Cepstrum Analysis applied on Event Detection in NILM

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Abstract

Event detection plays an important role in non-intrusive load monitoring to accurately detect the switching of appliances in a residential environment. Improving the detection ratios of those methods while keeping the computational cost under control is important. This paper presents a new event detection mechanism that works in the frequency domain and uses Cepstrum smoothing to eliminate noise. We explore the potential of our method by comparing with the χ^2 GOF method on the BLUED dataset. The results indicate that our method is competitive with the state-of-the-art having as advantage that the same feature can also be used for appliance detection.

1. Introduction

Non-Intrusive Load Monitoring (NILM) concerns the analysis of the aggregate power consumption of electric loads in order to recognize the existence and the consumption profile of each individual appliance. (Hart, 1992) was the first one to describe the steps of NILM : 1) measuring the aggregated power consumption with a sensor attached to the main power cable, 2) detecting state-transitions of appliances (events) from the captured data, 3) clustering similar transitions using a well-chosen feature vector, 4) matching the on-transitions with the off-transitions, 5) recognizing and monitoring each appliance.

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This paper summarizes the work previously presented in (De Baets et al., 2016) presenting an event detection method that uses smoothed frequency components. The remainder of this paper is structured as follows: in Section 2 a brief overview of related work is introduced, in Section 3 the proposed method is described and in Section 4, its performance is benchmarked and discussed.

2. State-of-the-art

Three efficient algorithms that are commonly used for real-time event detection in NILM are: the Generalized Likelihood Ratio (GLR) test (Anderson et al., 2012b), the chi-squared goodness-of-fit (χ^2 GOF) (Jin et al., 2011) and the CUmulative SUM (CUSUM) filtering (Trung et al., 2014). All three methods are statistical tests, work in the time domain and divide the signal into windows. In addition to these statistical methods, more computational costly machine learning algorithms such as kernel clustering (Volpi et al., 2012), Hidden Markov Models (Luong et al., 2012), Support Vector Machines (Grinblat et al., 2013), and Bayesian methods (Gu et al., 2013) have been proposed to address event detection.

Cepstrum analysis was first introduced in 1963 where it was originally used to analyse the echoes within seismic signals produced from earthquakes (Bogert et al., 1963). Since then, it has proven to be a potent technique in several domains, like passive sonar (Kiran et al., 2012), and speech recognition (Hirsch & Pearce, 2000). Very recently it is also shown that Cepstrum coefficients can be used in a NILM setting as discriminative features in appliance recognition (Kong et al., 2015). In our work we explore and demonstrate the use of Cepstrum analysis for event detection.

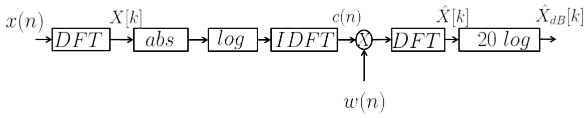

Figure 1. A schematic overview of the transformation from a time signal to spectral smoothed dB-scaled frequency components.

3. Method

Events are detected in the frequency domain where smoothing occurs in the quefrency domain, rather than the time domain. The different steps are outlined in Figure 2. Consider a window x of length n from a power signal p, $x = \{p_i, p_{i+1}, ..., p_{i+n}\}$ then the goal is to detect if there is an event or not. First, this window will be converted from the time to the frequency domain, by using the Fourier transform. By transforming this information from the frequency domain into the quefrency domain, Cepstrum components $c(n)$ are computed. This is done by applying the inverse Fourier transform to the logarithm of $|X|$. These Cepstrum components are smoothed by means of a filter w that is defined as one minus the Hann window. As a result, only the very low and high frequency components remain. In the time-power domain this corresponds respectively to a steady-state signal and step change. The filtered components are transformed back to frequency components $\hat{X}[k]$ by applying the Fourier transformation. Because the relative difference in values of the components is more informative than the absolute difference, the frequency components are converted to a dB scale $\hat{X}_{dB}[k]$. If all the components $\hat{X}_{dB}[k]$ are higher than a chosen threshold τ, then the window $x(n)$ is labelled as an event. This threshold should however be trained, to obtain good detection ratios. How this is done, will be mentioned in next section.

4. Results

In this section the proposed method is compared with the χ^2 squared method by using the BLUED benchmark dataset (Anderson et al., 2012a). From this data, the aggregated active power signal of 60Hz from a family residence in the United States for a whole week is considered. Every state transition of each appliance is labelled providing the ground truth. This power occurs in two phases, namely phase A and B. In total, 904 transitions are captured in phase A and 1578 in B. Each phase has its own properties, e.g. phase B is more noisy than phase A. For that reason, phase A and B are trained and tested separately.

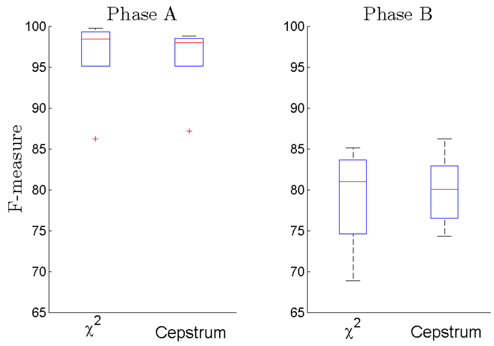

Figure 2. The spread of the F-measure when applying the χ^2 GOF method and Cepstrum analysis on phase A and B of the BLUED dataset.

To obtain the results, we split our data in five equal parts. One part is used for testing and the other four for training. On this training set we apply 5-fold cross-validation in order to avoid overfitting. From this cross-validation, optimal configuration settings for the methods are obtained and the evaluation on the test set gives us the final performance. This initial splitting is done 10 times so that the stability of our performance is proven. For the evaluation of the results, the advice given in (Makonin & Popowich, 2015) is followed. To assess the detection ratio's, the F-measure is used which is defined as the harmonic mean of precision and recall.

The experiments are repeated 10 times and the minimum, first quantile (Q1), median, third quantile (Q3) and maximum of the F-measure are reported in Figure 2. If all these values are close together, then this means that the algorithm is stable which is the case for both methods. Looking at the F-measure, it can be concluded that the Cepstrum analysis is as good as the χ^2 GOF statistic showing $\sim 98\%$ perfect event detection for phase A and $\sim 80\%$ for phase B.

5. Conclusion

In this paper an event detection method is proposed that works in the frequency domain and uses Cepstrum smoothing for eliminating noise. With a reported F-measure equal to 98.01% for phase A and 80.03% for phase B on the BLUED dataset, the method is competing with the state-of-the-art. Although the method is more opaque than the traditional χ^2 method, a big advantage of this method is that the frequency components can be used for both event detection and appliance recognition. More details will be reported in a forthcoming paper.

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