ICASSP 2022 – Path signatures for non-intrusive load monitoring

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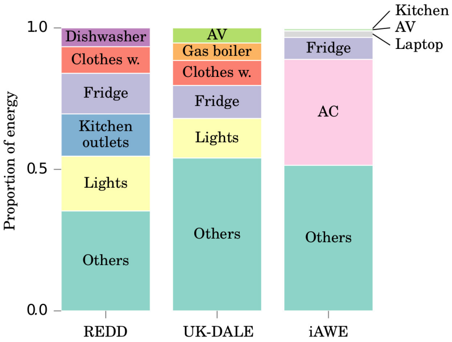
Introduction

- Electricity load monitoring
  - Monitoring voltage and current at the supply to a house
  - Using this signal to identify appliances
- The Path Signature
  - A way of generating features from time–ordered data
- Experiments
  - Predicting the appliance from the supply wire signal

Electricity load monitoring

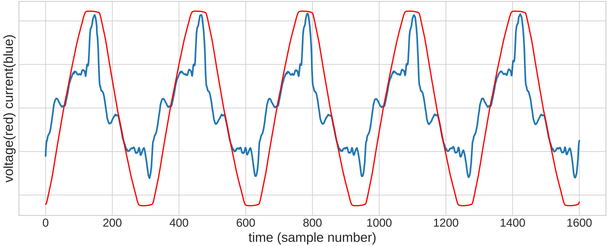


Energy usage from different countries

- Load monitoring is needed to monitor appliance usage.
- Individual appliance monitoring is impractical.
- Non-intrusive monitoring is where we monitor at the supply.

image source: Batra et al. 2015, with permission

Supply wire data (input)



- The plot shows the voltage (red) and current (blue) from one house.
- The voltage is roughly sinusoidal while the current is more irregular.
- The data forms the input for appliance classification.

Current-Voltage (I-V) Graphs

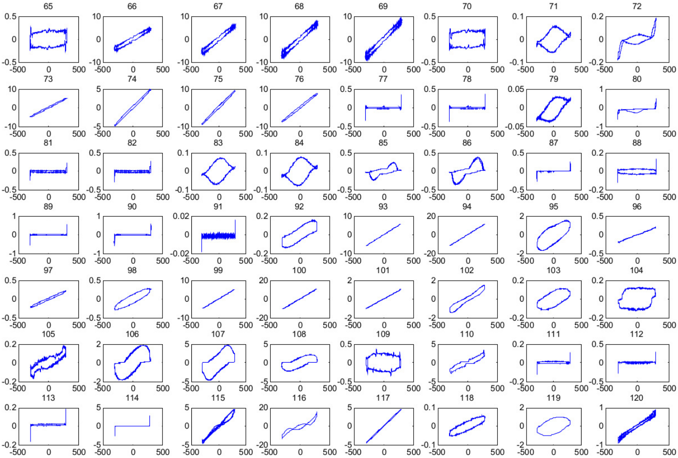
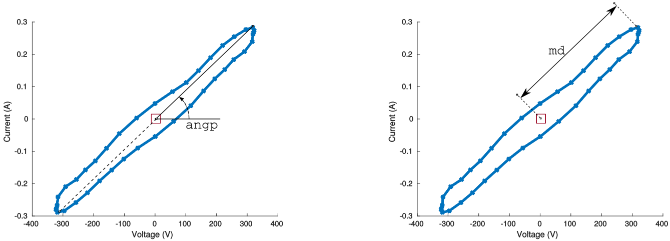


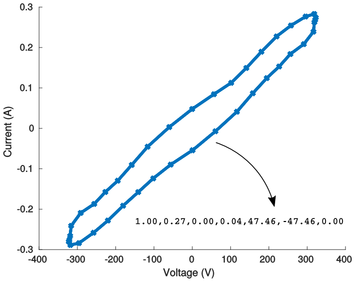
image source: Ting et al. 2005, with permission

Shape features



- Two shape features from the I-V trajectory; left: angle of the maximum-minimum line; right: distance from the centroid to the maximum point.
- In the experiments we use the set of 12 shape features from Mulinari *et al.*

The Path Signature



- The path signature transforms the V-I trajectory into a sequence of numbers which can be used as features in machine learning.
- The sequence length is determined by the signature degree. See Chevyrev and Kormilitzin.
- Python packages esig and iisignature are available to compute the path signature,

```
import esig.tosig as ts
degree = 2
path_signature = ts.stream2sig(path, degree)
```

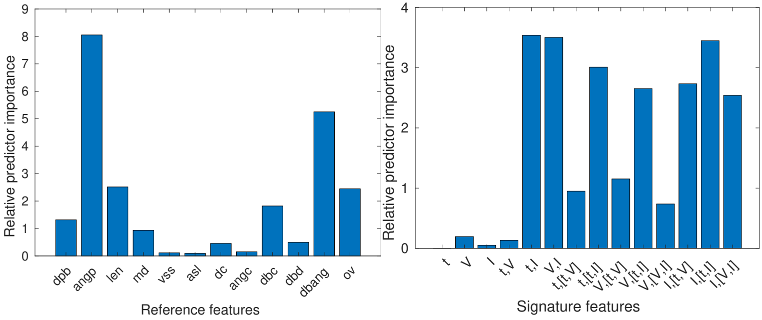
Experiments

Number and type of appliances in the COOLL dataset

No.	Appliance type	No. of appliances	No. of samples
1	Drill	6	120
2	Fan	2	40
3	Grinder	2	40
4	Hair dryer	4	80
5	Hedge trimmer	3	60
6	Lamp	4	80
7	Paint stripper	1	20
8	Planer	1	20
9	Router	1	20
10	Sander	3	60
11	Saw	8	160
12	Vacuum cleaner	7	140
	Total	**42**	**840**

- We predict the appliance using 1) shape features, and 2) path signatures.
- Data used in the experiments is from the Controlled On/Off Loads Library (COOLL).
- All models are trained by 5-fold cross-validation on 80% of the 840 samples, and use the remaining 20% as a test set.

Predictor importance



- Left - the relative importance of each shape feature.
- Right - the relative importance of each term in the signature.

Predicting appliance labels - results

Predicting appliance labels

Set	Features	Number	Accuracy(SD)	Test set
Full	Shape	12	97.77 (0.74)	97.62
	Signature	28	98.81 (1.13)	98.81
Selected	Shape	5	98.51 (1.17)	99.40
	Signature	7	99.11 (0.82)	98.81

Accuracy shown as percentage correct with standard deviation in brackets.

- Accuracy of appliance classification comparing shape features with path signature features.
- Full and selected features sets are shown. The penultimate column is for cross-validation on the training set, and the last column shows a test set accuracy.
- The path signature performs as accurately as shape features.

Conclusion

- The path signature uniquely characterizes a V-I trajectory with a sequence of real numbers which can be used as a feature vector for machine learning.
- The shape features were engineered over a period of more than a decade, but we found path signatures gave similar results with a few days' work.
- The path signature can be used for many applications with multivariate, time–ordered data.

Bibliography

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Thanks to Bruna Mulinari for help in reproducing the results in Mulinari et al.