Statistical Classification and System Identification Techniques for Partial Discharge Analysis

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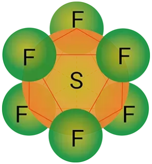
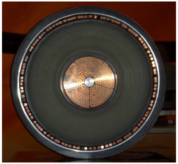
High Voltage Insulators

- Insulators are used to isolate energized conductors from ground and one another.



(a) Gas


(b) Liquid


(c) Solid


(d) Combined

- Safe and reliable operation of high voltage systems highly depends on their insulation system.

- Insulation condition monitoring is important (Cost, safety, reduced investment, etc.).

Partial Discharges (PD)

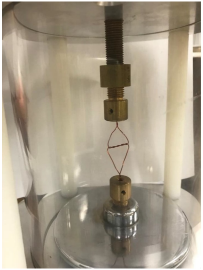
- Partial discharge: “localized electrical discharge that partially bridge the insulation" (Kuffel et al., 2000).
- PDs emit acoustic, optical, and electromagnetic energy.
- Caused by damages in the insulator
  - cracks/voids in a solid insulator
  - bubbles in a liquid insulator.
  - etc.
- Repeated exposure will lead to irreversible damage of the insulation (Gao and Noda, 2005).
- PD analysis, a symptom of insulation deterioration is widely used to perform real-time condition monitoring.

Problem Motivation

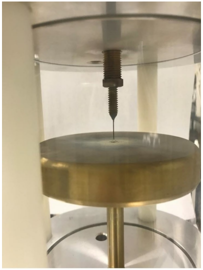
- PD source identification is a useful tool to assess the risk.
  - e.g. To create a system to alert of potential risks.
- Most literature classifies a single PD source. Multiple PD source classification is not widely studied (Janani et al., 2017).
- Some methods require a skilled operator to classify the sources or extracts some key features (amplitude, rise time, etc.)
- This research aims to provide an approach to automatically identify single/multiple sources which are not separable visually.
- Based on a basis function expansion.

Experimental Setup

- Studied two types of partial discharge sources (twisted pair of wires and needle-plane setup).
- Partial discharge sources were connected to a high voltage source of 3 kV.
- The other end connected to a PD measurement system, which is connected to an oscilloscope.



(a) Twisted pair of wires.



(b) Needle-plane setup.

Collected PD Signals

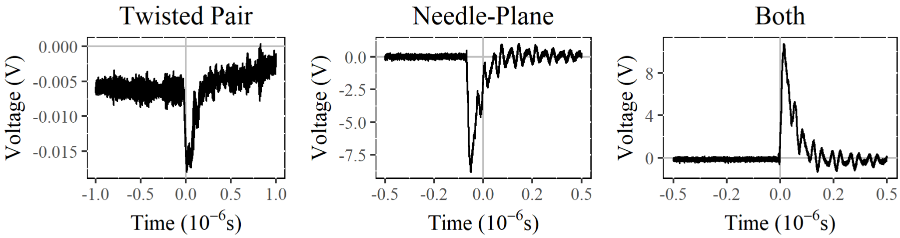
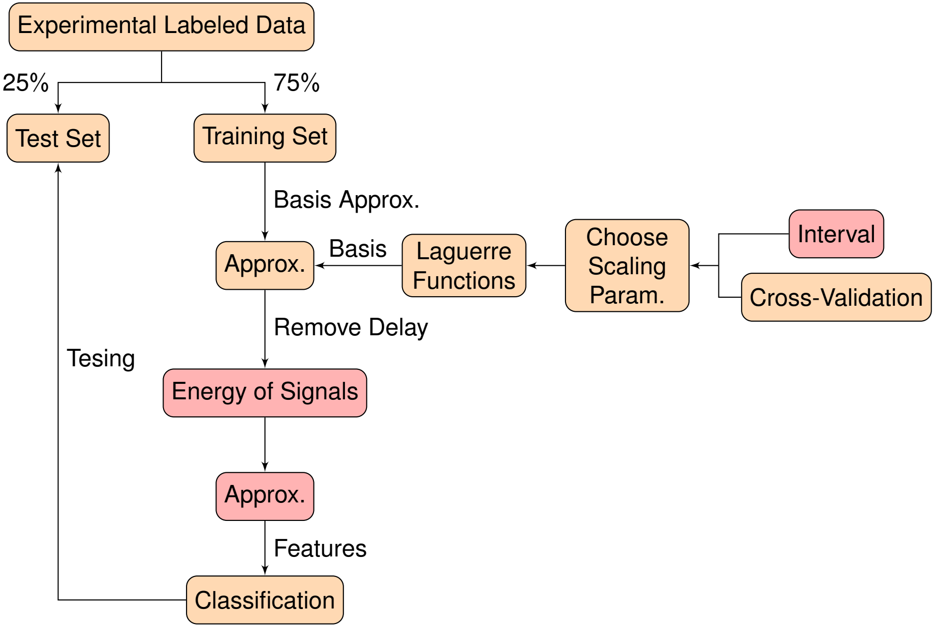


Figure: Sample of PD pulses for the three sources.

- 653 pulses from twisted pair and needle-plane setup.
- 512 from the combined source.
- Signals have a starting delay.

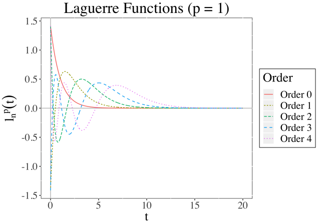

Experimental Labeled Data
25%
75%
Test Set
Training Set
Basis Approx.
Approx.
Basis
Laguerre Functions
Choose Scaling Param.
Interval
Cross-Validation
Remove Delay
Tesing
Energy of Signals
Approx.
Features
Classification

Laguerre Basis Expansion

- Laguerre basis expansion for the mathematical form of PD signals.

$$y(t) \simeq \sum_{j=0}^{k_y} y_j l_j^p(t) \quad \text{with} \quad l_j^p(t) = (-1)^j \sqrt{2p} e^{-pt} \left[\sum_{k=0}^{j} \binom{j}{k} \frac{(-2pt)^k}{k!} \right].$$

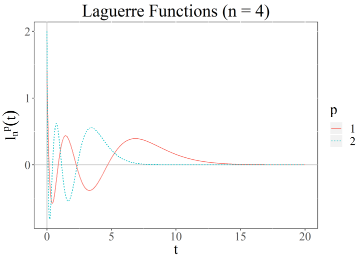
- $l_j^p(t)$ is a Laguerre function with order j, scaling parameter $p(> 0)$ (Budke, 1989).



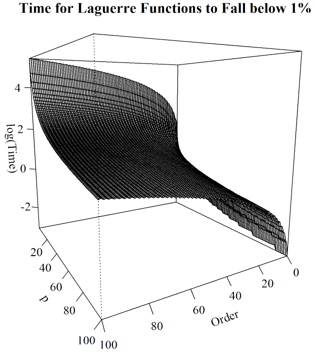
- y_j are expansion coefficients.
- Least squares, least absolute and Lasso objective functions used to estimate y_j.
- Additionally, estimates based on the inner product was used $y_j = \int_0^\infty y(\tau) l_j^p(\tau)\, d\tau$. - Approximated numerically.
- Laguerre basis was selected due to a property used in system identification.

Choosing p

- p changes the rate at which the Laguerre function goes to zero.
- It may not be able to cover the entire signal.
- Improved method by Saboktakinrizi (2011) to select a suitable p.
- $f_T^{1\%}(n, p)$: time the Laguerre function with p and n takes to fall to 1% of it's peak.



(a) Laguerre functions with changing p.



(b) Relationship of n and p with $\log\left(f_T^{1\%}(n, p)\right)$.

Choosing p

- Quadratic regression model is used for the relationship.
- If τ is the time window of the signal that needs to be approximated

$$\tau \leq f_T^{1\%}(n, p)$$

$$\log(\tau) \leq 0.84 + 74.34n - 82.85p - 9.84np - 27.53n^2 + 33.35p^2$$

- If τ is fixed to 1,

n	0	40	80	120	160	200
Lower Interval	0	0	0	0	0	0
Upper Interval	2.5	43	85.7	128.4	171.1	213.8

Table: Interval for p for different orders.

Estimated PD Signals

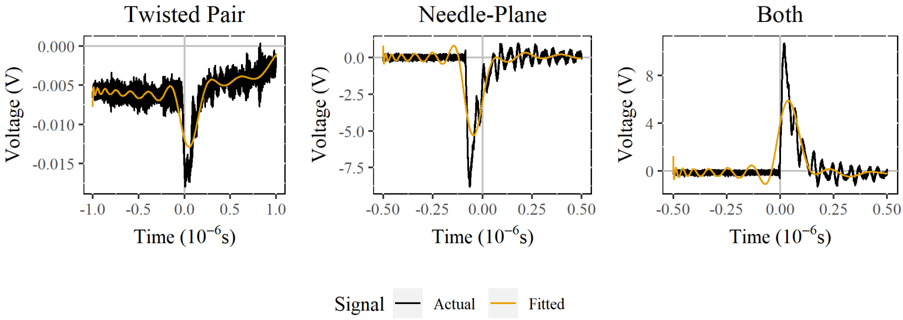


Figure: Sample of estimated PD pulses for the three sources.

- Entire shape of the signal is not captured by the approximation.
- An automatic procedure is introduced to remove the delay from the signal.

Automatically Remove Signal Delay

- Proof is not provided.
- The objective is to find T such that $E_T = E_\infty P$.
- E_T is the energy of the signal at time T.
- E_∞ is the total energy of the signal.
- P is a desired proportion.

$$T \geq \frac{1}{2} \log \left[\frac{2E_\infty P}{B_p C_p} + 1 \right]$$

- $E_\infty = \sum_{i=0}^{\infty} y_i^2$.
- $B_p = \left[\frac{\Gamma\left(p+\frac{1}{2}\right)}{\Gamma(p+1)\left|\Gamma\left(p+\frac{1}{2}\right)\right|} \right]^2$.
- $C_p = \sum_{i=0}^{\infty} \sum_{j=0}^{\infty} |y_i||y_j| \frac{(i+p)(j+p)\Gamma(i+p)\Gamma(j+p)}{i!j!}$.
- y_j are coefficients of the Laguerre basis approximation.

Automatically Remove Signal Delay
Classification Features

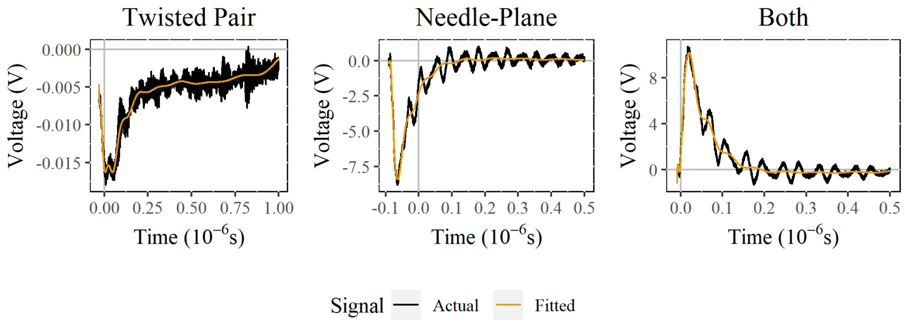


Figure: Sample of estimated PD pulses with delays removed.

- This shows an improved fit.
- Coefficients of the expansion are used as features for classification.

Classification

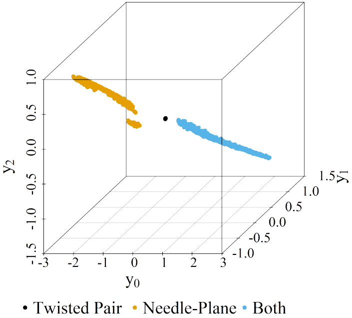


Figure: First 3 Laguerre Coefficients for all sources.

- LDA, QDA and SVM (Gaussian kernel) classifiers are used.
- First 3 coefficients used.
- 0% misclassification for QDA and SVM. 0.48% misclassification for LDA.

Classification

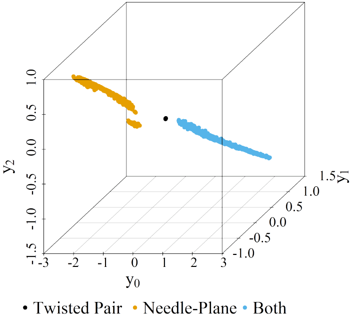


Figure: First 3 Laguerre Coefficients for all sources.

- LDA, QDA and SVM (Gaussian kernel) classifiers are used.
- First 3 coefficients used.
- 0% misclassification for QDA and SVM. 0.48% misclassification for LDA.
- Signals for different sources are distinguishable through visual inspection.

Normalized Signals

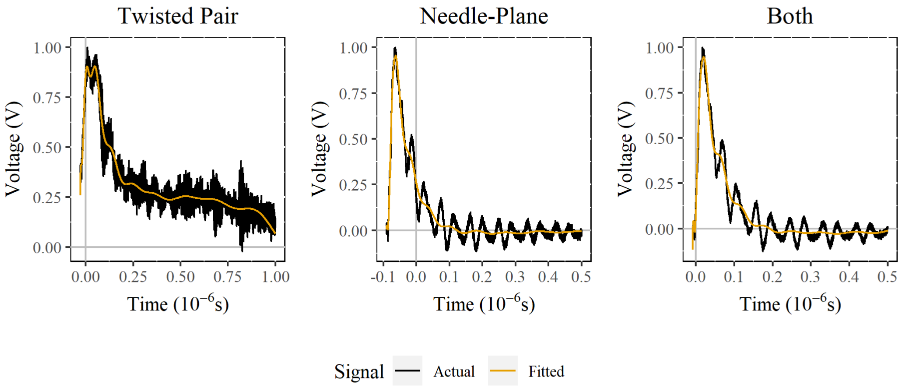


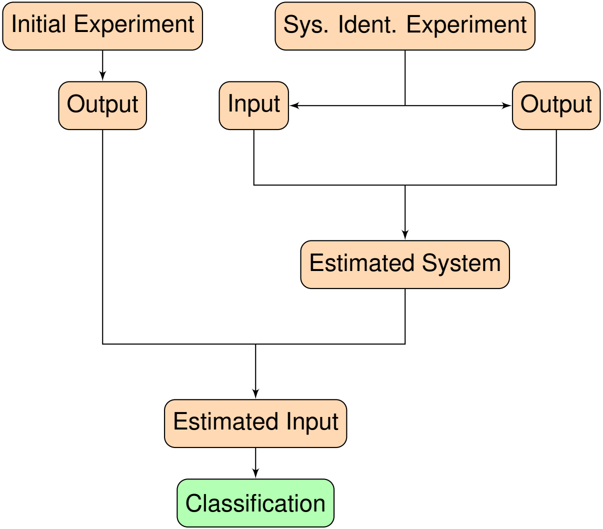
Figure: Sample of normalized PD pulses.

- 5.97%, 2.63% and 0.95% for LDA, QDA and SVM.
- If 7 Laguerre coefficients are used, a perfect classification can be observed.

System Identification

Figure: A black box system.

- A known input $x(t)$ and output $y(t)$ used to estimate the system $h(t)$.
- If some conditions are satisfied, $y(t) = h(t) * x(t)$.


Initial Experiment
Sys. Ident. Experiment
Output
Input
Output
Estimated System
Estimated Input
Classification

System Identification

- Write all functions using Laguerre expansion.
- Developed a recursive formula and used group Lasso (Friedman et al., 2010) objective function to estimate the system.
- Recursive formula (Proof not provided):

$$h_m = \frac{1}{x_0}\left(\sqrt{2p}y_m - \sqrt{2p}\left(\sum_{j=1}^{m}(-1)^{m+j}y_{j-1}\right) - \sum_{i=0}^{m-1} h_i x_{m-i}\right)$$

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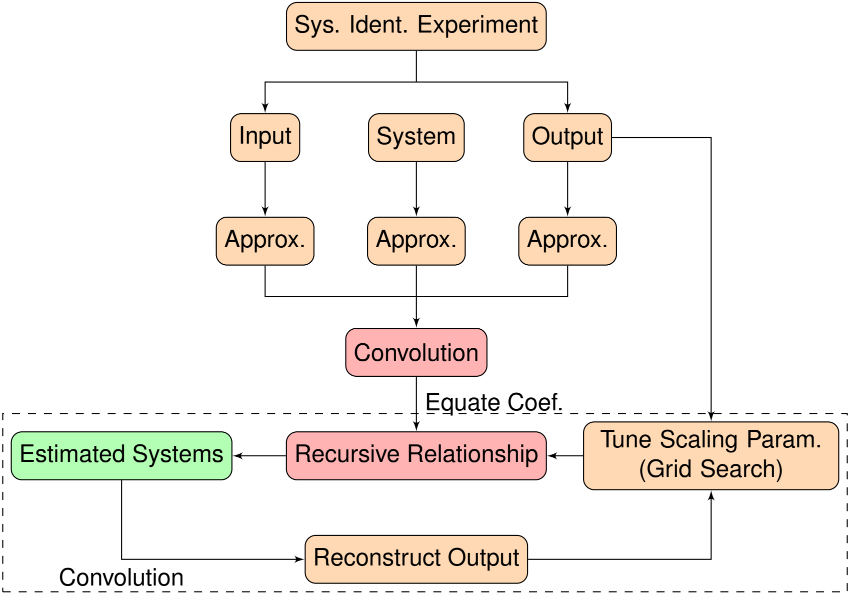
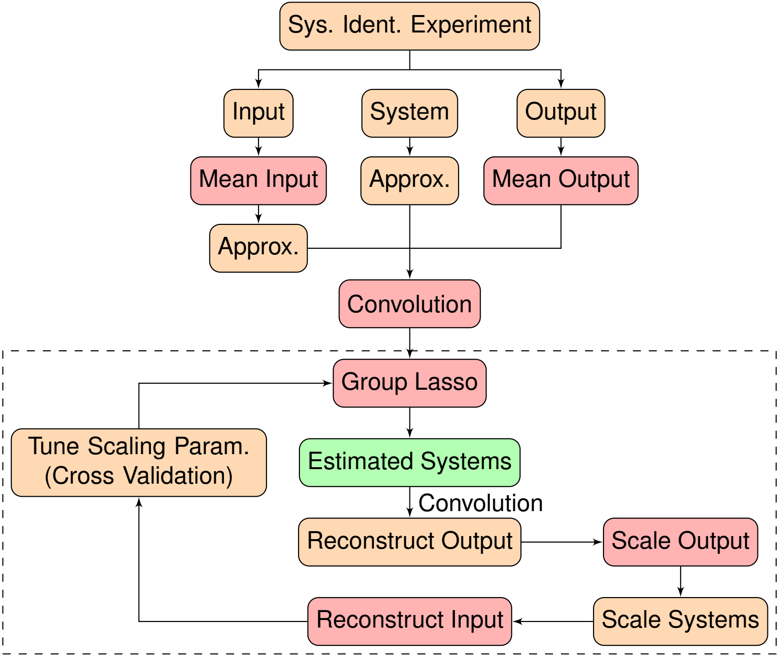
- No improvement in classification when classifying on the input.


Sys. Ident. Experiment
Input
System
Output
Approx.
Approx.
Approx.
Convolution
Equate Coef.
Estimated Systems
Recursive Relationship
Tune Scaling Param.
(Grid Search)
Reconstruct Output
Convolution


Sys. Ident. Experiment
Input
System
Output
Mean Input
Approx.
Mean Output
Approx.
Convolution
Group Lasso
Tune Scaling Param.
(Cross Validation)
Estimated Systems
Convolution
Reconstruct Output
Scale Output
Reconstruct Input
Scale Systems

Final Comments

Final Comments

- Selecting a proper p is essential.
- There were many numerical limitations.
- When generating Laguerre functions with small time gaps.
- Singular design matrices when least squares objective functions are used.
- Further research includes to find the effect of the group sizes in group Lasso.

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Saboktakinrizi, S. (2011). *Time-Domain Distortion Analysis of Wideband Electromagnetic Field Sensors Using Orthogonal Polynomial Subspaces Master of Science*. Ph. D. thesis, University of Manitoba.

Questions?

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Thank You.