Anthony Faustine,Dirk Deschrijver and Tom Dhaene

Improved Appliance Classification in NILM using Recurrence Plots and Convolutional Neural Networks

1. Introduction

Problem:

– Recognizing loads in buildings is a challenging problem.

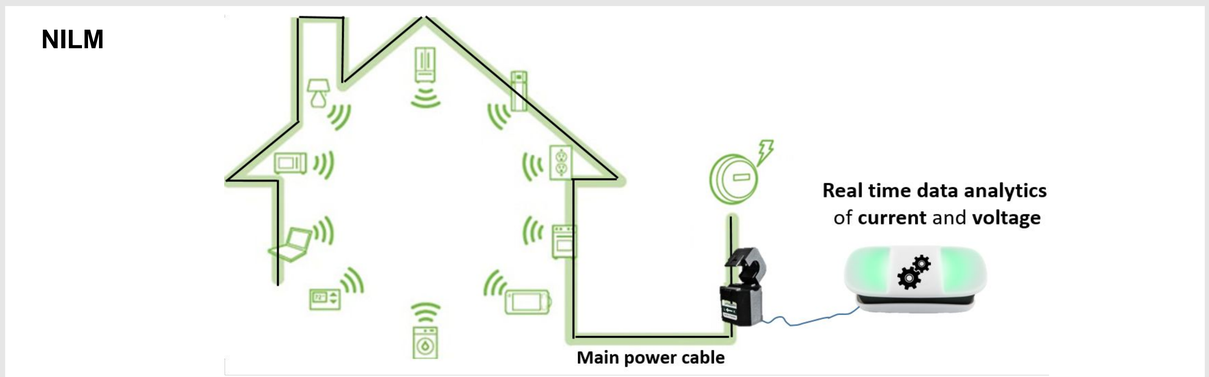
– The performance of the existing approaches is yet unsatisfactory.

Goal:

– To improve performance of appliances classification using RP and CNN

Major assumption:

– only one appliance is active at a time



2. Method

– Extract 20 cycles of voltage and current just after an event has been detected.

– Align the extracted cycles at the zero-crossing of the voltage and extract one-cycle event current and voltage with size $T_s = \frac{f_s}{f}$

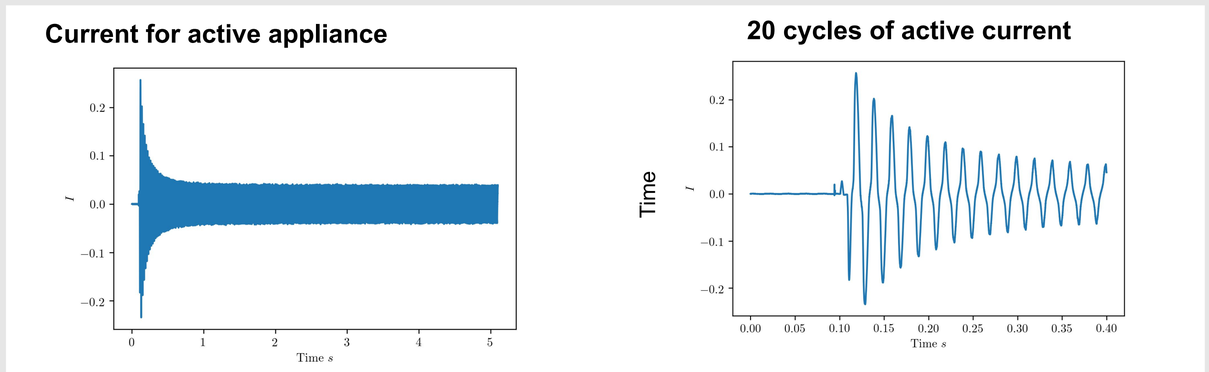
– Apply Piecewise Aggregation Approximation (PAA) to reduce dimension from $(T_s, 1)$ to $(w, 1)$

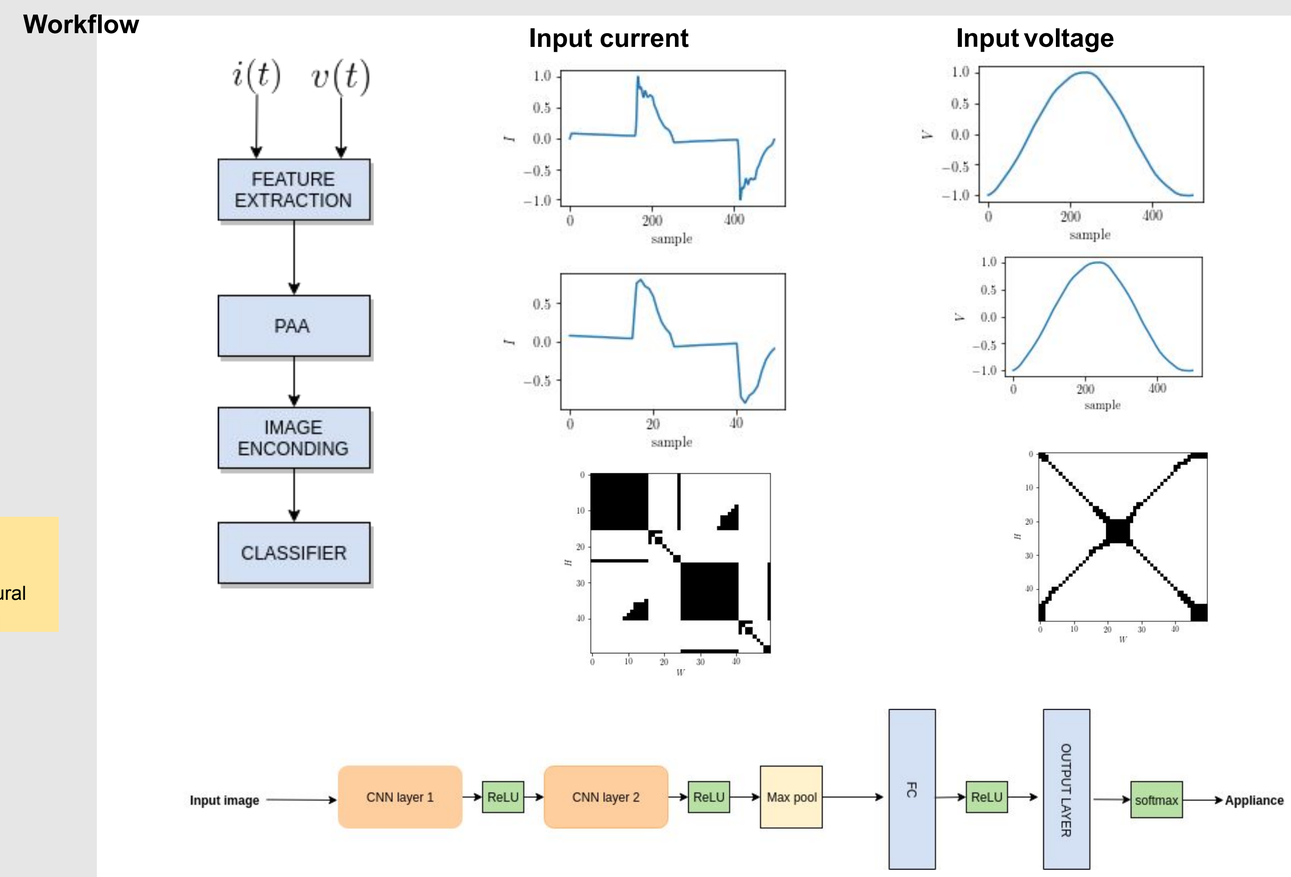
– Compute R_{ij} based on aligned event current and voltage such that:

$$R_{i,j} = \begin{cases} 1 & \text{if} \quad dm_{i,j} \geq \epsilon \\ 0 & \text{otherwise} \end{cases}$$

dm_{ij} euclidean norm ϵ recurrence threshold

– Use generated RPs as input of CNN





3. Experiment:

Experimental set-up

– Leave-one-house-out cross validation

– SGD optimisation with lr = 0.01, m = 0.9

– Use macro averaged F score to evaluate performance

$$F_{macro} = \frac{1}{K}\sum_{i=1}^{K} F_1^{(i)}$$

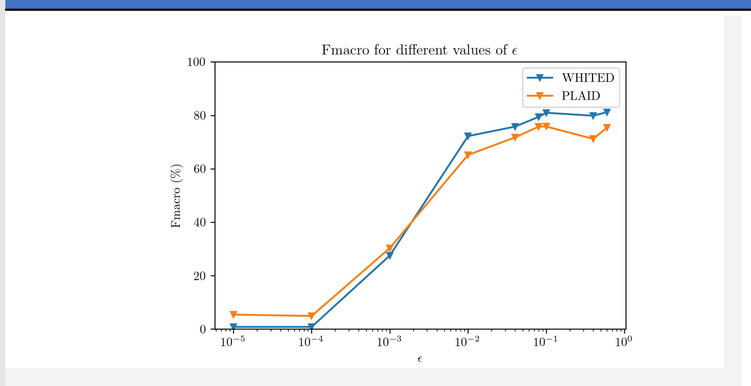
– Benchmark with VI

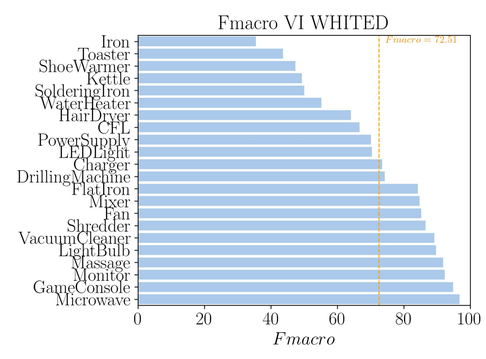
[De Baets, Leen, et al. (2017) "Appliance classification using VI trajectories and convolutional neural networks", Energy and Buildings]

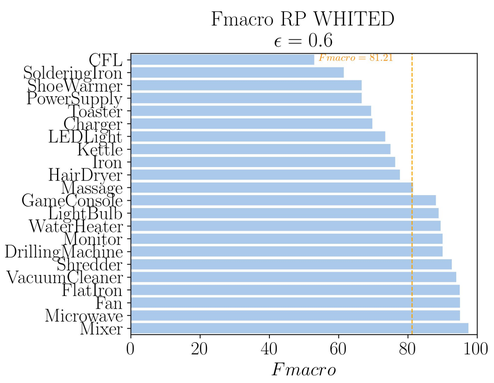
Dataset:

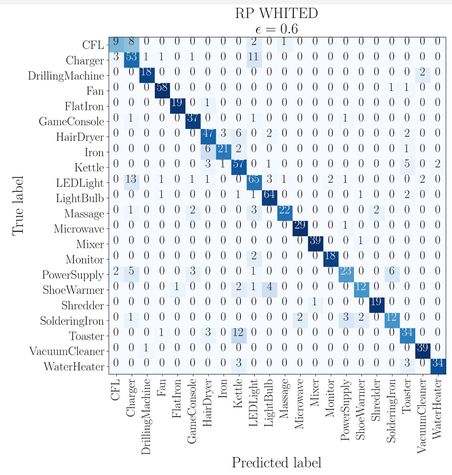
– PLAID: 11 appliance types, 55 households, submetered at 30 kHz

– WHITED: 45 appliance types, submetered at 41.1 kHz

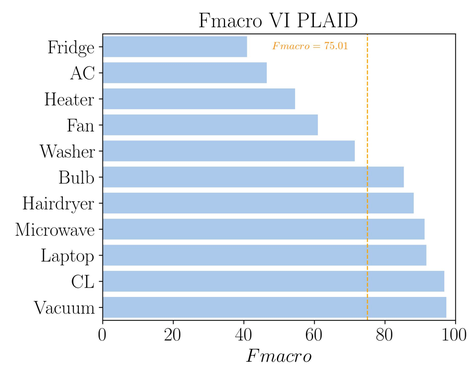


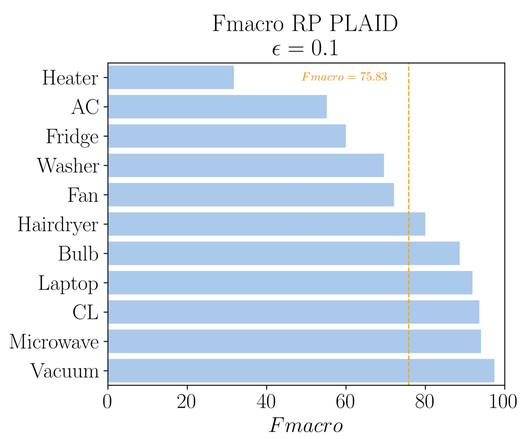






Dataset	VI	RP
WHITED	72.51 %	81.21%
PLAID	75.01%	75.83%





4. Conclusion

- **RP achieve good performance when** $0.01 \leq \epsilon \leq 1$
- **RP image encoding are a viable alternative: favourable performance over VI based method.**

Contact
anthony.faustine@ugent.be
www.ugent.be/ea/idlab/en/

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