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Sparse Linear Models applied to Power Quality Disturbance Classification

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Introduction

- The automatic recognition of Power Quality (PQ) disturbances can be seen as a pattern recognition problem, in which different types of waveform distortion are differentiated based on their features [1].
- PQ disturbances can be decomposed into time-frequency dependent components by using time-frequency or time-scale dictionaries.
- Previous works about PQ disturbance classification have been restricted to the use of one of the above dictionaries.
- Taking advantage of the theory behind sparse linear models (SLMs), we introduce a sparse method for PQ representation, starting from overcomplete dictionaries.

Materials and Methods

Power quality (PQ) disturbances

PQ determines the fitness of the electric power to consumer devices, evaluating the quality of electrical signals. This paper is focussed on six types of disturbances: sag/swell events, interruption events, voltage variations, harmonic distortions and oscillatory transients [1].

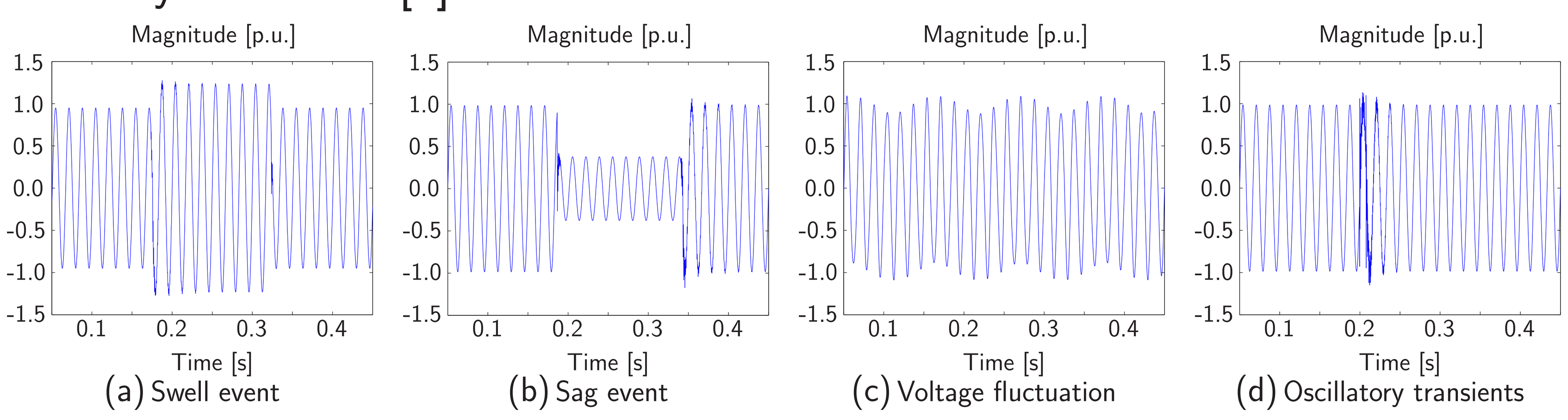

Figure : PQ disturbance examples for (a) a swell, (b) a sag, (c) a voltage fluctuations, and (d) an oscillatory transient.

Overcomplete representation (OR)

Let $\mathbf{y} \in \mathbb{R}^N$ be a PQ disturbance. Then, its completely representation is given by

$$\mathbf{y} = \Phi \boldsymbol{\beta},$$

where $\Phi = (\phi_\gamma : \gamma \in \Gamma)$ contains the collection of atoms ϕ_γ, and it is known as a dictionary [2]. The vector $\boldsymbol{\beta} \in \mathbb{R}^M$ is the vector of representation coefficients.

An OR is performed by the combination of several dictionaries, $\Psi = (\Phi_g : g \in G)$, where G represents the amount of dictionaries employed for the synthesis [2].

Table : Atom structures for the Gabor transform (GT), the Mexican hat Wavelet transform (MHWT), and the Stockwell transform (ST).

Dictionary	Interpretation for γ	Structure of the atoms $\phi_\gamma[n]$
GT	$\gamma = (f_k, m_l)$	$\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-(n-m_l)^2/2\sigma_o^2\right\} \cdot \cos\left(2\pi f_k(n-m_l)\right)$
MHWT	$\gamma = (m_l, \sigma_\nu)$	$\frac{2}{\sqrt{3\sigma_\nu}\,\pi^{1/4}}[1-(n-m_l)^2/\sigma_\nu^2] \cdot \exp\{-(n-m_l)^2/2\sigma_\nu^2\}$
ST	$\gamma = (f_k, m_l, \sigma_\nu)$	$\frac{1}{\sqrt{2\pi\sigma_\nu^2}} \exp\left\{-(n-m_l)^2/2\sigma_\nu^2\right\} \cdot \cos\left(2\pi f_k(n-m_l)\right)$

Sparse linear models (SLMs) for grouped variable selection

To deal with grouped variable estimation, a Group Lasso version was proposed in [3]. Group Lasso assumes that $\boldsymbol{\beta}$ is partitioned in G groups where the penalty is an intermediate between ℓ_1 and ℓ_2 regularizations,

$$\hat{\boldsymbol{\beta}}_\lambda = \arg\min_{\boldsymbol{\beta}} \left\{ \|\mathbf{y} - \Psi\boldsymbol{\beta}\|_2^2 + \lambda \sum_{g=1}^{G} \|\boldsymbol{\beta}_g\|_{\mathbf{K}_g} \right\}, \tag{1}$$

where $\|\boldsymbol{\beta}_g\|_{\mathbf{K}_g} = (\boldsymbol{\beta}_g^\top \mathbf{K}_g \boldsymbol{\beta}_g)^{1/2}$. The algorithm to solve the problem from Equation (1) is given in [3]. In this paper, each group g corresponds to a single dictionary.

Dataset

We simulated the PQ disturbances from an electrical power distribution model based on [5]. We generated 1200 PQ disturbances, 200 samples per each type.

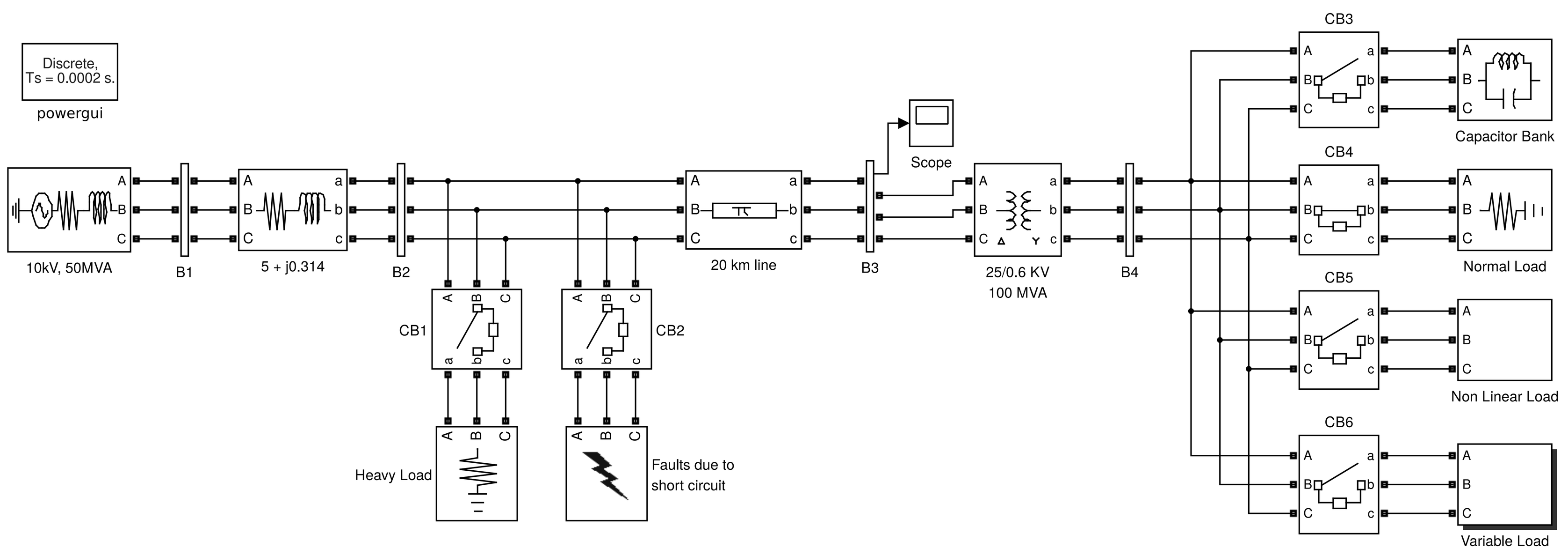

Figure : Simulink diagram of the electrical power distribution model used.

Procedure

- We compute the following features over $\{\boldsymbol{\beta}_p\}_{p=1}^{P}$: mean of the absolute values, standard deviation, kurtosis, Shannon's energy and RMS value. We also add the mean of the absolute values of the derivative $\boldsymbol{\beta}'$.
- We use several classifiers from the state-of-the-art: K-nearest neighbours (K-NN), Bayesian classifiers based on linear (LDC) and quadratic (QDC) discriminant functions, support vector machines (SVM), and neural networks (ANN) [4].

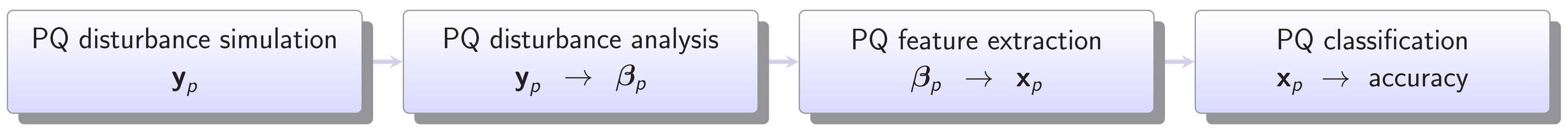

Figure : Block diagram of PQ disturbance classification procedure.

Results

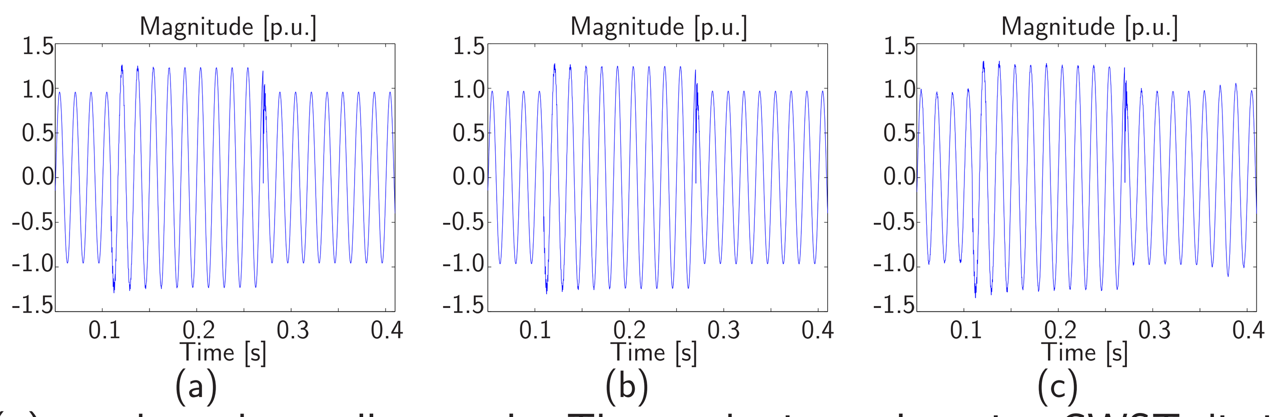

Figure : In (a) we show the swell example. The synthesis results using GWST dictionary are showed for the approach (b) without SLM and (c) using Group Lasso.

Table : Sparsity percentages using GWST with Group Lasso.

PQ Disturbance	Dictionary: Harmonics	GT	MHWT	ST
Harmonic distortion	6.0750	53.0061	21.9631	33.9341
Swell event	32.6000	47.8226	10.7996	38.1105
Sag event	13.4750	33.2939	6.6398	26.4847
Interruption event	9.4750	24.9780	4.8516	19.8153
Voltage fluctuation	10.9750	77.0085	14.1627	68.7561
Oscillatory transients	31.4750	67.1982	20.8467	46.0506

Table : Performance of the classifiers without SLM and using Group Lasso for GT, MHWT, ST and combining all the dictionaries (GWST).

Classifier	Dictionary: GT + Harmonics $\mu \pm \sigma$	MHWT + Harmonics $\mu \pm \sigma$	ST + Harmonics $\mu \pm \sigma$	GWST + Harmonics $\mu \pm \sigma$
without SLM				
1-NN	0.8710 ± 0.0149	0.6311 ± 0.0216	0.8322 ± 0.0175	0.7292 ± 0.0159
3-NN	0.8592 ± 0.0102	0.6360 ± 0.0197	0.8261 ± 0.0186	0.7246 ± 0.0166
LDC	0.5956 ± 0.0199	0.5363 ± 0.0203	0.6560 ± 0.0204	0.5121 ± 0.0296
QDC	0.8053 ± 0.0122	0.5808 ± 0.0327	0.7200 ± 0.0184	0.6550 ± 0.0180
SVM	0.8471 ± 0.0177	0.6546 ± 0.0170	0.8082 ± 0.0208	0.7144 ± 0.0179
ANN	0.8510 ± 0.0830	0.6399 ± 0.0336	0.8299 ± 0.0420	0.7285 ± 0.0459
with Group Lasso				
1-NN	0.8629 ± 0.0140	0.8908 ± 0.0117	0.8821 ± 0.0147	**0.9396 ± 0.0168**
3-NN	0.8628 ± 0.0121	0.8882 ± 0.0159	0.8763 ± 0.0152	**0.9382 ± 0.0179**
LDC	0.7565 ± 0.0198	0.7126 ± 0.0235	0.7101 ± 0.0220	**0.7925 ± 0.0191**
QDC	0.8179 ± 0.0170	0.7760 ± 0.0163	0.8157 ± 0.0102	**0.8996 ± 0.0177**
SVM	0.8649 ± 0.0143	0.8461 ± 0.0199	0.8454 ± 0.0226	**0.9128 ± 0.0133**
ANN	0.8457 ± 0.0447	0.8754 ± 0.0189	0.8681 ± 0.0375	**0.8978 ± 0.0675**

Conclusion and Future works

- We introduced the concepts of OR and SLM for PQ disturbance classification. We combined different time-frequency dictionaries. We introduced Group Lasso assuming that each dictionary is a group in the SLM.
- Group Lasso improves the performance of PQ disturbance classification for both linear and non-linear classifiers compared to methods without SLM.
- Due to SLMs can carry out OR, ensuring a high performance for PQ disturbance classification, this framework removes the uncertainty about which dictionary should be used for which type of distortion.

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