On Using Graph Signal Processing for Electrical Load Disaggregation

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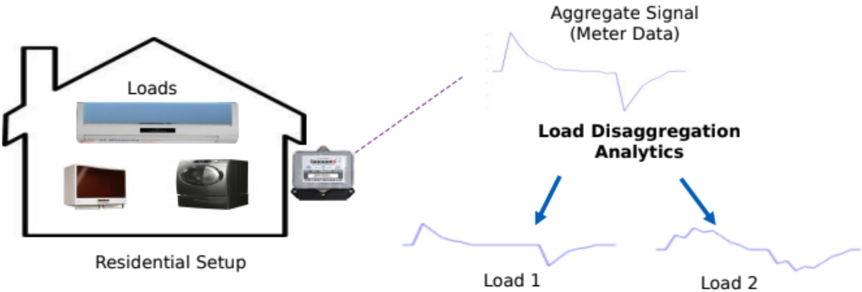
Outline

- Electrical Load Disaggregation - Motivation
- Problem Formulation
- Introduction to graph signal processing
- Proposed solution using Graph Signal Processing (GSP)
- Experimental Results
- Conclusion
- References

Electrical Load Disaggregation-Motivation

- **Electrical Load Disaggregation/ Non-Intrusive Load Monitoring:** an instance of **Source Separation** Problem
- Disaggregate overall household energy consumption into load level without using any devices/ plugs to capture consumption data from individual loads



- Knowledge about the energy consumption of individual loads is key in demand energy optimization.

Problem Formulation

- **Problem:** Given the aggregate power measurement $\boldsymbol{X}(t)$, it is required to compute the contribution of individual loads $\boldsymbol{X}_m(t)$ which could have resulted in that measurement
- The aggregate power can be expressed as:

$$\boldsymbol{X}(t) = \sum_{m=1}^{M} \boldsymbol{X}_m(t) + \boldsymbol{\eta}$$

- Here $m \in M$,, where M is the total number of loads of interest and η is the measurement noise at time instant t
- **Objective:** Load identification and consumption estimation
- One recent attempt is to use Graph Signal Processing (GSP) to solve it

Graphs

Online social media

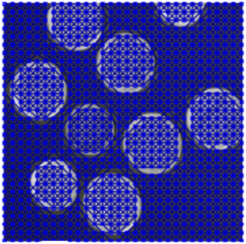
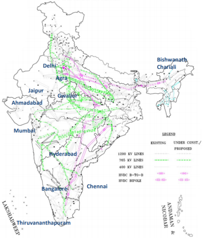
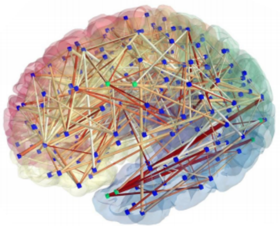


Image-graph

POWER MAP OF INDIA
POWERGRID LINES





functional connectivity between brain regions

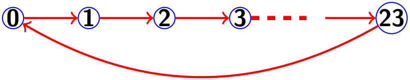
1

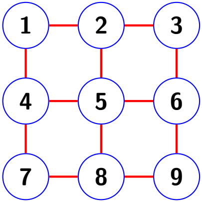
[1] Google images

- Formally, a graph G (or a network) is a triplet $(\mathcal{V}, \mathcal{E}, W)$.

- Unweighted and directed graphs

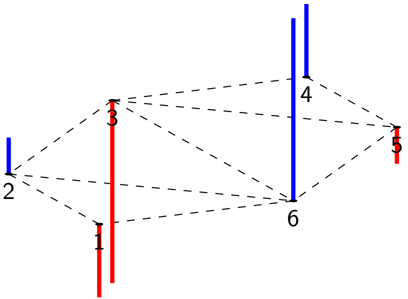
- $\mathcal{V} = \{1, 2, \ldots, N\}$
- $\mathcal{E} = \{(0,1), \ldots, (22,23), (23,0)\}$
- $W : (n,m) \to 1$; for all $(n,m) \in \mathcal{E}$





- Unweighted and undirected graphs
- $\mathcal{V} = \{1, 2, \ldots, N\}$
- $\mathcal{E} = \{\{1,2\}, \{2,3\}, \ldots, \{8,9\}, \{1,4\}, \ldots \{6,9\}\}$
- $W : (n,m) \to 1$; for all $(n,m) \in \mathcal{E}$

- Graph signals are mappings $x : V \to R$
- Defined on the vertices of the graph
- May be represented as a vector $x \in R^N$
- x_n represents the signal value at the nth vertex in V
- Inherently utilizes an ordering of vertices



$$s = \begin{bmatrix} -0.3 \\ 0.2 \\ -0.5 \\ 0.3 \\ -0.2 \\ 0.7 \end{bmatrix}$$

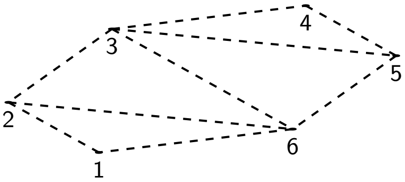
- same ordering as in adjacency matrices

Adjacency matrices

- Given a graph $G = (\mathcal{V}, \mathcal{E}, W)$ of N vertices,
- Its adjacency matrix $\mathbf{A} \in \mathbb{R}^{N\times N}$ is defined as

$$A_{nm} = \begin{cases} w_{nm}, & \text{if(n, m)} \in \mathcal{E} \\ 0, & \text{otherwise} \end{cases}$$

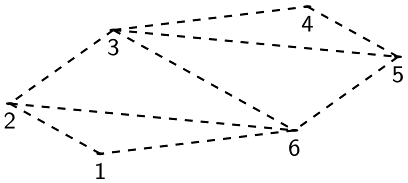
- A matrix representation incorporating all information about $\mathcal{G}$
  - For unweighted graphs, one represent connected pairs
- Inherently defines an ordering of vertices



$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 1 & 0 \end{bmatrix}$$

Degree matrix

- The degree matrix D $\in \mathbb{R}^{N\times N}$ is a diagonal matrix s.t. D_{ii} =deg(i)
- Given a weighted and undirected graph G= $(\mathcal{V}, \mathcal{E}, W)$.
- The degree of a node is the sum of the weights of its incident edges
- Equivalently, in terms of the adjacency matrix **A**
  - deg(i)=$\sum_j A_{ij} = \sum_j A_{ji}$.



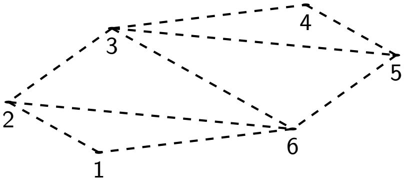
$$D = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 4 \end{bmatrix}$$

Laplacian of a graph

- Given a graph G with adjacency matrix A and degree matrix D
- We define the Laplacian matrix $\mathcal{L} \in \mathbb{R}^{N \times N}$ as

$$\mathcal{L} = D - A$$

$\mathcal{L}$ =Laplacian matrix



$$\mathcal{L} = \begin{bmatrix} 2 & -1 & 0 & 0 & 0 & -1 \\ -1 & 3 & -1 & 0 & 0 & -1 \\ 0 & -1 & 4 & -1 & -1 & -1 \\ 0 & 0 & -1 & 2 & -1 & 0 \\ 0 & 0 & -1 & -1 & 3 & -1 \\ -1 & -1 & -1 & 0 & -1 & 4 \end{bmatrix}$$

- The normalized Laplacian can be obtained as $\mathcal{L} = D^{-1/2}\mathcal{L}D^{-1/2}$

Laplacian quadratic form

- We can also define the Laplacian quadratic form of x

$$s^\top \mathcal{L} s = \frac{1}{2} \sum_{j \in \mathcal{N}_i} w_{ij} (s_i - s_j)^2$$

- $s^\top \mathcal{L} s \geq 0$ for $s \neq 0, \mathcal{L}$ is positive semi-definite
- Total variation of a signal is defined as the sum of squared differences in consecutive signalsamples $\sum_n (s_n - s_{n-1})^2$

$$TV_{\mathcal{G}}(s) = \sum_{i=1}^{N} \sum_{j \in \mathcal{N}_i} w_{ij} (s_i - s_j)^2 = s^\top \mathcal{L} s$$

- A constant vector $\mathbf{1}$ is an eigenvector of $\mathcal{L}$ with eigenvalue $\mathbf{0}$

$$\mathbf{1}^\top \mathcal{L} \mathbf{1} = \frac{1}{2} \sum_{j \in \mathcal{N}_i} w_{ij} (1 - 1)^2$$

GSP Based Load Disaggregation

- Load disaggregation can be formulated as t optimization problem:

$$\min_{\mathbf{X}_m} \beta \left\| \mathbf{X} - \sum_{m=1}^{M} \mathbf{X}_m \right\|_2^2 + \alpha \sum_{m=1}^{M} Tr(\mathbf{X}_m^T \mathbf{L}_m \mathbf{X}_m) \tag{1}$$

- The above minimization problem in (1) is NP hard especially when number of loads M and time instants N are large
- **Proposed Method:** Graph Laplacian based regularization approach.
  - Embed the structure of the $X(t)$ on to a graph G=($\mathcal{V}, \mathcal{E}, W$)
  - Represent the $\mathbf{X}_m(t)$ as a signal S on the graph $\mathcal{G}$
- **Assumption:** Graph signal is piecewise smooth graph total variation is small

Graph Total Variation is given by: $s^\top \mathcal{L} s = \frac{1}{2} \sum_{j \in \mathcal{N}_i} w_{ij}(s_i - s_j)^2$

where, s is the graph signal and $\mathcal{L}$ is the graph Laplacian

- For a N length vector of aggregate data $x, i = 1, \ldots, N$, suppose the individual load power data is known for n samples $(i \leq n < N)$
- The graph signal associated with the individual load power measurements $\boldsymbol{X}_m$ has two parts corresponding to train and test and is given as $\boldsymbol{X}_m(1:n) = \boldsymbol{X}_m^{train}$ and $\boldsymbol{X}_m(n+1:N) = \boldsymbol{X}_m^{test}$. The load signal is represented as $\boldsymbol{X}_m = [\boldsymbol{X}_m^{train} | \boldsymbol{X}_m^{test}]$.
- the load signal in the test phase $\boldsymbol{X}_m^{test}$ is estimated by re-formulating the optimization problem in (1) as:

$$\min_{\boldsymbol{X}_m^{test}} \beta \left\| \boldsymbol{X}^{test} - \boldsymbol{X}_m^{test} \right\|_2^2 + \alpha Tr(\boldsymbol{X}_m^T \boldsymbol{L}_m \boldsymbol{X}_m) \tag{2}$$

- problem with a closed form solution:

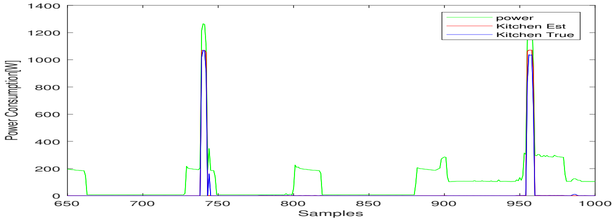
$$\begin{aligned} \boldsymbol{X}_m^{test} = (\beta I(n+1:N, n+1:N) + \alpha \boldsymbol{L}_m(n+1:N, n+1:N))^{-1}. \\ (\beta \boldsymbol{X}^{test} - \alpha \boldsymbol{L}_m(n+1:N, 1:n) \boldsymbol{X}_m^{train}) \end{aligned} \tag{3}$$

Proposed algorithm

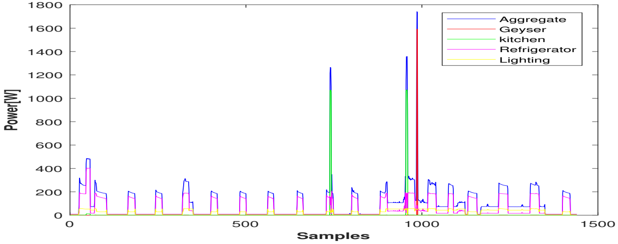
Algorithm 1 Electrical Load Disaggregation using GSP

1. Input: aggregate power $\boldsymbol{X}$, individual loads powers $\boldsymbol{X}_m(i)$ where $1 \leq i \leq n$, $\alpha = 0.9$ and $\beta = 0.1$
2. Set m = 1 (Consider one load at a time)
3. While $m \leq M$ do
4. Construct a graph $\boldsymbol{G}_m$ using $\boldsymbol{W}_m$ from using Gaussian kernel based on X
5. Compute $\boldsymbol{D}_m$ and $\boldsymbol{L}_m$ from $\boldsymbol{W}_m$ using definitions.
6. Evaluate $\boldsymbol{X}_m^{test}$ using (3)
7. Modify the aggregate by setting $X = X - [X_m^{train} | X_m^{test}]$
8. Modify the test aggregate by setting $\boldsymbol{X}^{test} = \boldsymbol{X}^{test} - \boldsymbol{X}_m^{test}$
9. Set $m = m + 1$
10. Stop

Disaggregation Results – REDD 1 Min sampled Data

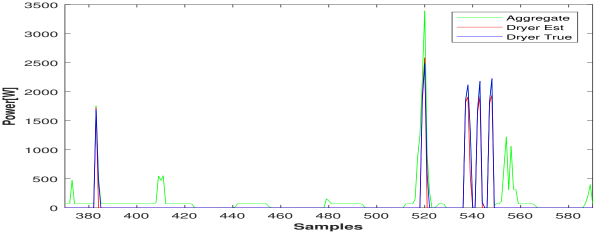


Disaggregation Results for Kitchen outlets with 1 minute Data

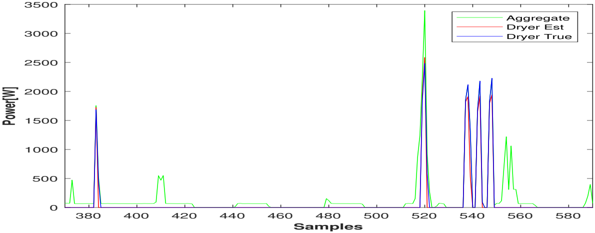


Disaggregation Results for all loads with 1 minute Data

Disaggregation Results – REDD 15Mins sampled Data



Disaggregation Results for Dryer with 15 minutes Data



Disaggregation Results for Dryer with 15 minutes Data

Results Summary with 1 minute sampled REDD

Performance Analysis		
Load	**F-score**	**% Acc**
Geyser	0.98	98
Kitchen	0.94	94
Refrigerator	0.96	97
Lighting	0.92	96

Results Summary with 15 minutes sampled REDD

Performance Analysis		
Load	**F-score**	**% Acc**
Dryer	1	90.5076
Dishwasher	0.888	82.93
Geyser	0.81899	88.056
Lighting	0.9083	79.7326

Conclusion

- Graph signal processing based algorithm.
  - Formal Data-driven approach,
  - Robust,
  - Scalable and flexible,
  - Low-complexity, even with a large amount of data
- GSP based methods outperform the conventional methods for load disaggregation
- Future direction of electrical load disaggregation is graph is learned based on total aggregate power measurement.

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Thank you