# Advance Program (Subject to change)

**December 16, 2013**

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Non-Intrusive Appliance Load Monitoring with Feature Extraction from Higher Order Moments

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Abstract

A pattern recognition (PR) system is addressed for non-intrusive appliance load monitoring. For the effective recognition of two home appliances (specifically, an electric iron and a cook top), we consider a novel feature extraction method employing higher order moments of power signals from the appliances. Through simulation results, we have confirmed that the PR system with the features from the proposed higher order moment technique and kernel discriminant analysis can effectively separate the two appliances.

1. Introduction

Operating conditions of home appliances are valuable information for electrical power companies to predict electric power demands and to operate electric power facility efficiently. In order to monitor operating conditions of home appliances, non-intrusive load monitoring (NILM) [1] systems have been developed. In NILM systems, the energy consumption of individual appliances is estimated by observing current and voltage waveforms of the total load of appliances in a house.

It is known that NILM has several common principles [2]. First, specific appliance features need to be selected and characterized mathematically. Second, a hardware installation (sensor and data acquisition system) that can collect the selected features is required. Lastly, a mathematical algorithm for the detection of the specific appliance with the features in the overall signal is required.

In this paper, we present a pattern recognition (PR) system for NILM. For effective recognition, we propose a novel feature extraction method employing the information of high-order moments of power signals from appliances. Then, in order to improve the performance further, the kernel discriminant analysis (KDA) [3] is incorporated into the PR system as a secondary feature extraction.

2. Power Signal Recognition

2.1. Problem Description

Consider a recognition problem of two home appliances, an electric iron (EI) and a cook top (CT). Typical power signals of an EI and a CT in operation are shown in Fig. 1. From Fig. 1, it is observed that an EI and a CT operate in a very similar way. Furthermore, if we take a variation of power signals due to manufacturers and operation modes of the appliances into consideration, our task of the recognition becomes more difficult.

2.2. Pattern Recognition System

Let us assume that a discrete-time power signal is being observed. The signal is first segmented by windowing with overlap. For each segmented signal, our purpose is to determine which appliance, an EI or a CT in this paper, is turned on based on some discriminative information from the segmented signal.

Similar to typical PR systems, the proposed system is composed of two sub-systems of feature extraction and classification. Feature extraction is a procedure of extracting some important information from data for a given task, and generally results in reducing the dimension of the data. Once an effective feature extractor (FE) is derived, the efficiency and processing speed of the subsequent classification step can be improved with the features.
3. Feature extraction

3.1. High-Order Moments

In the proposed system, we use the information of high-order moments of the segmented signals as discriminative features. Let us denote a segmented signal by a vector \( \mathbf{x} = [x_1, x_2, \ldots, x_N]^T \), where \( N \) is the length of the segmented signal. The feature vector of \( \mathbf{x} \) is then calculated as

\[
\mathbf{F}_1(\mathbf{x}) = [v_1(\mathbf{x}), v_2(\mathbf{x}), \ldots, v_5(\mathbf{x})]^T ,
\]

where

\[
v_i(\mathbf{x}) = \frac{\sigma}{m} \tag{2}
\]

and

\[
v_i(\mathbf{x}) = \frac{\mu_i + 1}{\sigma + 1} \tag{3}
\]

for \( i = 2, 3, 4, 5 \). Here, \( m \) and \( \sigma \) are the sample mean and standard deviation of \( \mathbf{x} \), respectively, and

\[
\mu_i = \frac{1}{N} \sum_{n=1}^{N} (x_n - m)^i \tag{4}
\]

is the \( i \)th central moment of \( \mathbf{x} \). Note that \( v_1(\mathbf{x}) \), \( v_2(\mathbf{x}) \), and \( v_3(\mathbf{x}) \) are the coefficient of variation, skewness, and kurtosis [4] of \( \mathbf{x} \), respectively. The skewness \( v_2(\mathbf{x}) \) is a measure of the extent to which the probability distribution function (pdf) of \( \mathbf{x} \) is asymmetric, and the kurtosis \( v_3(\mathbf{x}) \) is a measure of the peakedness of the pdf of \( \mathbf{x} \) compared to the normal distribution.

3.2. Kernel Discriminant Analysis

As an extension of the linear discriminant analysis which is one of the most fundamental and powerful feature extraction methods, the KDA provides generally good PR performance, especially in linearly inseparable PR problems. Note that our PR problem is a linearly unseparable one, which will be shown shortly.

Adopting the KDA for the secondary feature extraction in the proposed system, the final feature of \( \mathbf{x} \) is given by

\[
\mathbf{F}_2(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{F}_1(\mathbf{x})) + b, \tag{5}
\]

where \( \phi: \mathbb{R}^d \rightarrow \mathbb{R}^{d'} \) is the mapping function (\( d = 5 \) in this paper), the \( d' \)-dimensional real column vector \( \mathbf{w} \) is called the kernel discriminant vector (KDV) and the scalar \( b \) is called the bias.

Specifically, the KDV of the KDA can be obtained as

\[
\mathbf{w}_K = \arg \max_{\mathbf{w}} \frac{\mathbf{w}^T \mathbf{S}_B^\phi \mathbf{w}}{\mathbf{w}^T \mathbf{S}_W^\phi \mathbf{w}} \tag{6}
\]

In (6), \( \| \cdot \| \) indicates the Euclidean norm,

\[
\mathbf{S}_B^\phi = \left( \mathbf{m}_1^\phi - \mathbf{m}_2^\phi \right) \left( \mathbf{m}_1^\phi - \mathbf{m}_2^\phi \right)^T \tag{7}
\]

is the \( d' \times d' \) kernel between-class scatter, and

\[
\mathbf{S}_W^\phi = \Phi(\mathbf{X}) \Phi^T(\mathbf{X}) - \sum_{l=1}^{L} \mathbf{N}_l \mathbf{m}_l^\phi \left( \mathbf{m}_l^\phi \right)^T \tag{8}
\]

is the \( d' \times d' \) kernel within-class scatter, where

\[
\mathbf{m}_l^\phi = \frac{1}{N_l} \sum_{i \in Z_l} \phi(\mathbf{F}_1(\mathbf{x}_i)) \tag{9}
\]
denotes the kernel sample mean vector for class \( l \);

\[
\mathbf{X} = \left[ \mathbf{F}_1(\mathbf{x}_1), \mathbf{F}_1(\mathbf{x}_2), \ldots, \mathbf{F}_1(\mathbf{x}_{LM}) \right] \tag{10}
\]
denotes the \( d \times M \) training data matrix after the first feature extraction of (1); and

\[
\Phi(\mathbf{X}) = \left[ \phi(\mathbf{F}_1(\mathbf{x}_1)), \phi(\mathbf{F}_1(\mathbf{x}_2)), \ldots, \phi(\mathbf{F}_1(\mathbf{x}_{LM})) \right] \tag{11}
\]
denotes the \( d' \times M \) data matrix in the kernel space with \( Z_l = \{ i : \mathbf{x}_i \in \text{class } l \} \) denoting the index set for class \( l \) and \( N_l \) denoting the number of elements in \( Z_l \). Here, \( M \) is the number of training data.

Among several KDA-related schemes which differ in terms of implementation, we adopt the following three schemes and compare the performances in this paper: Approximated KDA based on a perturbation method (KDAP) [3], generalized discriminant analysis (GDA) [5], and null space-based kernel Fisher discriminant analysis (NKFDA) [6].

4. Classification

We employ the nearest neighbor (NN) classifier for classification based on the fact that the NN classifier is a simple and intuitive scheme, and shown to be quite effective [7,8] in many cases. A PR system with the NN classifier operates in the following way: The final feature \( \mathbf{F}_2(\mathbf{x}_{test}) \) of a testing sample \( \mathbf{x}_{test} \) and features \( \{ \mathbf{F}_2(\mathbf{x}_j) \}_{j=1}^{M} \) of training samples \( \{ \mathbf{x}_j \}_{j=1}^{M} \) are calculated via (1) and (5) after the acquisition of the kernel FE. Then, based on the Euclidean distance

\[
d(\mathbf{x}_{test}, \mathbf{x}_j) = \| \mathbf{F}_2(\mathbf{x}_{test}) - \mathbf{F}_2(\mathbf{x}_j) \| \tag{12}
\]

between \( \mathbf{F}_2(\mathbf{x}_{test}) \) and \( \mathbf{F}_2(\mathbf{x}_j) \), the NN classifier estimates the label for the testing sample \( \mathbf{x}_{test} \) as \( y_{test} = y_m \), where \( y_m \in \{ 1, -1 \} \) is the label of \( \mathbf{x}_{test} \), and \( m \) is an integer such that \( d(\mathbf{x}_{test}, \mathbf{x}_m) \leq d(\mathbf{x}_{test}, \mathbf{x}_j) \) for all \( j \in \{ 1, 2, \ldots, M \} \). Note that the PR accuracy of a PR system will be 100% for any subset of training samples due to the intrinsic characteristics of the NN classifier.

5. Simulation Results

Given 11 power signals collected from EIs and CTs in operation on various modes, we have first obtained 159 signal segments (53 segments for EIs and 106 segments for CTs) where the appliances are on. For each of the signal segments, after the extraction of features as proposed in (1), the first three elements of each feature vector are illustrated in Fig. 2. In Fig. 2, it is observed that EIs and CTs can be separated quite well in the feature space with high-order moments (although there still exists a bit of linear unseparability).

Among the 159 signal segments, 2k \( (k \text{ for each appliance}) \) signal segments are used for training the proposed system, and the remaining 159 − 2k segments are employed for testing. The average PR accuracies over 250 repetitions for \( k = 10, 20, 30, \) and 40 are given in Table 1. From the simulation results shown in Table 1, it is observed that the PR system with the proposed high-order moment features and KDA can classify the power signals of the two appliances with very high accuracy. Specifically, the PR accuracies are over 90% for all the three KDA-related schemes, except when the number \( k \) of training data is very small. In the case of the GDA, the best PR accuracy reaches around 94%.
Figure 2. The first three elements of each feature vector for power signals of EIs and CTs in operation on various modes.

Table 1. PR Accuracy performance

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<td>10</td>
<td>85.59%</td>
<td>87.85%</td>
<td>86.16%</td>
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<tr>
<td>20</td>
<td>91.44%</td>
<td>92.06%</td>
<td>90.64%</td>
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<td>30</td>
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<td>40</td>
<td>93.35%</td>
<td>93.93%</td>
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6. Conclusion

In this paper, we have presented a pattern recognition system for non-intrusive appliance load monitoring. For two home appliances of similar characteristics, an electric iron and a cook top, we have proposed a novel feature extraction method using information of high-order moments of power signals from the appliances. Simulation results have confirmed that the proposed system with the high-order moment features and kernel discriminant analysis can effectively separate the two appliances.

7. References