Load Identification of Non-intrusive Load-monitoring System Based on Time-frequency Analysis and PSO-SVM

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Abstract. This paper presents a method for non-intrusive load monitoring (NILM) identification which is based on transient analysis and steady-state harmonic analysis. Each appliance has its own characteristics which results in a unique magnitude when it is switched on and have unique frequency spectrum in the steady-state. So based upon these analysis, frequency spectrum is used in combination with time domain analysis to identify loads. And the proposed NILM system employs the Particle Swarm Optimization (PSO) Algorithm with the Support Vector Machines (SVM) to perform load classification. The identification results confirm that the proposed system is suitable for identifying different loads.

Introduction

Home electrical power monitoring plays an important role in reducing energy usage, and non-intrusive appliance load monitoring (NIALM) techniques are the most effective approach for estimating the electrical power consumption of individual appliances. NILM was addressed originally at MIT by Hart [1] in the 1980’s, and has attracted many interests[4,9] in recent years due to the fast development of smart metering technologies. NILM employs a centralized monitoring device installed at the main breaker level, combined with intelligent load identification technologies to break down the operational information and power consumption of each appliance. NILM can be useful for homeowners and building managers to monitor energy consumption on an appliance-by-appliance basis without having to install dedicated sensors.

The original and extended NILM methods by MIT [1] use low-frequency hardware devices that only provide steady, coarse, and macroscopic signatures such as active and reactive power (P–Q). Recently, most researchers have agreed that the high-frequency hardware installation, which is capable of providing not only the conventional steady signatures but the microscopic transient signatures, can reach high accuracy of appliance detection and identification.

Several intelligent algorithms have been proposed for appliance identification by researchers in the past a few years. In [12], the artificial neural network (ANN) was used to identify the appliance by simply teaching the ANN to learn specific features. In [12, 14], the neural network was also used for the electrical appliance identification. The previous works in the literature based on intelligent systems which are based on a large amount of training from operational data. This training effort work will hinder the industrial application of the NILM technologies. There are still no complete available NILM solutions till now such that further research is still needed [2].

In this paper, an NILM system, which combines feature extraction and load identification methods, is proposed and used to identify the operation status of different types of appliances. The features are extracted from the harmonic analysis of identified transient current waveform. And the SVM with optimized parameters based on PSO is used as load identification to perform load identification.

This paper is organized as follows. In Sec. 2, the proposed NILM system is introduced. In Sec. 3, the acquisition of required data and the extraction of feature are given. In Sec.4, the PSO-SVM classification model is introduces. In Sec.5, the experimental results and discussion are described. Finally, the conclusions are presented in Sec. 6.
Proposed Non-Intrusive Load Monitoring System

Figure 1 shows the flowchart of the proposed NILM system. The proposed system extracts the characteristics of time domain and frequency domain, and the characteristics of transient and steady state are also involved. The system employs SVM optimized by PSO for classification. Details are described in following sub-sections.

Data Acquisition and Signature Extraction

In this study the current signal of ten appliances (lamp, refrigerator, Electric heating, television, fan, desktop computer, microwave oven, water dispenser, 1500W kettle, 1800W kettle) were collected using a sampling frequency of 5kHz. A low-pass filter is used in order to filter high frequency noise. The cut-off frequency of the low-pass filter in the study is 500Hz. The event detection algorithm to identify the operation status of different types of appliances is adopted from [10].

After a load energizing or de-energizing event is detected, the process of the transient and steady-state feature extraction starts. The following deals with the feature extraction.

Figure 1. Flowchart of the proposed NILM system.

Figure 2. The transient waveform of some appliances.
From Figure 2 we can see that each appliance has its own characteristics which results in a unique magnitude when it is switched on. So the maximum amplitude of the turned on current waveform was extracted for load identification in this paper.

**Time Domain Signature Extraction**

\[ I_p = \max(I(k)) \quad (k \in \text{ transient}) \]  

(1)

In the steady-state the Peak to Peak value of current also distinguishing among different appliances.

\[ I_{pp} = \max(I(k)) - \min(I(k)) \quad (k \in \text{ steady-state}) \]  

(2)

**Harmonics Analysis**

To identify the nonlinear loads, harmonic analysis is essential. The required initial data for each appliance harmonic analysis is 5 period (i.e. 100ms) of the current waveform. The signal obtained is afterwards transformed using a fast Fourier transform (FFT). The current waveform and amplitude spectrum of some appliances are shown in Figure 3.

![Figure 3. The current waveform and amplitude spectrum of some appliances.](image)

Through the whole spectrum we can obtain the following feature values to describe the differences of harmonic components of the appliances.

The Total Harmonic Distortion (THD) of current. It is the percentage of the RMS value of each harmonic’s effective value and fundamental wave. It’s defined as:

\[ THD_i = \left( \sqrt{\sum_{i=2}^{\infty} I_i^2} \right) / I_1 \]  

(3)

The RMS of the distorted current waveform
The proportion of n-th harmonic current, it presents the proportion of a harmonic of distorted current waveform.

\[ HRI_n = \frac{I_n}{I_1} \times 100\% \]  

(5)

**PSO-SVM Model**

Support vector machine is an effective supervised machine learning algorithms especially for small samples. The penalty factor and the parameters of kernel function are the key factors to the accuracy of the prediction by SVM. As an intelligent optimization algorithm, PSO possess the character of high convergence rate and global optimization. This paper employs PSO algorithm to optimize the parameters c and g of SVM. The SVM model with optimized parameters is used for loads identification. The model combines the advantages of the improved PSO’s efficient global optimization ability with SVM’s good learning ability. The flowchart of SVM based on PSO algorithm is shown in Figure 4.

![Figure 4. SVM based on PSO algorithm flowchart.](image-url)
Experimental Data and Results

Experimental Datas

In the balanced three-phase system, owing to the symmetrical relationship, even harmonics have been eliminated, and only odd harmonics exist. So we extract only odd harmonic, in order to ignore the difference between the same types of loads. Table 1 shows the signatures extracted from each appliance.

Table 1. Signatures of each appliance.

<table>
<thead>
<tr>
<th>Appliances</th>
<th>Imax</th>
<th>Ipp</th>
<th>Fundamental wave</th>
<th>THDi</th>
<th>RMS</th>
<th>HR13</th>
<th>HR15</th>
<th>HR17</th>
<th>HR19</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lamp</td>
<td>2.5451</td>
<td>0.0156</td>
<td>0.0069</td>
<td>0.0070</td>
<td>0.0069</td>
<td>0.0224</td>
<td>0.0089</td>
<td>0.0103</td>
<td>0.0084</td>
</tr>
<tr>
<td>Refrigerator</td>
<td>2.8590</td>
<td>0.1505</td>
<td>0.0702</td>
<td>0.0081</td>
<td>0.0703</td>
<td>0.0203</td>
<td>0.0236</td>
<td>0.0088</td>
<td>0.0056</td>
</tr>
<tr>
<td>Electric heating</td>
<td>2.6155</td>
<td>0.2182</td>
<td>0.1118</td>
<td>0.0035</td>
<td>0.1118</td>
<td>0.0147</td>
<td>0.0116</td>
<td>0.0117</td>
<td>0.0065</td>
</tr>
<tr>
<td>Television</td>
<td>2.5402</td>
<td>0.0478</td>
<td>0.0172</td>
<td>0.0458</td>
<td>0.0181</td>
<td>0.3000</td>
<td>0.0794</td>
<td>0.0190</td>
<td>0.0571</td>
</tr>
<tr>
<td>Fan</td>
<td>2.5259</td>
<td>0.0128</td>
<td>0.0052</td>
<td>0.0230</td>
<td>0.0053</td>
<td>0.1434</td>
<td>0.0117</td>
<td>0.0147</td>
<td>0.0131</td>
</tr>
<tr>
<td>1500W Kettle</td>
<td>2.6987</td>
<td>0.3859</td>
<td>0.1974</td>
<td>0.0032</td>
<td>0.1974</td>
<td>0.0188</td>
<td>0.0064</td>
<td>0.0066</td>
<td>0.0050</td>
</tr>
<tr>
<td>1800W Kettle</td>
<td>2.7783</td>
<td>0.4697</td>
<td>0.2416</td>
<td>0.0036</td>
<td>0.2417</td>
<td>0.0180</td>
<td>0.0109</td>
<td>0.0102</td>
<td>0.0061</td>
</tr>
<tr>
<td>Desktop Computer</td>
<td>2.5180</td>
<td>0.0241</td>
<td>0.0046</td>
<td>0.1423</td>
<td>0.0064</td>
<td>0.8098</td>
<td>0.4715</td>
<td>0.2715</td>
<td>0.1208</td>
</tr>
<tr>
<td>Microwave Oven</td>
<td>2.9453</td>
<td>0.3762</td>
<td>0.1126</td>
<td>0.0760</td>
<td>0.1276</td>
<td>0.5026</td>
<td>0.1701</td>
<td>0.0254</td>
<td>0.0183</td>
</tr>
<tr>
<td>Water Fountain</td>
<td>2.5417</td>
<td>0.0749</td>
<td>0.0377</td>
<td>0.0040</td>
<td>0.0377</td>
<td>0.0214</td>
<td>0.0078</td>
<td>0.0096</td>
<td>0.0066</td>
</tr>
</tbody>
</table>

Experimental Results

In this paper, all the samples were carried out several cross-validation through Crossvalind function. The signature were extracted through combining the transient state and steady state as well as combining time and frequency domain, and employed SVM whose parameters were optimized by PSO to perform load classification. From Table 2 and Figure 5, it can be easily observed that the presented appliance identification method has a very good accuracy with ten different types of appliances. The average recognition accuracy rate can reach 98%, and the recognition accuracy rate of each load are all above 95%.

![Figure 5. The Result comparison between SVM and PSO-SVM.](image-url)
Table 2. Recognition result of each appliance by two kinds of signatures.

<table>
<thead>
<tr>
<th>Appliances</th>
<th>Harmonics Recognition Statistics</th>
<th>Result(%)</th>
<th>Harmonics+I_max(transient)+I_pp(steady) Recognition Statistics</th>
<th>Result(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lamp</td>
<td>25/25</td>
<td>100</td>
<td>25/25</td>
<td>100</td>
</tr>
<tr>
<td>Refrigerator</td>
<td>10/25</td>
<td>40</td>
<td>23/25</td>
<td>92</td>
</tr>
<tr>
<td>Electric heating</td>
<td>25/25</td>
<td>100</td>
<td>25/25</td>
<td>100</td>
</tr>
<tr>
<td>Television</td>
<td>25/25</td>
<td>100</td>
<td>25/25</td>
<td>100</td>
</tr>
<tr>
<td>Fan</td>
<td>24/25</td>
<td>96</td>
<td>25/25</td>
<td>100</td>
</tr>
<tr>
<td>Desktop Computer</td>
<td>23/25</td>
<td>92</td>
<td>25/25</td>
<td>100</td>
</tr>
<tr>
<td>Microwave Oven</td>
<td>22/25</td>
<td>88</td>
<td>25/25</td>
<td>100</td>
</tr>
<tr>
<td>Water Fountain</td>
<td>13/25</td>
<td>52</td>
<td>24/25</td>
<td>96</td>
</tr>
<tr>
<td>1500W Kettle</td>
<td>23/25</td>
<td>92</td>
<td>24/25</td>
<td>96</td>
</tr>
<tr>
<td>1800W Kettle</td>
<td>25/25</td>
<td>100</td>
<td>25/25</td>
<td>100</td>
</tr>
</tbody>
</table>

Conclusions

This paper has presented a new appliance identification method used in the NILM system for signature extraction and load classification in residential dwellings. The proposed system that uses the PSO-SVM as the load identifier is able to identify load operation status with many kinds of loads in different experimental environments. Finally, the identification rates for the experiments of the proposed approach are higher than 95%. The result confirms that the proposed NILM system is robust.

Acknowledgments

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References


