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Short communication

Appliance classification using VI trajectories and convolutional neural networks

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ABSTRACT

Non-intrusive load monitoring methods aim to disaggregate the total power consumption of a household into individual appliances by analysing changes in the voltage and current measured at the grid connection point of the household. The goal is to identify the active appliances, based on their unique fingerprint. An informative characteristic to attain this goal is the voltage–current trajectory. In this paper, a weighted pixelated image of the voltage–current trajectory is used as input data for a deep learning method: a convolutional neural network that will automatically extract key features for appliance classification. The macro-average *F*-measure is 77.60% for the PLAID dataset and 75.46% for the WHITED dataset.

1. Introduction

A basic but crucial step towards increased energy efficiency and savings in residential settings, is to have an accurate view of energy consumption. To monitor residential energy consumption cost-effectively, i.e., without relying on per-device monitoring equipment, non-intrusive load monitoring (NILM) provides an elegant solution. It identifies the per-appliance energy consumption by first measuring the aggregated energy trace at a single, centralized point in the home and then disaggregating this power consumption for individual devices using machine learning techniques.

Classifying active appliances is mostly done by extracting features from the monitored data and training a machine learning classifier. These features are often extracted once it is detected that a device is switched on/off [1]. The type of features depends strongly on the sampling rate of the measurements. When using low frequency data ($\leqslant$1 Hz), the most common features are the power levels and the on/off durations [2]. A drawback of this approach is that only energy-intensive appliances can be detected. This can be alleviated by performing fine-grained measurements at the cost of an increased data storage rate and more complex data analytics. It is then possible to calculate features like the harmonics [3] and the frequency components [4] from the steady-state and transient behavior of the current and voltage signal. More recently, the possibility to consider voltage–current (VI) trajectories has also been considered [5–7]. Once the features are extracted, they can be fed into different classification methods, like support vector machines (SVM) [13], decision trees [14], or nearest neighbors [15]. Some methods use the complete aggregated power signal as feature. In [16], this is used as input for different convolutional neural networks (one per appliance) that each determine the total power consumption of the corresponding appliance. The total power consumption can also be disaggregated in power traces per appliance. This could be done with the discriminative sparse coding [17], deep neural networks like long short-term memory networks (LSTM), and denoising autoencoders [18,20], or recurrent LSTMs [19,20].

In order to distinguish appliances based on their VI trajectories, powerful measuring devices must be used that are able to sample high frequency data.

In this letter, it is proposed to interpret the VI trajectories as weighted pixelated VI images that can be used as inputs for a CNN. Such networks are often used for classification tasks in computer vision, due to their excellent discriminative power to classify images [8]. In this paper, it is shown that a CNN approach can also be valuable in a NILM context to discriminate active appliances based on the weighted pixelated VI image. The results of this novel approach are benchmarked on the PLAID [10] and WHITED [11] datasets.

2. Weighted pixelated VI image

The VI trajectory of an appliance is obtained by plotting the voltage against the current for a defined time period when the

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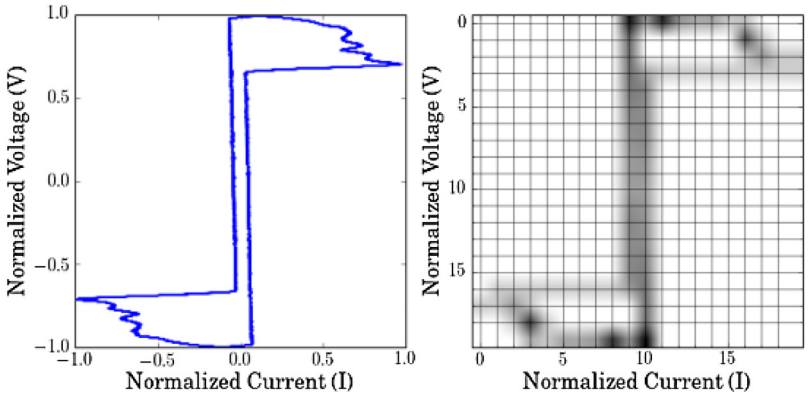

Fig. 1. Transformation from a continuous VI trajectory of a compact fluorescent lamp (left) into the weighted pixelated VI image (right) for $n = 50$.

appliance is turned on. It is shown in [5] that manually extracted features from the VI-trajectory like the enclosed area, slope of the middle segment, etc. can be used to classify the appliances.

Nevertheless, extracting features from the VI trajectory is not straightforward. As an alternative, the VI trajectory can be converted into a pixelated VI image ($n \times n$ matrix) by meshing the VI trajectory. In [6,7], each cell of the mesh is assigned a binary value that denotes whether or not it is traversed by the trajectory. Based on this pixelated VI image, several features can be extracted to classify different power loads [6]. Examples of features are the number of continuums of occupied cells, the binary value of the left horizontal cell and central cell. In [7], the pixelated VI image is re-arranged into an input vector that can be fed directly into a classifier, like random forests, to classify different appliances.

Previous approaches compress the information contained in the VI-trajectory into a limited amount of correlated summary statistics. To take full advantage of the information contained in the VI trajectory, this letter proposes to represent the VI trajectory as a weighted pixelated image. In contrast to [6,7] where the image has continuous values instead of binary values. The necessary processing steps are:

1 Taking the voltage V and the current I when the appliance is active over a certain amount of time (the steady-state behaviour),
2 Normalizing such that $[V, I] \in [-1, 1]^2$,
3 Creating the continuous VI trajectory,
4 Overlaying it with a $n \times n$ mesh,
5 Counting for each cell in the mesh the amount of trajectory points it contains,
6 Normalizing the values of the cells such that the maximum value of the cells is one.

Fig. 1 illustrates the transformation from the continuous VI trajectory to the weighted pixelated VI image.

3. Convolutional neural networks

Once the VI trajectory is transformed into the weighted pixelated image, a CNN is applied for the classification task. CNNs are a type of neural networks (NNs) that are often used in computer vision because they are highly suitable to classify images [8]. The (C)NN takes training samples as input and classifies them by automatically extracting informative features from the data. To this end, an architecture and training procedure is needed.

The architecture of a NN consists of different layers, see Fig. 2. The first layer is always the input layer containing as many nodes as the dimension of a sample (here, $n \times n$). This is followed by one (or more) fully connected layers which are hidden. Each of these layers contains a certain number of nodes that have learnable weights and biases and each of the nodes receives some inputs, performs a dot product and optionally applies a non-linearity. This non-linearity is often obtained by using a rectified linear unit that replaces all negative values by zero. At the end, the output of the last fully connected layer is fed into the output layer. Since the NN is used for classification, the output layer has K nodes with K equal to the number of classes. The values of the output nodes are chosen to lie between 0 and 1 and sum to 1, which is achieved by applying the softmax function. In other words, each node represents the probability that a VI image corresponds to certain class. The output node with the maximal value represents the predicted class.

To create a CNN from a NN, convolutional layers are added. These are placed between the input and output layers as desired and are consequently also hidden. The main difference between a convolutional and fully connected layer is that each node in a convolutional layer is connected to a small region of the input matrix exploiting local correlation, see Fig. 2. In each node, a convolution is performed by adding each element of the input image to its local neighbours, weighted by a matrix called a filter. After the convolutional layer, it is common to implement a pooling layer to downsample the convolved matrix. This reduces the spatial size of the representation, and the amount of parameters, and hence also manages overfitting. This downsampling is achieved by sliding a $d \times d$ window over the input (here, with $d = 2$) and each time outputting the largest element of the window.

The implemented CNN in this letter has the following structure: it takes as input the weighted pixelated VI image (a $n \times n$ matrix, with $n = 50$), and has the following hidden layers: a convolutional layer with f filters of size 5, a pooling layer, another convolutional layer with f filters of size 5, another pooling layer, a fully connected layer with n^2 nodes and an output layer with K nodes. The number of filters f is set to 50. The number of output nodes K is determined by the number of different appliances present in the dataset (i.e., the number of classes). An analysis of alternative parameter settings for n and f proved no significant changes in the results.

4. Model training

Once the architecture is specified, a training procedure is initiated so that the CNN learns to classify the different classes. To this end, multiple training examples are needed. These are images $\mathbf{X} = (X_1, X_2, \ldots, X_N)$ labelled with their corresponding class $\mathbf{t} = (\mathbf{t}_1, \mathbf{t}_2, \ldots, \mathbf{t}_N)$ where $\mathbf{t}_i$ is a 1-of-K coding of the classes. The aim of the training is to find weights and biases such that a cost function is minimized. Since the class labels are categorical, the cost function is defined as the cross-entropy function [9]:

$$L = -\sum_{i=1}^{N}\sum_{k=1}^{K} t_{i,k} \log(y_{i,k}) \tag{1}$$