Improving Appliance Detection and Energy Disaggregation based on Power-line Topology Information

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Abstract— **Non-intrusive appliance load monitoring (NIALM or NILM) system which offers a convenient tool for appliance detection and energy disaggregation of a house has attracted great interest in recent years. Previous studies usually assume that the overhead introduced by the power lines delivering electricity in a house can be ignored. However, our experimental results indicate that power-line topology of a house and the locations of appliances influence the appliance detection and energy disaggregation. In this study, we propose a method to learn the power-line topology information of a house based on appliance usage patterns. By utilizing the power-line topology information, we can improve the accuracy of NILM.**

Keywords— Non-intrusive appliance load monitoring; power-line topology; appliance detection; energy disaggregation

I. INTRODUCTION

Non-intrusive appliance load monitoring (NIALM or NILM) technology was first proposed by Hart in MIT in 1980' [1], and its basic idea is to install one single meter in the main power breaker of a house to observe the total energy consumption [2]. By analyzing the characteristics of alternating current (AC) power such as voltage, current, harmonics, etc., the meter can detect the appliances, recognize their states and disaggregate the energy consumption of an appliance from the total energy consumption. The technology attracts great interest recently due to the booming of IC technologies for better voltage/current sensing, and computing technologies such as deep learning for processing large amount of sensing data.

NILM studies mainly concentrated on the improvement of the appliance detection algorithms and energy disaggregation [12][14]. Some research further utilized the appliance usage patterns to interpret high-level user behaviors and activities [15]. Previous studies usually assumed that the supply voltage from the utility company are fixed and the same for all houses and the overhead introduced by the power lines can be ignored. However, according to our experiments, the overhead introduced by power lines delivering electricity in a house is serious. The power transmission line is not ideal conductive material and it is composed of resistor (R), an inductor (L), and a capacitor (C) parts. Our experiments show that the L and C parts of power lines can be ignored, but resistor (R) part may influence the results. The appliance detection becomes less accurate if an appliance changes its location, the supply voltage from the utility company varies, and/or the other appliances in the same power loop are turned on and generate loads. Therefore, it is important to gather the power-line topology information which can be further used to adjust power signatures of an appliance to improve the NILM in a dynamic environment.

In this study, we first propose a method to learn power-line topology information. We then utilize the power-line topology information to improve the appliance detection and energy disaggregation. The contributions of this study are:

- We describe and evaluate the accuracy of appliance detection and energy disaggregation of NILM by taking the power-line topology information into consideration.
- We propose a method to learn the power-line topology and the locations of appliances in a power-line network.
- We adjust the power signatures of appliances based on the power-line topology information and improve the appliance detection and energy disaggregation.

The rest of the paper is organized below. Section II reviews related work. Section III presents the method to learn the power-line topology. Section IV proposes the solution to adjust the signatures of appliances. Section V discusses the experimental results. Finally, we conclude this study in Section VI.

II. RELATED WORK

A state of an appliance can be associated with a set of load signatures (LS) such as voltage, current, active and reactive power, instantaneous current and voltage waveforms, instantaneous power waveform, etc. [3] Laughman et al. considered the harmonic [4] [5], and Norfold and Leeb used not only steady-state signatures but also transient-state signatures for appliance detection [6] [7]. The conventional load signatures and algorithms are not suitable for small power loads and/or continuous-load-changing devices, e.g. consumer electronic devices. These appliances usually use switched-mode power supply (SMPS) which generates high frequency electromagnetic interference (EMI). Patel et al. thus extracted the electronic noises from voltage as signature and can detect appliances [8][9][10][11].

Many of the existing appliance detection solutions do not consider environmental interferences and may become less accurate when they are applied to real world test-beds. For example, power transmission lines are not ideal conductive material. We can assume that each power-line segment contributes a small equivalent resistor. If a heavy-load appliance attaches to the power-line segment and it is turned on, the appliance consumes large current and high energy consumption. The large current flows through the power-line segment and results in significant power consumption and voltage drop. Below is an example that we use the same hair dryer plugging in different power sockets of a house and measure the power consumption from an NILM meter. Table I reveals that large energy consumption differences of the same appliance are observed by the NILM meter. In this study, we consider power-line topology in an NILM system. According to our observations, the power consumption would vary when other appliances in the same power loop are turned on/off. We call the phenomenon "inter-appliance influence". Moreover, when a heavy-load appliance is plugged to different locations and its power consumption becomes different. The signature of this application is "location-dependent". If we can gather the power-line topology information, we can use the information to recover inter-appliance influences and adjust location-dependent signatures.

TABLE I. POWER CONSUMPTION OF A HAIR DRAYER AT DIFFERENT LOCATIONS IN A HOUSE.

Locations	Power (W)
Entrance hall	1038
Kitchen	967
Living room #1	903
Living room #2	926
Reading room	896

III. LEARNING POWER-LINE TOPOLOGY INFORMATION

The actual power-line topology may look like the left-hand side of Fig. 1 and we can translate the topology into a binary tree like the right-hand side of the figure. Each edge in this binary tree indicates a power-line segment, and the appliances only appear at leaves of the tree.

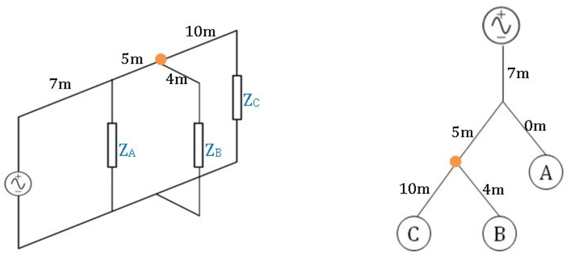


Fig. 1. Actual power-line connections and an abstract power-line topology.

The procedures to learn the power-line topology are illustrated in Fig. 2. In an NILM system, a meter detects the change of the AC power. The power signatures are calculated and the system searches the nearest signatures in an appliance signature database. Here, we assume no event overlapping, i.e., there is only one appliance state change within a detection period. When a new event is detected, the NILM system applies the K-nearest neighbor (KNN) algorithm to search the similarity of incoming signatures and appliance signature database. Our method relies on the difference of the power signature of the detected event and the normalized appliance signatures as a clue to derive the power-line topology. The normalized appliance signatures are the signatures of an appliance when the supply voltage is given and fixed, say 110V or 220V. Since we compare the signature of the detected event and the signature database, if the signature drifts from the normalized appliance signatures, there is a chance that the NILM meter recognizes a wrong appliance state. In that situation, the physical power-line distance between the appliance and the meter that we calculate may be also wrong. Therefore, we should correct the wrong detections as many as we can before we start the power-line topology calculation. We use an integer linear programming (ILP) model to correct the wrong detections.

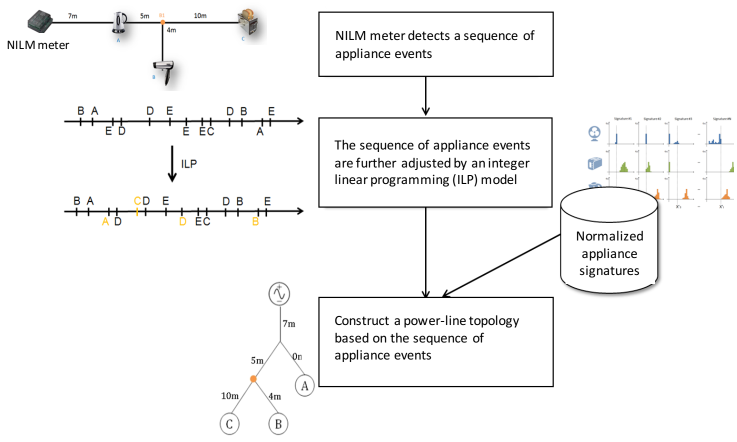


Fig. 2. The procedures to learn power-line topology.

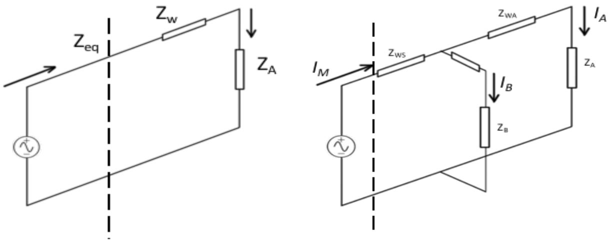
Next, we calculate the physical distances, i.e. the length of power-line segment, between the NILM meter and each appliance. To determine the physical distance, we first calculate the power-line impedance, so that the physical distance can be solved by the resistivity formula of copper [13]. Our physical distance is stored in the format of the resistance of the power-line segment. The topology includes two parts. The first one is the distance from each appliance to the NILM meter. The second part is the shared power-line segment length between every two appliances. We can store these distances in a distance matrix D.

$$D = \begin{bmatrix} d_{0,0} & \dots & d_{0,N} \\ \dots & \dots & \dots \\ 0 & \dots & d_{N,N} \end{bmatrix}$$

The first part is stored at the first row as $d_{0,j}, j = 1\ to\ N$. The second part is stored at $d_{i,j}, i = 1\ to\ N, j = 1\ to\ N$. Since the shared power-line segment length is the same from appliance 1 to appliance 2, and from appliance 2 to appliance 1, the distance matrix D is an upper triangular matrix. We pick up the events at which there was only one appliance at ON state. That is, there is no precondition for the current event. In this situation, the impedance measured by the meter is the equivalent circuit impedance Z_{eq}. From Fig. 3 (a), it is the appliance impedance Z_A and power line impedance Z_W connected in series. The impedance of Z_A can be found in the normalized appliance signature database, so we can simply obtain the value of Z_W by equation (1).

$$Z_W = Z_{eq} - Z_A = \frac{V_m \angle \theta_v}{I_m \angle \theta_i} - Z_A \qquad (1)$$

Now we know the distance from the meter to every appliance, we then evaluate the relationship between appliances by observing the conditions that there were exactly two appliances at ON state. The topology can be built according to the shared power-line length.



(a) (b)

Fig. 3. The equivalent circuit when (a) there is only one appliance at ON state (b) there are two appliances at ON state.

In Fig.3(b), Z_A and Z_B are the two appliances at ON state, and the power line impedance shared by the two appliances is Z_{WS}. If we apply the nodal analysis at where the circuit starts to split into two parallel circuits, we can obtain equation (2).

$$I_M = I_A + I_B = \frac{V - Z_{WS} \cdot I_M}{Z_{WA} + Z_A} + \frac{V - Z_{WS} \cdot I_M}{Z_{WB} + Z_B} \tag{2}$$

, where Z_{WA}+Z_{WS} is the impedance from appliance A to the meter; $Z_{WB} + Z_{WS}$ is the impedance from appliance B to the meter. Z_A, Z_B are given within the signature database, I_M and V are measured by the meter, so the shared power line impedance is the only unknown variable. Therefore equation (2) is solvable. We apply this nodal analysis to every two appliances, and get the distance matrix D. Finally, we convert the distance matrix into power-line topology. In the distance matrix, the physical meaning of the value $d_{i,j}$ is the length of the shared power line between appliance i and j.

IV. Adjustment of Appliance Signatures

Based on the power-line topology we derived, we can adjust the signature of an appliance. We divide the adjustment procedures into two phases. First, we perform the signature adjustment based on the topology location of an appliance. Then, in the second phase, we use the adjusted signature of an appliance to perform appliance detection. We show an example of the derived power-line topology in Fig. 4.

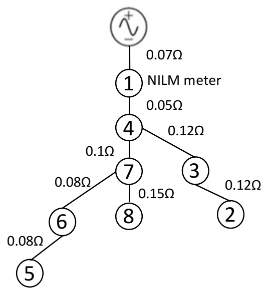


Fig. 4. An example of the power-line topology we dervied .

From Eq. 3 the real energy consumption of an appliance attached to a given location is determined by the impedance of a power-line segment, R_{tail} and the resistance, R_{Load}, of the appliance.

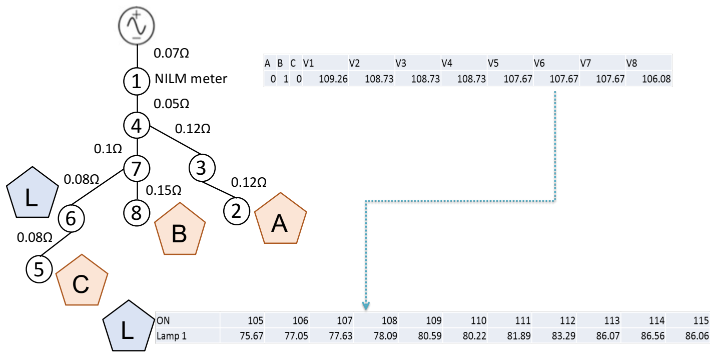
$$PL_i = \left(\frac{V_{source}}{R_{tail}(i)+R_{Load}}\right)^2 * R_{Load} \tag{3}$$

If we install an NILM meter at position (**1**) of Fig. 4, the energy consumption observed by the meter is:

$$PM_i = \left(\frac{V_{source}}{R_{tail}(i)+R_{Load}}\right)^2 * (R_{Load} + R_{tail}(i) - R_{tail}(0)) \tag{4}$$

As we can see from the equation, depending on the location of the appliance, the signatures that the NILM meter reports are different. If we know the location of an appliance and the power-line topology before conducting appliance detection, we can adjust the signature of the appliance first and then search the database.

The power-line topology and the location of an appliance play an important role when the heavy-load appliances are turned on/off. Therefore, we design a voltage-updater when we detect a heavy load. The voltage-updater updates every location's voltage based on power-line topology information and the locations of the heavy-load appliances. For example, we consider three heavy-load appliances, plugged them into three locations, say (2), (8) and (5) of Fig. 4 with marks A, B and C. When appliance A, B, and C turn on, we mark "1" in the table. Otherwise, we mark "0" as off. If appliance B turns on and then voltage of each location can be updated with a new voltage shown in the upper table in Fig. 5. If a lamp is in location (6) and it is turned on, and we can detect the power consumption between 77.63 to 78.09. In this case, we can detect it as a lamp. The topology information together with adjustments help the NILM meter to achieve a better accuracy of appliance detection.



A	B	C	V1	V2	V3	V4	V5	V6	V7	V8
0	1	0	109.26	108.73	108.73	108.73	107.67	107.67	107.67	106.08

ON	105	106	107	108	109	110	111	112	113	114	115
Lamp 1	75.67	77.05	77.63	78.09	80.59	80.22	81.89	83.29	86.07	86.56	86.06

Fig. 5. Detecting a lamp under appliance B is turned on.

V. Experiemntal Results

We use Tektronix DMM-4040 which is a 6-1/2 digit-precision multi-meter to measure the impedance and power consumption of a power line. We used five different kinds of appliances, an AC source as the power supply, and 2.0 mm power transmission lines to construct our test-bed. Fig. 6 shows the topology of the test-bed. The five appliances are a lamp, fan (big), fan (small), 25-ohm standard load and water cooler, and they are connected to different sockets, each has a socket meter to measure the individual power consumption. We thus can get the power, voltage and current of an appliance separately. Finally, we installed our own NILM meter right after the breaker shown in Fig. 6. The internal resistance of our NILM meter is 1.101 ohm.

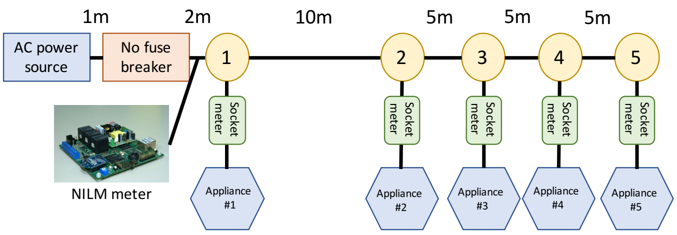


Fig. 6. The power-line topology of the test-bed.

We compared four training cases. "One signature" means that we only measure the signature of an appliance once. Then, we stored the only instance of the signature into the normalized appliance signature database. "Two signatures" means we measure the signature of an appliance twice. We record both signatures and insert them into the database. More instances of the signature of the same appliance implies better coverage of the signature and better quality of signature database. However, it spends more time to measure and requires more database space. "Ten signatures" means we record ten instances of the signature of the same appliance. Our method uses only one signature for each appliance and can calculate the possible signatures of each appliance based on power-line topology information. The results show that we can improve detection accuracy from 52% (one signature) to 88% (one signature with adjustment).

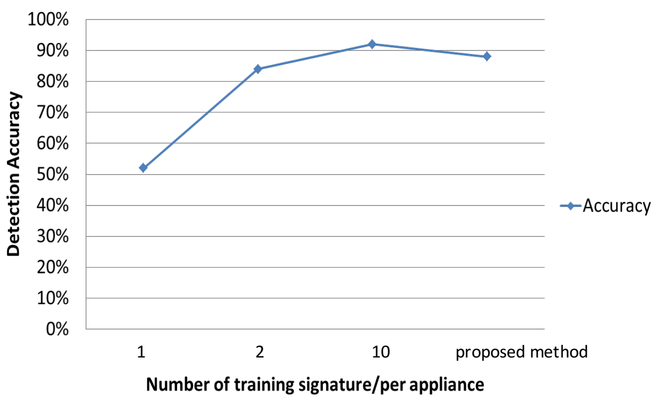


Fig. 7. The accuracy under different number of training signatures.

VI. CONCLUSIONS

In this study, we proposed a method to learn power-line topology of a house based on appliance usage patterns. We then adjust the signatures of appliances according to their locations and the status of appliances in the same power loop. The experimental results demonstrate the power-line topology can be used to improve the NILM and the proposed method can improve more than 30% appliance detection accuracy compared with the conventional approaches under the same database size.

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