4. The signature of appliances characterized by the average power and first harmonic component of the power. (a) The On and Off signature waveform of a air handling unit. (b) The On and Off signature waveform of a fridge. (c) The On and Off signature waveform of a microwave. (d) The On and Off signature waveform of an oven.



(a)



(b)

Figure 5. A snapshot of average power data collected in a residential building testbed with detected events by the proposed GOF test and the conventional GLR test. The change points for the events are labeled using the red □ for GOF and the green × for GLR. Event IDs are listed in Table 1 and 2. 5(a) Snapshot 1. 5(b) Snapshot 2.

Table 1. Labeled Appliance Event for Fig. 5

ID	Appliance Event Description
1	Fridge Light went to On
2	Fridge Light went to Off
3	Toaster went to On
4	Toaster went to Off
5	Fridge went to On
6	Microwave went to On
7	Microwave went to Off
8	Oven went to On
9	Oven went to Off
10	Tall Lamp Living Room went to On
11	Tall Lamp Living Room went to Off
12	Red Lamp Living Room went to On
13	Red Desk Lamp Living Room went to On
14	Red Desk Lamp Living Room went to Off
15	Hallway Light went to On
16	Hallway Light went to Off
17	Magic Bullet went to On
18	Magic Bullet went to Off
19	Vacuum went to On
20	Vacuum went to Off

Table 2. Labeled Appliance Event for Fig. 5

ID	Appliance Event Description
21	Bed Lamp Left went to On
22	Bed Lamp Left went to Off
23	Bed Lamp Right went to On
24	Oven went to Off
25	Flex Lamp Bedroom went to On
26	Fridge went to Off
27	Flex Lamp Bedroom went to Off
28	Air Handling Unit went to High
29	Air Handling Unit went to Off
30	Air Handling Unit went to Low
31	Air Handling Unit went to Off
32	Measurement Computer and Laptop and Monitor and Devices and UPS UNPLUGGED
33	Measurement Computer and Laptop and Monitor and Devices and UPS PLUGGED
34	Receiver went to On
35	Receiver went to Off
36	Hair Iron sent to On
37	Fridge went to On
38	Hair Iron went to Off

are marked with different symbols ($\square$ for GOF and $\times$ for GLR, respectively). The results show that the GOF correctly detects all the events ID $1 \sim 37$, while the GLR fails to detect events $1, 2, 12, 13, 21, 22, 23, 25, 28, 31,$ and 37. Note that the event IDs $6-7$, $8-9$, and 37 characterize the complex transients of the microwave, oven, and hair iron, respectively. The GOF detects all those transients, even the transition of the multi-stage transients, while the GLR failed to detect ID $8-9$ and 37. An appliance that features a multiple state-transition transient is resulted from multiple loads of the appliance. Thus, each load or transient needs to be detected in order to trigger the subsequent classification stage. By this standard, the GOF outperforms the GLRT.

2 Testing appliances with simple signatures

The second test utilizes data from the house testbed $\#2$ where a daily usage of appliances is recorded. This second data set appears to have recorded appliance signatures with relatively simple structures (i.e., no hair iron and oven data are recorded). We compute the correct detection rate P_d, defined as the ratio of the number of correctly detected events over the total number of events (ground truth), and the false alarm rate P_{fa}, defined as the ratio of the number of falsely detected events over the total number of events. The average detection rate and false alarm rate over 10 consecutive sets of collected current and voltage data from the house testbed are computed for the GOF detector (with a fixed threshold calculated by (20) and (21)) and the GLR detector (with an adaptive threshold through training). The GOF shows a superior performance over the GLRT test in terms of the correct detection rate 98% vs. 94% and the false alarm rate 1% vs. 17%. This result is consistent with the previously obtained detection performance.[11]

4. CONCLUSION

In this paper we develop a time-frequency approach for event detection in non-intrusive load monitoring applications. The proposed method uses windowed short time Fourier transform to calculate the average power and the first order harmonic of the instantaneous power signal calculated from the measured voltage and current signals. The event detector employs the goodness-of-fit χ^2 test for appliance event detection and the dominant peaks of the first harmonic of the spectrogram of estimate the change point of the transient. The preliminary results based on the power data collected from two residential building testbeds show that the GOF test requires limited training and achieves a superior performance than the conventional generalized likelihood ratio detector.

5. ACKNOWLEDGEMENT

Y. Jin is supported under a subcontract from Carnegie Mellon University funded by the NSF GOALI/CPS program under award no. CNS-093-868 and was supported in part by a 2010 Air Force Summer Faculty Fellowship award.

REFERENCES

[1] "Building energy data book," tech. rep., Department of Energy (2009).

[2] Zeifman, M. and Roth, K., "Nonintrusive appliance load monitoring: Review and outlook," *IEEE Transactions on Consumer Electronics* **57**, 76–84 (February 2011).

[3] Hart, G. W., "Nonintrusive appliance load monitoring," *Proceedings of the IEEE* **80**, 1870–1891 (December 1992).

[4] DeNucci, L. T., Cox, R., Leeb, S. B., Paris, J., McCoy, T. J., Laughman, C., and Greene, W. C., "Diagnostic indicators for shipboard systems using non-intrusive load monitoring," in [*2005 lEEE Electric Ship Technologies Symposium*], 413–420, IEEE (2005).

[5] Leeb, S. B., Kinky, J. L., and Shaw, S., "Transient event detection in spectral envelope estimates for non-intrusive load monitoring," *IEEE Transactions on Power Delivery* **10**(12), 1200–1210 (1995).

[6] Laughman, C., Lee, K., Cox, R., Shaw, S., Leeb, S., Norford, L., and Armstrong, P., "Power signature analysis," *IEEE Power and Energy Mag.* , 56–63 (March/April 2003).

[7] Shaw, S., Leeb, S., Norford, L., and Armstrong, P., "Nonintrusive load monitoring and diagnostic in power systems," *IEEE Transactions on Instrumentation and Measurement* **57**, 1445–1454 (July 2008).

[8] Norford, L. and Leeb, S., "Nonintrusive electrical load monitoring in commercial buildings based on steady-state and transient load-detection algorithms," *Energy and Buildings* **24**, 51–64 (1996).

[9] Kawahara, Y. and Sugiyama, M., "Change-point detection in time-series data by direct density-ratio estimation," in [*SIAM International Conference on Data Mining*], 389–400, SIAM (2009).

[10] Vaswani, N., "The modified cusum algorithm for slow and drastic change detection in general HMMS with unknown change parameters," in [*ICASSP'05*], **4**, 701–704, IEEE (2005).

[11] Jin, Y., Tebekaemi, E., Berges, M., and Soibelman, L., "Robust adaptive event detection in non-intrusive load monitoring," in [*Intl. Conf. Acoustic, Speech, Signal Processing (ICASSP'11)*], IEEE, Prague, Czech Republic (May 2011).

[12] Allen, J. B. and Rabiner, L. R., "A unified approach to shoft time Fourier analysis and synthesis," *Proceedings of the IEEE* **65**, 1558–87 (November 1977).

[13] Mitra, S. K., [*Digital Siganl Processing: A Computer Based Approach*], McGraw Hill, New York, NY (2011).

[14] Cohen, L., [*Time-Frequency Analysis*], Prentice-Hall, Englewood Cliffs, NJ (1995).

[15] Cochran, W. G., "The χ^2 test of goodness of fit," *Annals of Math. Stat.* **23**, 315–415 (1952).

[16] Hogg, R. V. and Craig, A., [*Introduction to Mathematical Statistics*], Prentice Hall, Upper Saddle River, NJ (1994).

[17] Thornburg, H., Leistikow, R. J., and Berger, J., "Melody extraction and musical onset detection via probabilistic models of framewise STFT peak data," *IEEE Transaction on Audio, Speech and Language Processing* **15**, 1200–1210 (May 2007).

[18] Bello, J. P., Daudet, L., Abdallah, S., Duxbury, C., Davies, M., and Sandler, M. B., "A tutorial on onset detection in music signals," *IEEE Transactions on Speech and Audio Processing* **13**, 1035–1047 (September 2005).