Automated plug-load identification from high-frequency measurements

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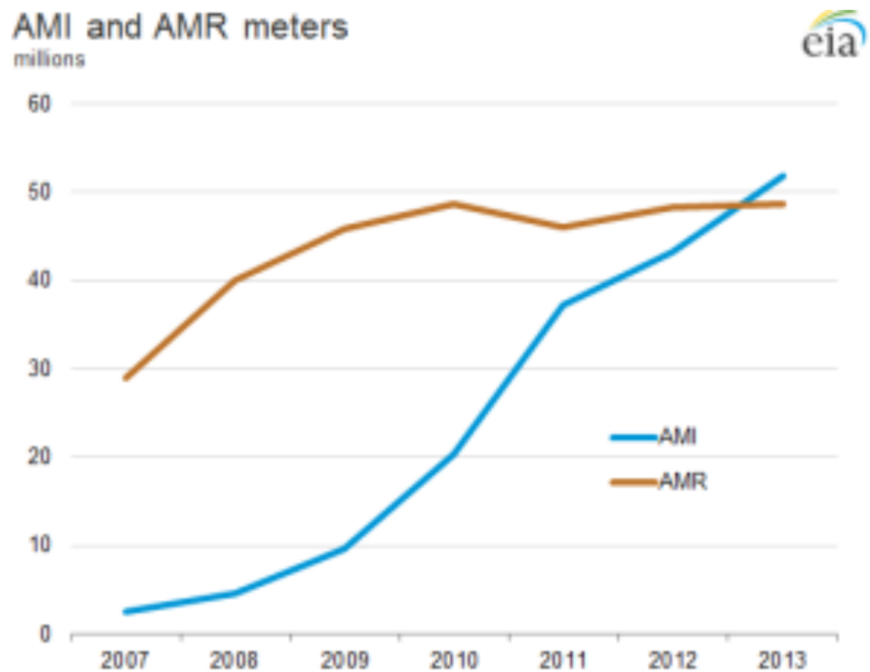
Motivation

- In US, up to 50 millions smart meters by 2013, 20% increase compared with 2012
- More fine level plug-loads meters are available in market, e.g., Belkin's WeMo, Plugwise, ThinEco, BOSS Smart Plugs
- Monitoring and understanding the loads connected with meters help reduce energy



Source: U.S. Energy Information Administration, Annual Electric Power Industry Report (Form EIA-861)

Challenges

- To install and maintain meters in a large scale, how to keep track of the identify of electrical loads connected to the meters?

- Manual label is expensive in large buildings and the loads connected could also change.

- Many applications need to verify the load is consistent with most recent label
  - e.g. direct load control of sensitive equipment

Research Question

Is it possible to determine what appliance is connected to a meter simply from measurements of voltage and current?

What are the representative features that can help the load identification?

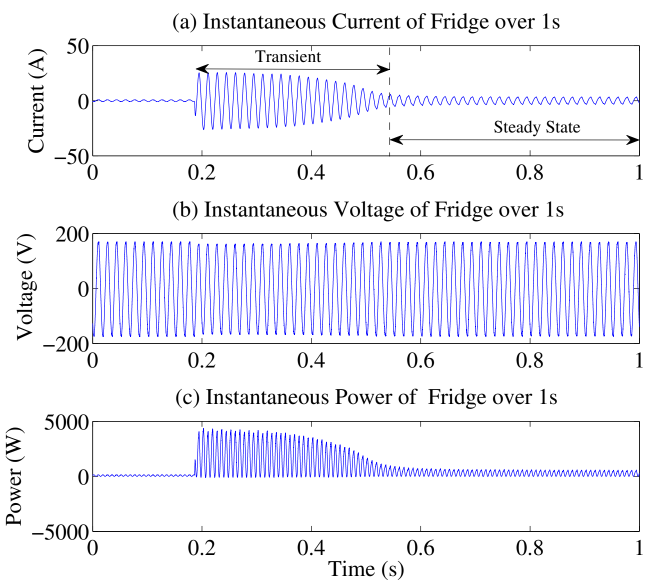
Objective

- To compare the classification performance of popularly used features, on the same dataset.

- To explore the relationship between classification accuracy and sampling rate, to better understand the hardware implementation constraints.

PLAID Dataset

- 30 kHz for 11 different types across 55 households



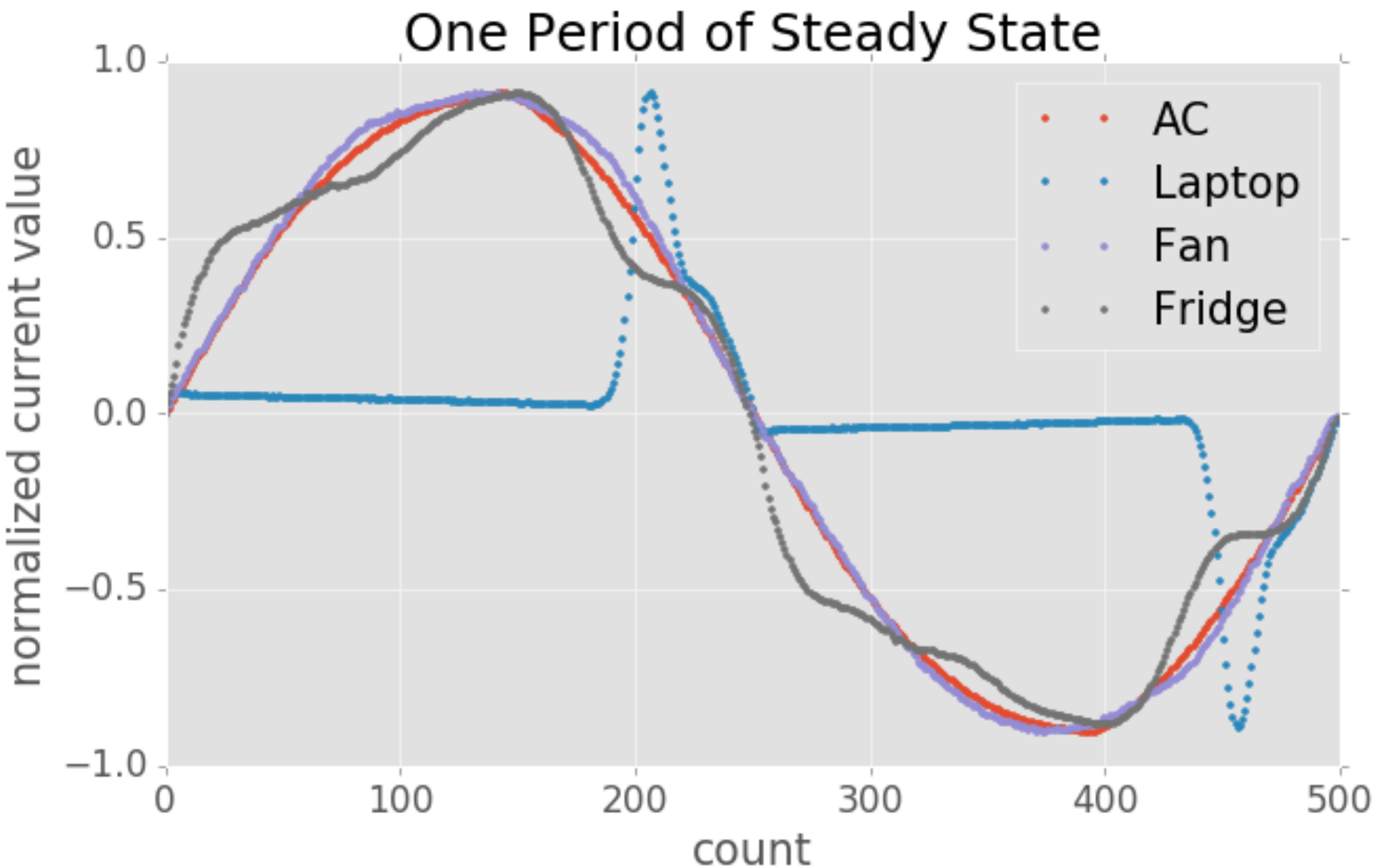
Appliance Type	# of Appliances	# of Instances
Air Conditioner(AC)	19	92
Compact Fluorescent Lamp(CFL)	35	173
Fridge	18	46
Hairdryer	31	156
Laptop	38	163
Microwave	23	135
Washing Machine	7	26
Bulb	25	117
Vacuum	7	35
Fan	23	114
Heater	9	37
Total	**235**	**1094**

- Analysis in this paper will focus on using one period of steady state of the appliances.

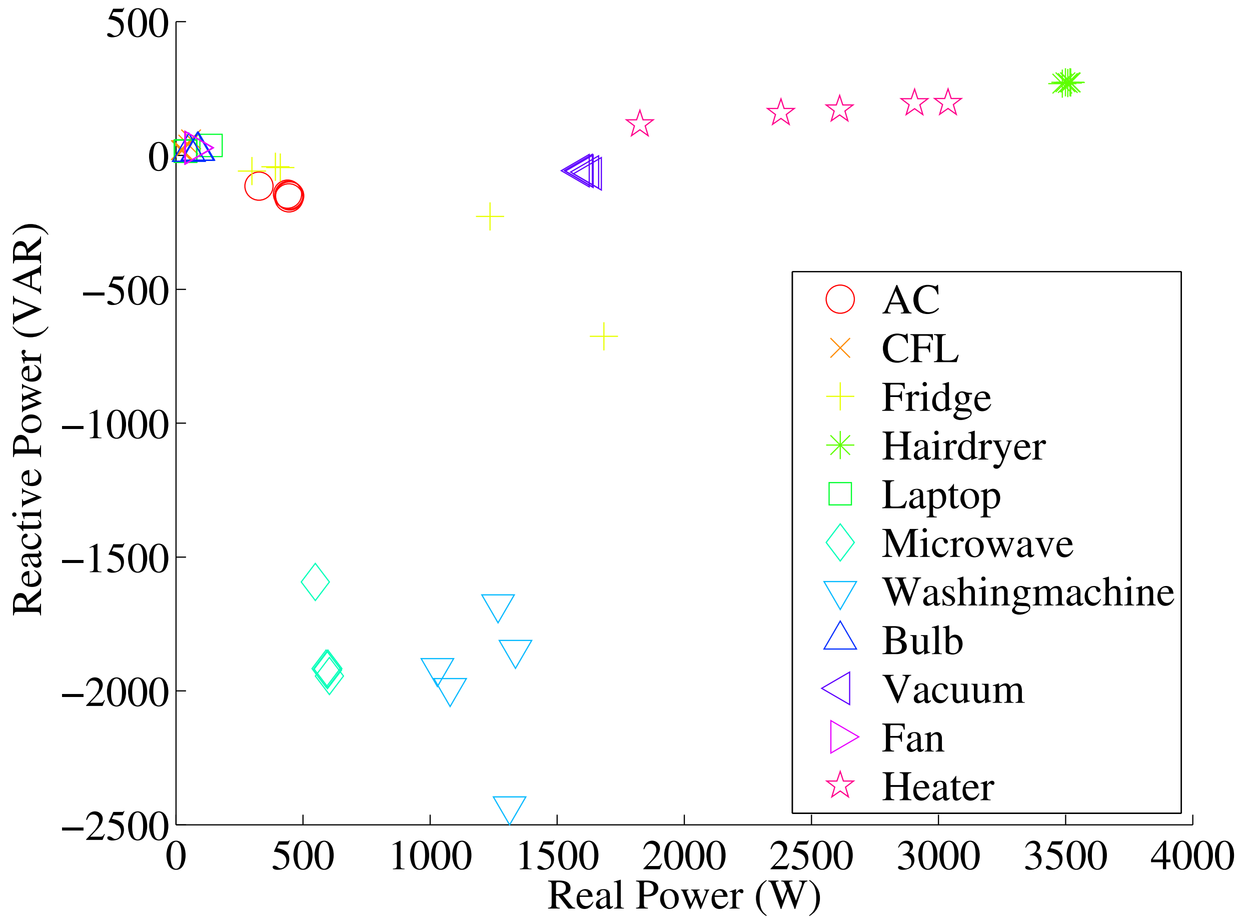
Exploration of Features

- Current waveform
- Real and reactive power (PQ feature)
- Harmonics
- Quantized waveforms
- VI binary images
- PCA for dimension reduction
- Combined features

Current Waveform

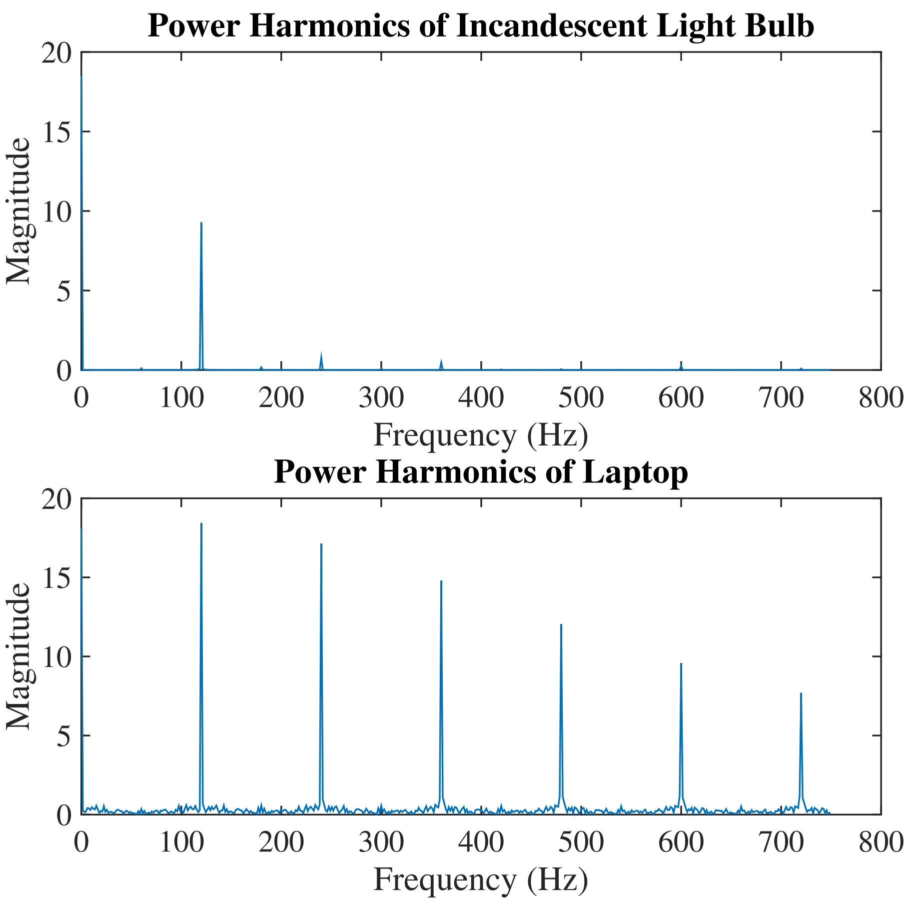


Real/Reactive Power

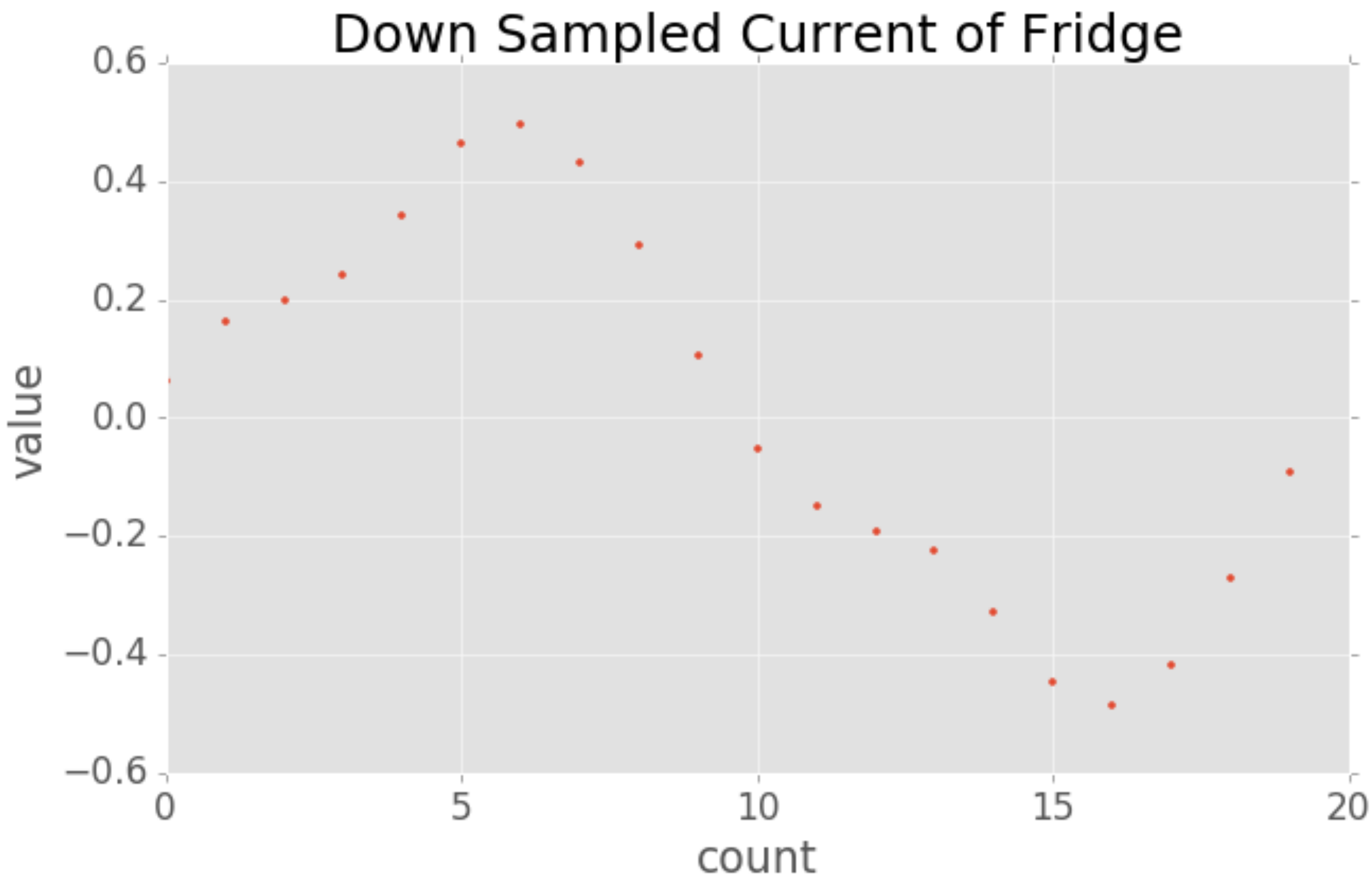


Harmonics

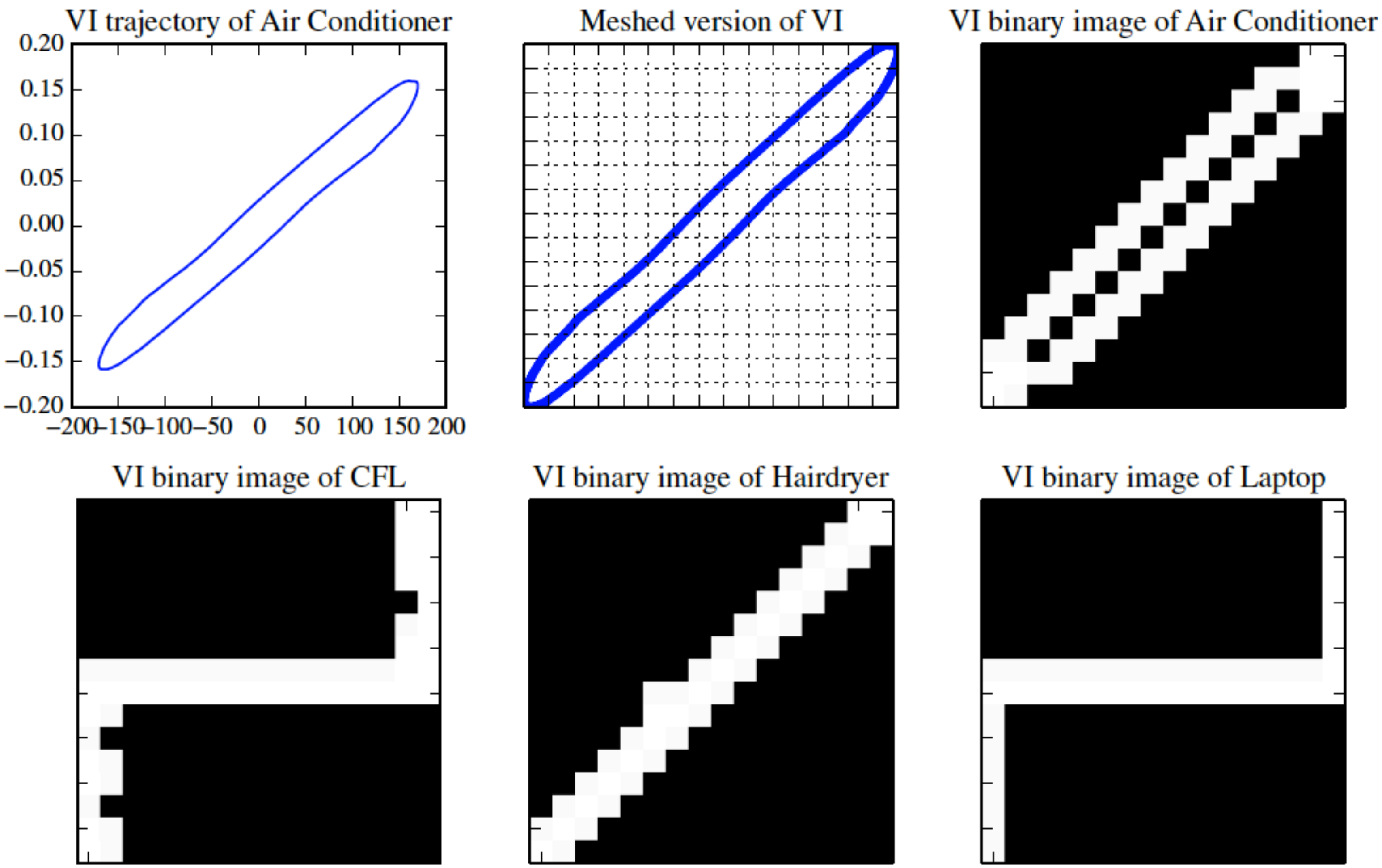
- FFT on instantaneous power signals
- Take the magnitude of integer multiples of fundamental frequency (120Hz)
- Up to 21st order of harmonics are used



Down Sampled Waveform



VI binary image



PCA for dimension reduction

- Apply PCA to keep the components which can explain 99% of variations

Features	Original dimension	Reduced dimension
Current	500	3
Quantized	40	1
VI image	256	110

Previous Work on Features

- Engineered features: real/reactive power [G. Hart 1992], harmonics signals[A. Reinhardt 2012; D. Srinivasan 2006], current draw[D. Zufferey 2012], VI trajectory[H. Lam 2007]
- Data driven features: dimension reduction (PCA), singular vectors (SVD)[H. Lam 2007]

Average accuracy ranges from 85% to 99% by using different settings and algorithms, on small experimental setups.

Classification Strategy

- Classifiers: kNN, GNB, LGC, Decision Tree, Random Forest, LDA, QDA, Adaboost
- Training on instances from 54 households and test on the instances from rest one.
- Use accuracy as the metric

$$\text{Acc} = \frac{\#\text{ of correct predictions}}{\#\text{ of total predictions}}$$

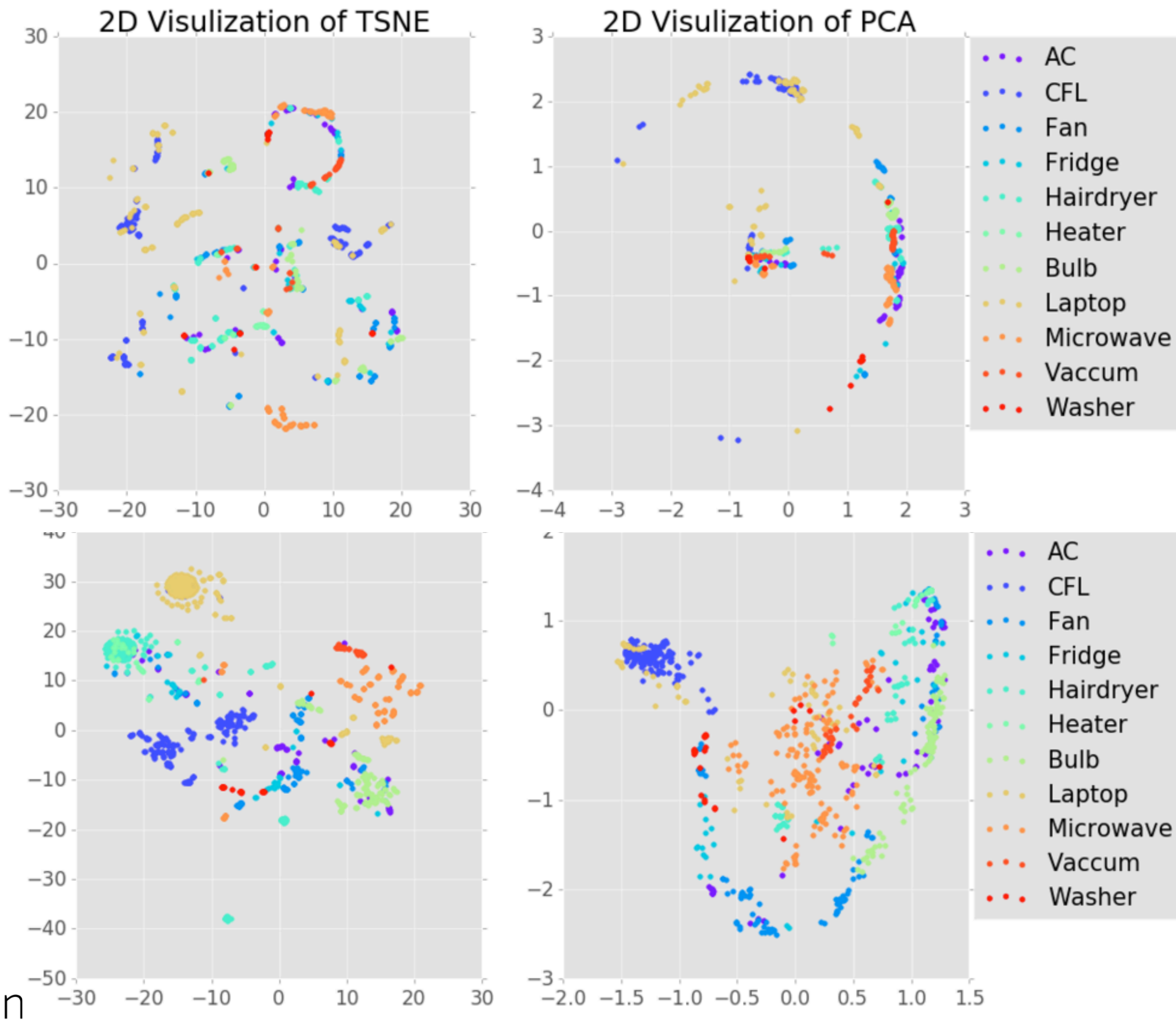
Experiment Results

	kNN(1)	GNB	LGC	DTree	RForest
Current	75.98%	61.73%	69.83%	70.67%	76.26%
Real/Reactive	55.40%	27.19%	29.14%	49.07%	51.58%
Harmonics	45.25%	18.72%	30.45%	42.18%	49.63%
Down Sampled	60.06%	57.17%	60.06%	73.09%	80.63%
VI Image	78.96%	51.96%	74.49%	76.07%	81.75%
PCA Current	44.13%	52.14%	46.37%	48.14%	45.07%
PCA Down Sampled	24.30%	18.06%	11.08%	25.98%	27.28%
PCA VI Image	69.93%	60.34%	64.53%	70.67%	77.65%
Combined	62.10%	59.22%	49.44%	74.49%	86.03%

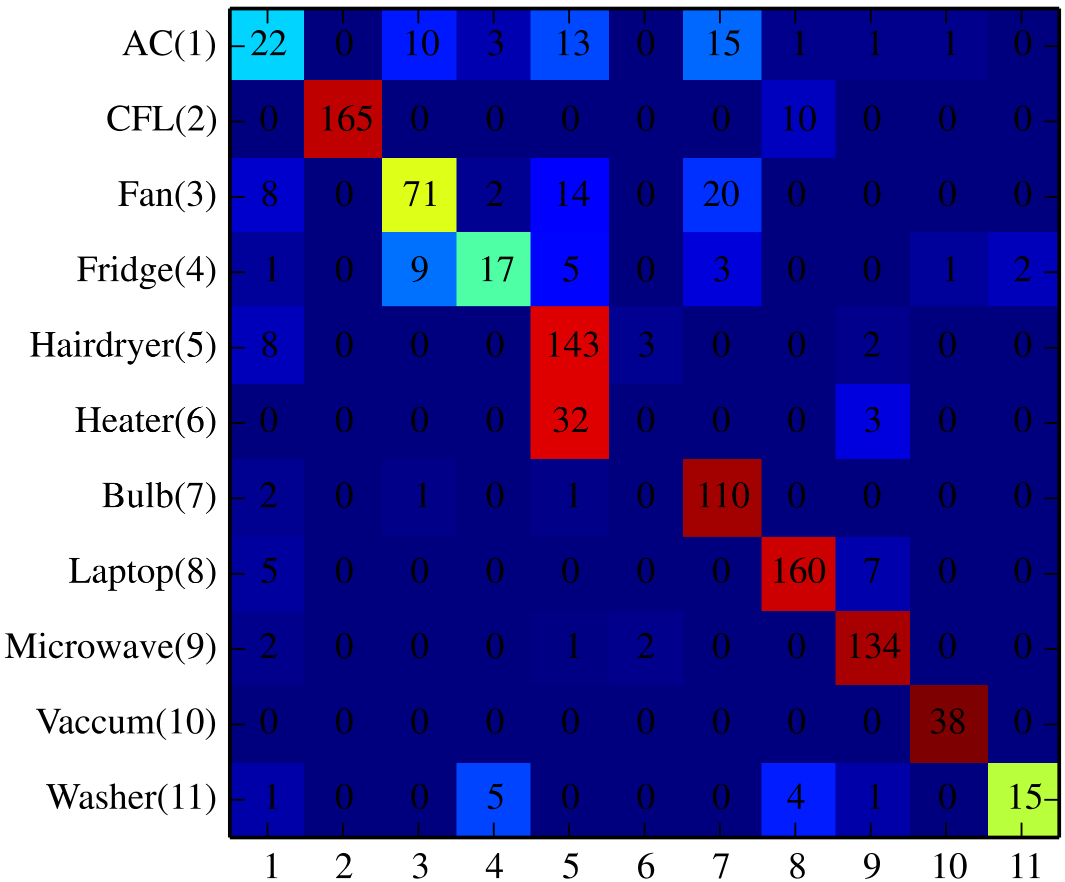
2D representation of features

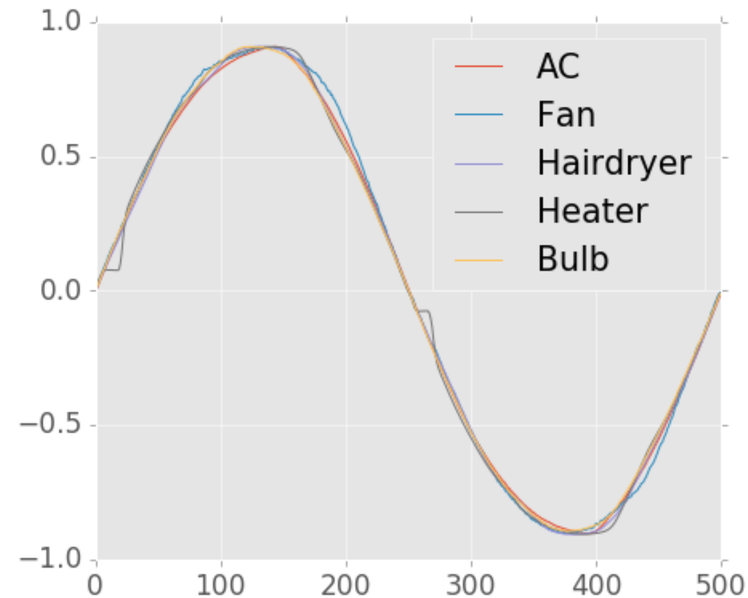
Down sampled

VI Binary Image



Confusion Matrix

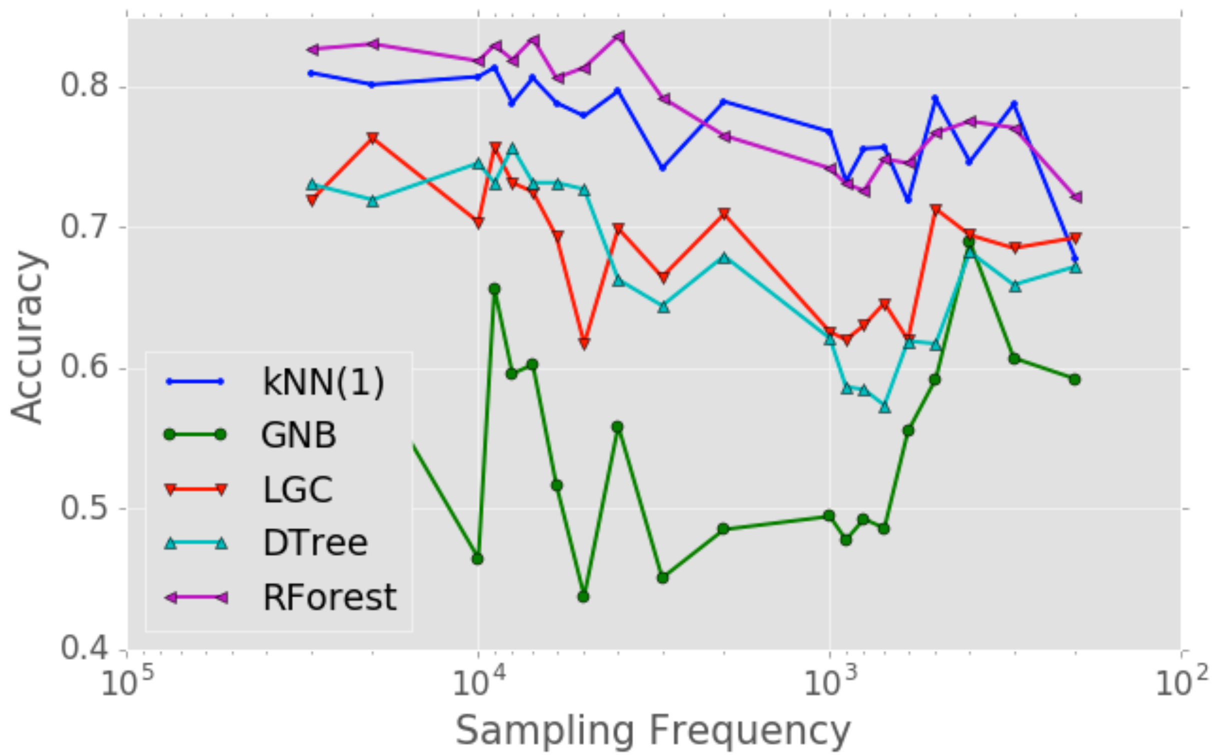




Normalized current signals of misclassified types

Implementation Feasibility

Down sample the dataset from 30K Hz to 200 Hz and testing with VI image feature.



Conclusion

- Combined features perform best across different classifiers, achieving 86.03% average accuracy using random forest.
- Sampling rates higher than 4 kHz is feasible to achieve an accuracy higher than 80%.
- The approach may be also applicable for aggregated signal by doing subtraction.

Future Work

- Study how to use the idea of subtraction (signals before and after events) to apply the VI binary image feature to aggregated signals.

- For appliances with similar steady states, it may be useful to look at transients.

- Collect more data and evaluate the methods in a larger scale.

Questions?

- PLAID Dataset: http://www.plaidplug.com/
- Source code: https://github.com/jingkungao/PLAID