CANONICAL CORRELATION BASED FEATURE EXTRACTION WITH APPLICATION TO ANOMALY DETECTION IN ELECTRIC APPLIANCES

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ABSTRACT

This paper proposes a canonical correlation based feature extraction method with application to anomaly detection in electric appliances. Electric appliances in homes, offices or manufacturing factories are nowadays monitored by Internet of Things (IoT) platforms and systems. For unsupervised anomaly detection in such IoT systems, learning a model is challenging, since normal and anomaly behavior coexist in time-domain signals and are difficult to identify. For accurate model training, we propose to split odd and even frequency harmonics of electric current signals and transform using canonical correlation analysis to extract discriminative features. Evaluations on real-world data demonstrates that proposed approach outperforms the conventional unsupervised feature extraction methods.

***Index Terms*—** Electric signal analysis, feature extraction, signal transformation, anomaly detection

1. INTRODUCTION

Recently, electric current signal (ECS) data is widely used in monitoring of home and industrial appliances. Electric appliances such as commercial machines are monitored continuously using current transformer (CT) sensors and edge computing devices [1, 2]. Mostly, CT sensors are placed in power distribution board which are distant from the operational area. To reduce mess of cables especially in homes and manufacturing factories, electricity sensing has been an effective and promising sensing solution. Also, these monitoring systems help in efficient maintenance of the electric appliances. The ECS is a signature of an electric appliance operations, since its internal parts mainly consist of resistors, inductors, capacitors and alike components.

Most of the electric appliances are likely to get damaged or require scheduled maintenance due to various malfunctions, thus anomaly detection becomes an important application to monitor real-time status of an appliance. For example, refrigerators in convenience-store, require scheduled maintenance to prevent from failures and to keep stable quality of food products. To detect failure events, appliance's power consumption is monitored and analyzed [3, 4]. However, power consumption is usually one-dimensional and highly mixed, thus not sufficient to detect a-

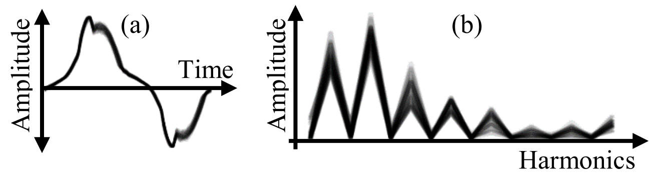


Fig. 1. Example of (a) ECS data and (b) its spectrum

nomaly behavior in real-world systems.

The emerging machine learning techniques have shown improvements in the field of signal processing [5, 6]. They learn relationship between signal and its corresponding label to model normal and anomaly behaviors. A major issue related to analysis of ECS is absence of ground truth labels indicating each process. One solution is to use additional sensors to mitigate the problem of labels as shown in [7]. However, it is difficult to place extra sensors for each appliance in large industries. A more promising approach (we used in this paper) is unsupervised machine learning [8, 9] which does not require training labels. However, in general, unsupervised approaches work well only when correct features are extracted from the data.

For unsupervised learning using time sequence data, the feature extraction method plays crucial role for governing the performance. These methods work on a mathematical objective function to generate the corresponding feature values (without the need of labels) of the original data. The transformed feature values are categorized into similar clusters, where each cluster represent a unique behavior. However, without the domain knowledge about ECS, it is challenging to estimate the clusters using high dimensional features [10, 11] and existing methods fail due to their generic characteristic of feature extraction.

In this paper, we propose unsupervised feature extraction method to separate the original ECS data into normal and anomaly behavior. The symmetric relation of high and low amplitudes in odd and even frequency harmonics (as shown in Fig. 1(b)) is important to recognize the difference between normal and anomaly behavior. For this reason, we split odd and even harmonics and extract features from canonical correlation analysis. We performed a controlled experiment on an automatic cup type coffee making vending machine and prepared labels for verification by recording time stamps of each experiment slots. Experiment on coffee machine proved the effectiveness of our approach when compared to the conventional unsupervised feature extraction methods.

2. MOTIVATION

Our motivation for unsupervised anomaly detection in electric current signal stems from the following real-world scenarios. Firstly, non-continuous measurement i.e. the electric signals are sampled in chunks in real world acquisition systems e.g. one 50/60Hz cyclic signal per second or one cyclic signal per minute. There is a significant time gap between each consecutive signal. Due to issues in either limited resources or hardware configuration of the measurement systems, the meaningful time-series information of real time is not retrieved.

Secondly, non-availability of true labels for each signal. The extracted features are difficult to examine if ground truth signal information is unknown, as is true with unsupervised approaches. In a given combined dataset of normal and anomaly signal, our goal is to find best transform which can separate two types of behavior in most efficient manner. In other words, features transformed by our proposed method should be independent and have maximum separability. Hence, our work is applicable (though not limited to), where labels of signals are not available and also in low sampled non-continuous data.

3. EXISTING METHODS

Given multiple electric current signals comprising of normal and anomaly behavior, where each ECS is sliced into 50/60Hz cyclic signal. Stacked electric signal forms a new matrix which is utilized as an input to feature extraction methods. Denote X as input matrix, which has size $N \times K$, where, N is the number of signal and K is the length of one 50/60Hz signal. The indices of each row in matrix X represent the time-stamps of signal acquisition. With an assumption, the joint analysis (normal and anomaly dataset) will result in two subsets where each subset represents the normal and anomaly behavior. Since, the domain knowledge about electric appliance is not available, verification of these subset becomes difficult. We thus find these subsets using clustering method and compare performance of state-of-the-art unsupervised feature extraction methods. We use scikit-learn [12] machine learning library in the experiments.

3.1. Principal Component Analysis (PCA)

PCA is a simple, standard and non-parametric method in data analysis that uses an orthogonal transformation to generate principal components. As a linear transformation method, it provides an optimal solution for the complex high dimensional data and is widely used technique for dimension reduction and data visualization. In case of ECS data, PCA feature value has been used in [13] for classification of home appliances. With an assumption to separate normal and anomaly behavior, we employed PCA on a single electric appliance ECS data and tested separability in the dimension-reduced PCA feature space.

3.2. Auto Encoder (AE)

AEs are neural network with three layers comprising of input layer, hidden layer and output layer. Auto-encoder trains with same data in input and output layer with same number of neurons, while hidden layer has no limit to number of neurons. It is also known as non-linear feature transformation method because it learns data coding with non-linear activation functions. The discriminability of features are verified in [14] by using Stacked Denoising Auto-encoders (SDAE) on asynchronous motor current signals. Based on this work, we employed three layer Auto-encoder to extract feature values by iteratively changing the number of neurons in hidden layer and test the normal and anomaly feature discriminability.

3.3. Canonical Correlation Analysis (CCA)

CCA [15] is a useful method to generate meaningful inferences from the two datasets. For example, it can be used to find correlations between genes and diseases, when given a set of patient's information. It finds multivariate correlations between a given $X = (X_1, \ldots, X_n)$ and $Y = (Y_1, \ldots, Y_m)$ random variables. This correlation space provides a common representation and separates the similar subsets in X and Y. CCA has been applied to several multimedia research work, such as image segmentation [16], cross-lingual retrieval, cross-modal multimedia retrieval [17], data fusion analysis [18] and feature extraction methods [19]. Our proposed method also includes CCA that can be used for discriminative feature extraction from a single dataset as explained in the next section.

4. PROPOSED METHOD

A combination of signal processing and machine learning techniques is proposed here as a feature extraction method. The proposed method consists of two main parts; i.e., discriminative feature extraction and cluster identification. The discriminative feature extraction uses CCA on frequency domain features. The cluster identification is an iterative method to identify a particular cluster is normal or anomaly.

4.1. Discriminative Feature Extraction

Each time-domain signal is treated as independent of the other signal (if data is non-continuous). We assume that cyclic signal $y(t)$ can be represented as Fourier expansion, as stated in (1). In case of a single cyclic ECS, the frequency components in frequency spectrum are multiples of fundamental frequency f_0 (f_0 is either 50Hz or 60Hz).

$$y(t) = A_0 + \sum_{n=1}^{\infty} A_n \sin(2\pi f_0 n t + \varphi_n), \qquad (1)$$

where, A=amplitude, f=frequency, φ=phase, n=f_0 harmonics.

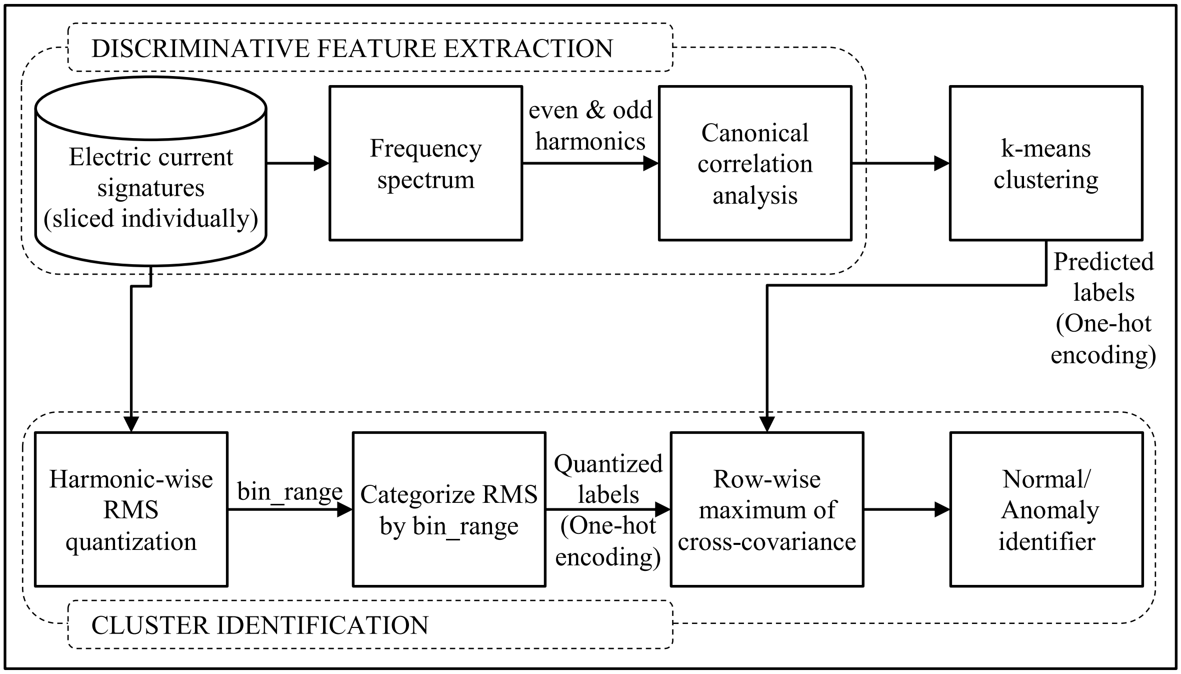


Fig. 2. Block diagram of proposed method

Our proposed method separates the odd and even number of frequency harmonics and analyses the symmetric behavior between high and low amplitudes of odd and even harmonics respectively. Since, existing methods are very general, it fails to detect changes in this symmetric relation when an anomalous event is occurred.

Figure 2 illustrates a combined block diagram of two parts of the proposed method. On each ECS, we apply fast Fourier transform (FFT) to transform into frequency domain and obtain amplitude spectrum. Since, applying FFT on each ECS, the frequency component will be harmonics of fundamental frequency (50/60Hz) in the spectrum. Before applying machine learning methods, the frequency domain feature values are normalized by summing each frequency frame to one and logarithm transformation is applied to convert it in decibel representation. As per (1) amplitudes of frequency components are added i.e. related with each other, we propose to split frequency spectrum into odd and even harmonics of fundamental frequency into odd harmonics and even harmonics matrices. Log-normalized frequency features are transformed into maximized correlated features by CCA. Dimension-wise mean is applied on CCA-transformed features that produces a single matrix. A commonly used k-means clustering method is used for training model on these discriminative feature values.

4.2. Cluster Identification

The clustering method predicts the labels $\{p\}$ of each ECS that belong to a particular cluster. Since the real behavior of each cluster is not available, we propose cluster identification method to identify predicted clusters as normal cluster or anomaly cluster. With an assumption that damage in rotating machines or appliances can be detected in high frequency components, an iterative approach is proposed to identify the predicted cluster behavior. Also, this additional part of cluster identification after clustering completely automates anomaly detection system. The cluster identification method consist of two subparts, first subpart i.e., harmonic-wise rms quantization searches the cutoff frequency f_k where, amplitudes are apart and a promising separation is found between normal and anomaly behavior. Second subpart identifies tag i.e., normal or anomaly of the predicted cluster labels.

The first subpart applies FFT to N sets of ECS, generating a frequency spectrum, denoted as matrix F. An iterative algorithm for searching cutoff frequency f_k by quantizing rms vector is summarized in Algorithm 1, which outputs the histogram bin ranges.

Algorithm 1 Harmonic-wise RMS quantization

Input: Given frequency feature values F.
Initialize: max_bin = [ ] and bin_range = [ ]
for $k = 1$ to number of harmonics **do**
1: Calculate high pass filter (cutoff= k)
2: Calculate inverse FFT.
3: Calculate root mean square.
4: Calculate 2-bins histogram.
5: Append maximum bin count to max_bin.
6: Append bin ranges to bin_range.
i =index where max_bin is minimum.
Output: Select bin ranges from bin_range at index i.

The second subpart uses the bin ranges calculated from the Algorithm 1 to categorize rms vector by upper and lower bin range into quantized labels $\{q\}$. RMS value in a RMS vector falls in which bin range is categorized. The tagging of lower bin range as 0 and higher bin range as 1 is performed. This is based on supposition that the low bin range values are normal and higher bin range values are anomaly instances. Prediction labels $\{p\}$ is obtained from clustering method, e.g. in case of two clusters, each instance will be predicted as either cluster number 0 or cluster number 1. One-hot encoding of $\{q\}$ and $\{p\}$ are set to Q and P respectively. One hot encoding is a process by which categorical variables are converted into binary form returning a sparse matrix. The matrix D is calculated, which is a 2×2 covariance matrix of Q and P, where rows represent quantized labels and columns represent predicted labels. The cluster with normal tag is maximum value in first row of matrix D and cluster with anomaly tag is maximum value in the second row. The normal/anomaly identifier block tags each ECS by identified cluster behavior. These tags can be used for further understanding, processing or classification of test data.

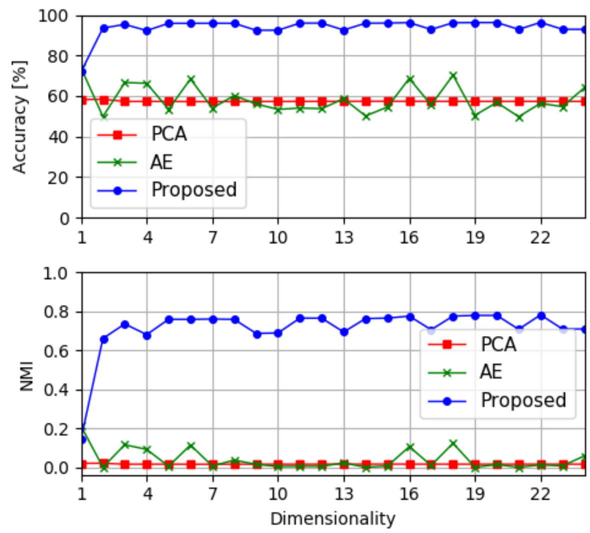
5. EXPERIMENTS

5.1. Setup

The controlled experiment was performed to measure normal and anomaly ECS of an automatic cup type coffee making vending machine. Here we define machine anomaly as change in motor operation from the normal condition. The motor operation was changed by reducing 40% of the coffee beans. While grinding the coffee beans, we observed that power consumption of the motor changed from the normal condition which was difficult to distinguish. Also, we observed that taste of the produced coffee was changed, which is a big concern in most convenience stores nowadays. The 16 coffee making sequences each of normal and anomaly condition was measured and later extracted motor bean grinding sub-sequences. For preparing verification labels, we noted the time when coffee machine was in normal and anomaly condition.

5.2. Approach

As described in Section 3, three methods are compared; where, CCA is included in the proposed method. The input to PCA and AE methods are log-normalized frequency feature values which are kept similar with CCA input for better result comparison. In order to avoid the problem of random starting-points in k-means algorithm, clustering with the same selected features are performed for 10 times, and, average results are recoded. We selected only 2 number of clusters, since we want to separate the two behavior. The training phase selects 10 cups each of normal and anomaly condition, while in testing phase remaining 6 cups each are selected, which is not shown in the training phase.



(a)

(b)

Fig. 3. Experimental results of k-means clustering (a) Accuracy (b) Normalized Mutual Information

5.3. Results

Two metrics including clustering accuracy and normalized mutual information (NMI) score are employed to measure the performance. Both of the metrics indicate better performance with a larger value. Accuracy calculation becomes straight forward since labels are prepared from the experiments. The other metric, NMI, is used to judge the separation quality of feature values in feature space and, is a measure of the similarity between the label assignments.

Figure 3(a) and 3(b) illustrate the experimental results of k-means clustering accuracy and NMI score respectively. The depicted results are obtained from the test data, i.e. not used in the training phase. From the figures it is evident that the proposed method significantly outperforms the other methods, in terms of both accuracy and NMI, which means the feature values are homogeneous, complete and have less over-lap in feature space. Also, it is pertinent to note that proposed method produces stable performance along the feature dimensions.

6. CONCLUSION

A canonical correlation based feature extraction method with application to anomaly detection in electric appliances has been proposed. Unsupervised feature extraction for each individual electric current signal by splitting odd and even harmonics generated the discriminative features without using the ground truth labels. The cluster identification part automated the overall system and provided the correct tag in all the iterations. It has been showed that proposed method outperformed the existing methods in experiment of an automatic cup type coffee making vending machine electric current signals. We further plan to develop a classification system for various subsequences in coffee making process.

7. REFERENCES

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