Multi-Layer Conditional Random Field for Classifying Railway Electrification System Objects Using Mobile Laser Scanning Data

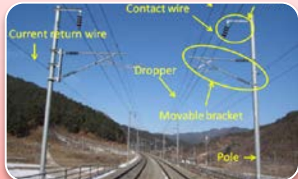
Leihan Chen

June 29th 2017

LASSONDE SCHOOL OF ENGINEERING
YORK UNIVERSITÉ UNIVERSITY
Department of Earth & Space Science & Engineering

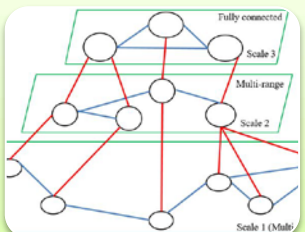
creative
passionate
rational
confident
ingenious

Presentation Outline



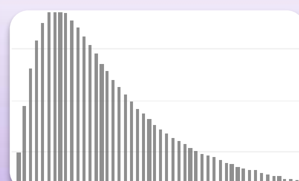
Research Overview

- Introduction
- Related Work

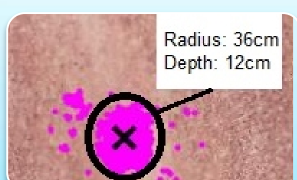


Methodology

- Conditional Random Field
- Architecture
- Layer Design

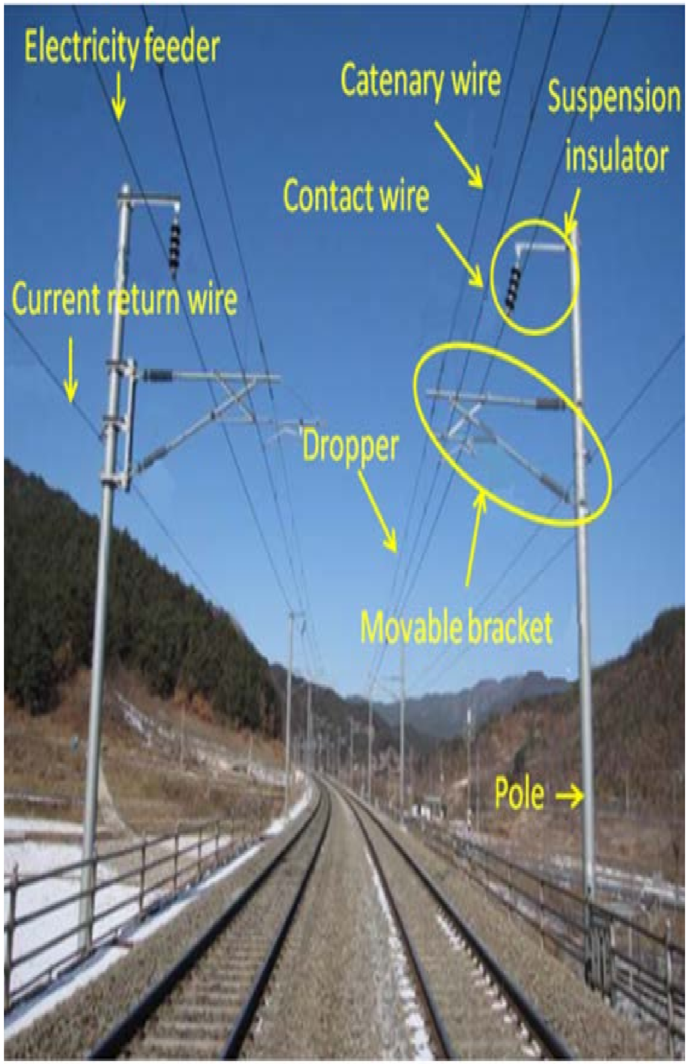


Experiment and Result



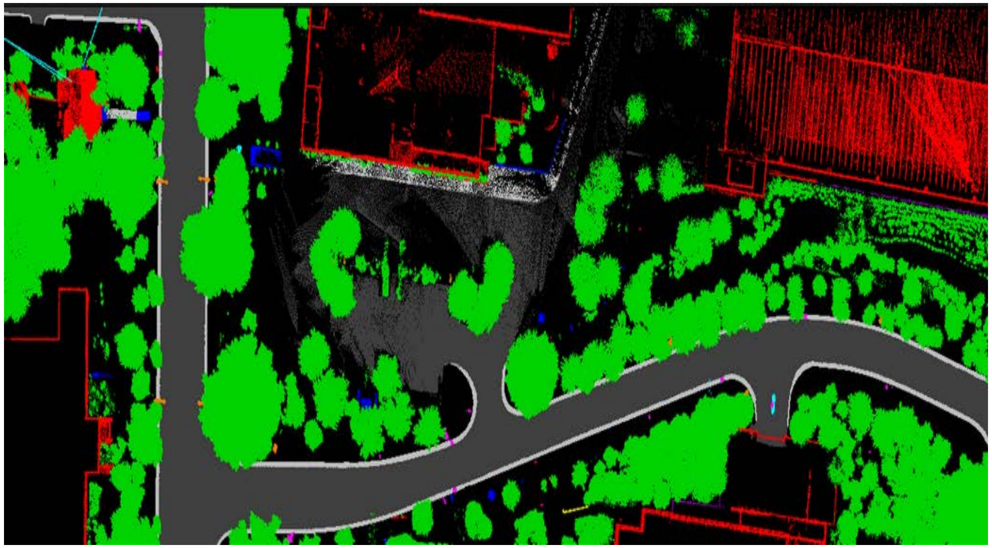
Future Plan

Introduction



Railway Electrification System

Mobile laser scanner



Mobile laser scanning data Classification

Related Work

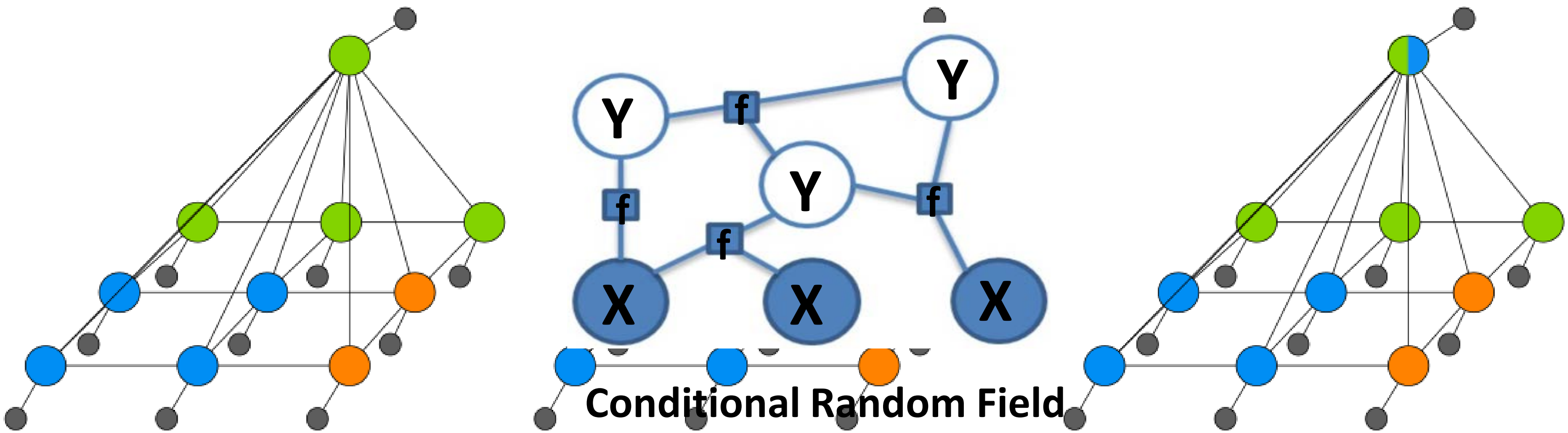
❑ Knowledge Based:
- Karman filter (Jwa and Gunho, 2012; Muhamad et al., 2013)
- Region growing (Arastounia 2012; Zhang et al. 2016; Zhu and Hyyppa, 2014;)

❑ Supervised Classifier Based:
- Random Forest (Kim et al. 2013)
- Joint Boost (Guo et al. 2016)
- ANN (Wang et al. 2011)

Limitation:
- Only rail tracks are extracted
- More detailed classes are needed
- Usually ground is pre-filtered
- Only local information is introduced to distinguish objects

Conditional Random Field

This is only semantic context !



Conditional Random Field

(Adapted from Sutton et McCallum, 2010)

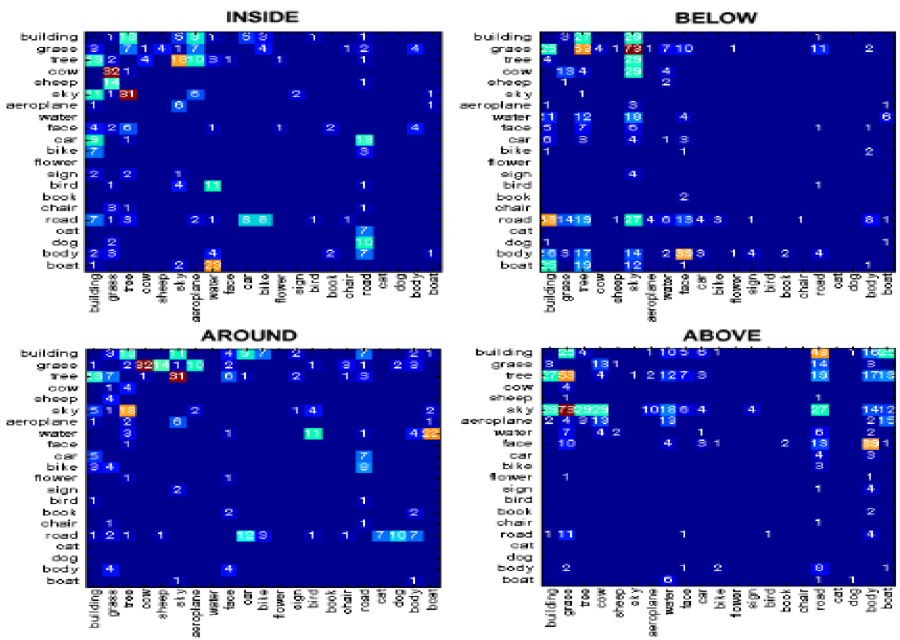
(a) Potts model (b) Robust P^N model (c) Harmony model

Three typical CRF structures

(Adapted from Lucchi et all. 2011)

Spatial Context

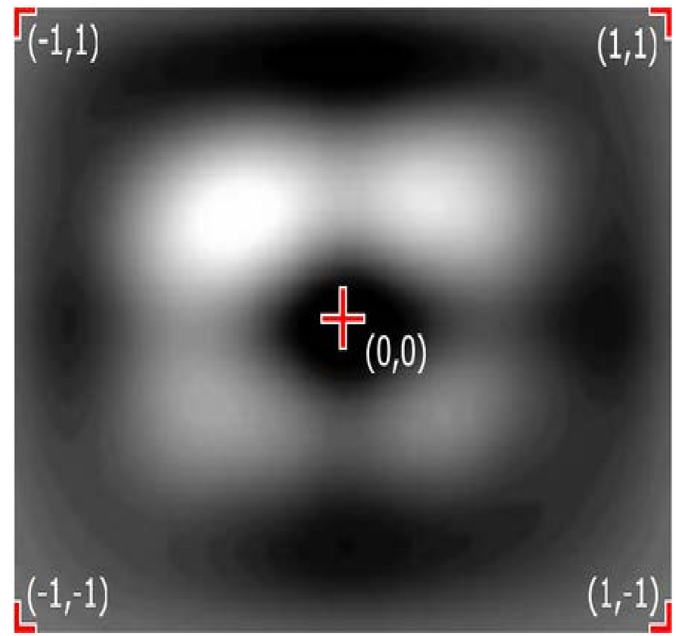
Scale



Objected based frequency matrix

(Galleguillos et all. 2008)

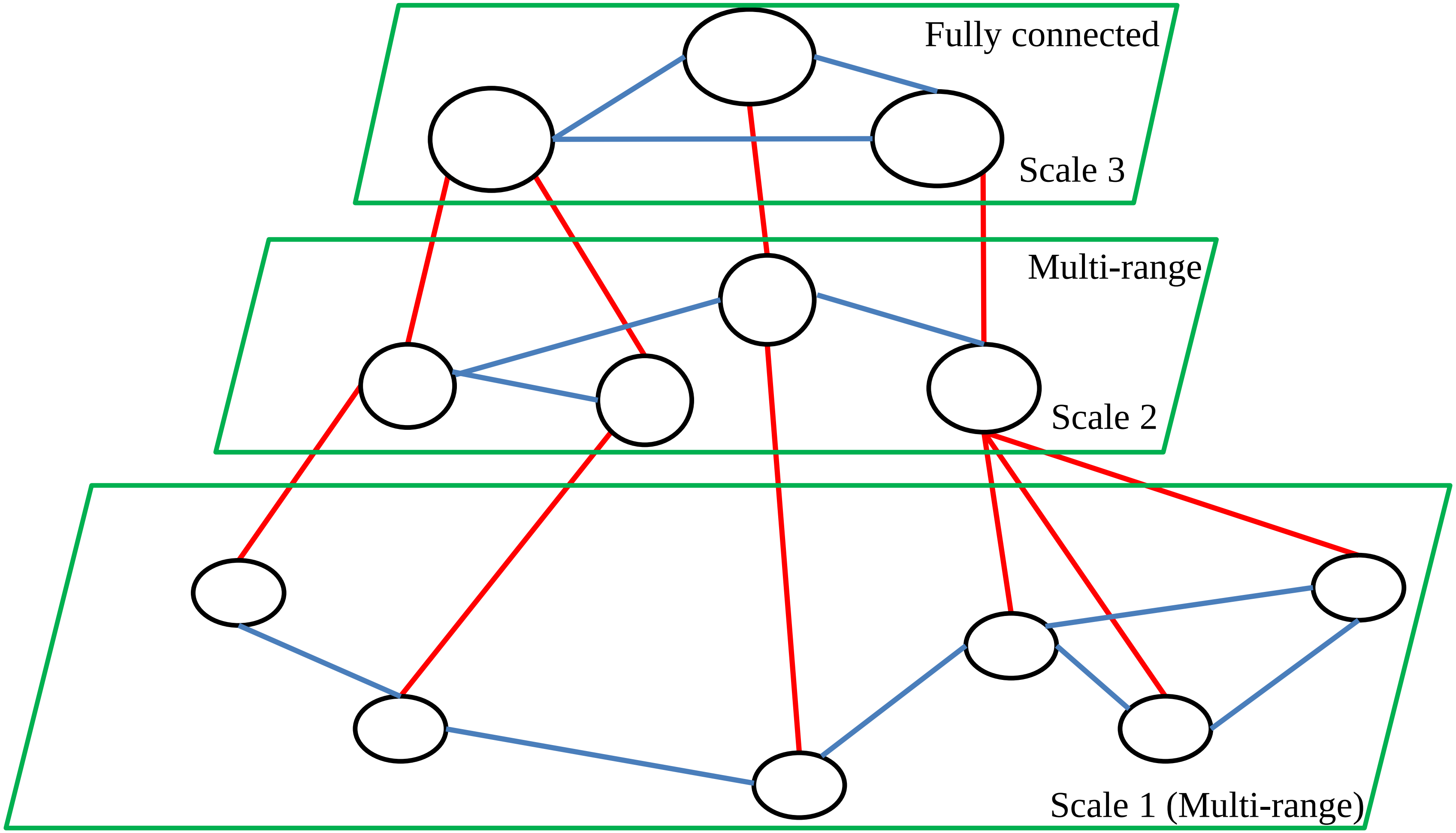
Range



Relative Location Prior

(Gould et all. 2008)

Architecture Design



Multi-layer CRF Model

$$p(Y|X) = \frac{1}{Z(X)} exp\left[\lambda \sum_{i \in B} \varphi_i(y_i, X) + \eta \sum_{i \in M} \varphi_i(y_i, X) + \delta \sum_{i \in T} \varphi_i(y_i, X) + \alpha \sum_{i \in B} \sum_{j \epsilon N_i^B} \varphi_{ij}^S(y_i, y_j, X) + \beta \sum_{i \in M} \sum_{j \epsilon N_i^M} \varphi_{ij}^M(y_i, y_j, X) + \gamma \sum_{i \in T} \sum_{j \epsilon N_i^T} \varphi_{ij}^T(y_i, y_j, X) + \rho \sum_{i \in BM} \sum_{j \epsilon N_i^{BM}} \varphi_{ij}^{BM}(y_i, y_j, X) + \omega \sum_{i \in MT} \sum_{j \epsilon N_i^{MT}} \varphi_{ij}^{MT}(y_i, y_j, X)\right]$$

B,M,T: Nodes in the graph which represent line primitives in the bottom, middle and top layer respectively

$N_i^{B,M,T}$: Adjacent edge in the bottom, middle and top layer respectively

$\varphi_i(y_i, X)$: Unary term

$\varphi_{ij}^{S,M,T}(y_i, y_j, X)$: pairwise potential in 3 different layers

$\left\{\begin{array}{l} \varphi_{ij}^{BM}(y_i, y_j, X): \\ \varphi_{ij}^{MT}(y_i, y_j, X): \end{array}\right.$ *intra-layer potential*

$\{\lambda, \eta, \delta, \alpha, \beta, \gamma, \rho, \omega\}$: Weight Matrix

Multi-range CRF Model

$$p(Y|X) = \frac{1}{Z(X)} exp\left[\lambda \sum_{i \in S} \varphi_i(y_i, X) + \alpha \sum_{i \in S} \sum_{j \epsilon N_i^S} \varphi_{ij}^S(y_i, y_j, X) + \beta \sum_{i \in S} \sum_{j \epsilon N_i^L} \varphi_{ij}^{LV}(y_i, y_j, X)\right.$$

S: Nodes in the graph which represent line primitives

N_i^S: Neighbors in the short range

N_i^L: Neighbors in the middle range

$\varphi_i(y_i, X)$: Unary term

$\varphi_{ij}^S(y_i, y_j, X)$: Short range pairwise potential

$\varphi_{ij}^{LV}(y_i, y_j, X)$: Middle range pairwise potential

$\{\lambda, \alpha, \beta\}$: Weight Matrix

Line Adjacency Graph

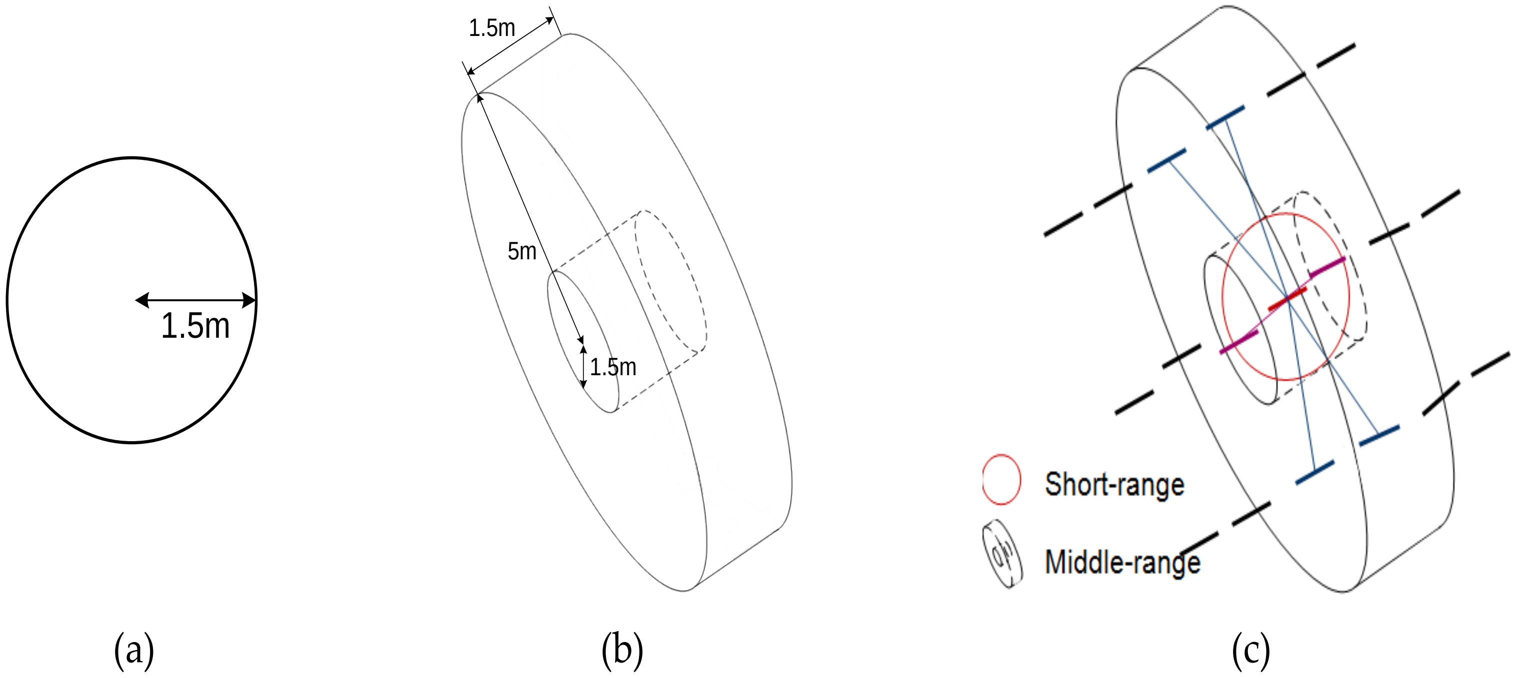


Figure 1. Neighboring systems: (**a**) for short-range graph; (**b**) for middle-range graph; and (**c**) combined neighboring systems (Jaewook et al. 2016).

Edge Potential

Short Range: Contrast Sensitive Potts Model

$$\varphi_{ij}^{BM}(y_i, y_j, X) = \begin{cases} 0 & if\, y_i = y_j \\ p1 + (1 - p1)e^{-\frac{{d_{ij}}^2}{2\sigma^2}} & Otherwise \end{cases}$$

Middle Range: Relative Location to Railway

$$\varphi_{ij}^{T}(y_i, y_j, X) = log\left(\frac{1}{M}\sum_{k=1}^{M} g_{y'|y}(d_k, d_{ij})\right)$$

- M: the number of displacement vectors from training data for class pair $\{i, j\}$
- $g_{y'|y}(d_k, d_{ij})$: the Gaussian kernel to measure the similarity between displacement vectors

Fully Connected Edge Potential

Relative Location Probability Map

Class Pair Distribution at Certain Relative Location

	EF	CAW	COW	CRW	CW	SI	MB	Dro	Pol	Gro
EF	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CAW	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
COW	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
CRW	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
CW	0.00	0.20	0.00	0.00	0.20	0.00	0.60	0.00	0.00	0.00
SI	0.50	0.00	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00
MB	0.00	0.25	0.00	0.25	0.50	0.00	0.00	0.00	0.00	0.00
Dro	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
Pol	0.00	0.00	0.00	0.75	0.00	0.00	0.00	0.00	0.25	0.00
Gro	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

- Count the number of displacement vectors from training data for every class pair at a certain distance.
- The map will be quantized into a 100*100*100 bin.
- Normalize the relative location probability map$\mathrm{M}_{c|c'}(u, v, k)$to confirm that $\sum_{c=1}^{k} \mathrm{M}_{c|c'}(u, v, k)$=1

Inter Edge Potential

$$\varphi_{ij}^{BM}\left(y_i, y_j, X\right) = \begin{cases} 0 & if\, y_i = y_j \\ p1 + (1 - p1)e^{-\frac{{d_{ij}}^2}{2\sigma^2}} & Otherwise \end{cases}$$

Contrast Sensitive Potts Model

(Boykov et al. 2001)

Training and Inference

Piecewise Training

- **Bottom & Middle Layer**
  - **Short Range**
    - ✓ Balancing parameters between smooth and data (set empirically)
  - **Middle Range**
    - ✓ Relative Displacement Vector
- **Top Layer**
  - **Long Range**
    - ✓ Relative Location Probability Map
- **Weight Matrix**
  - ✓ L-BFGS to simultaneously training all layers weight (all 7 parameters)

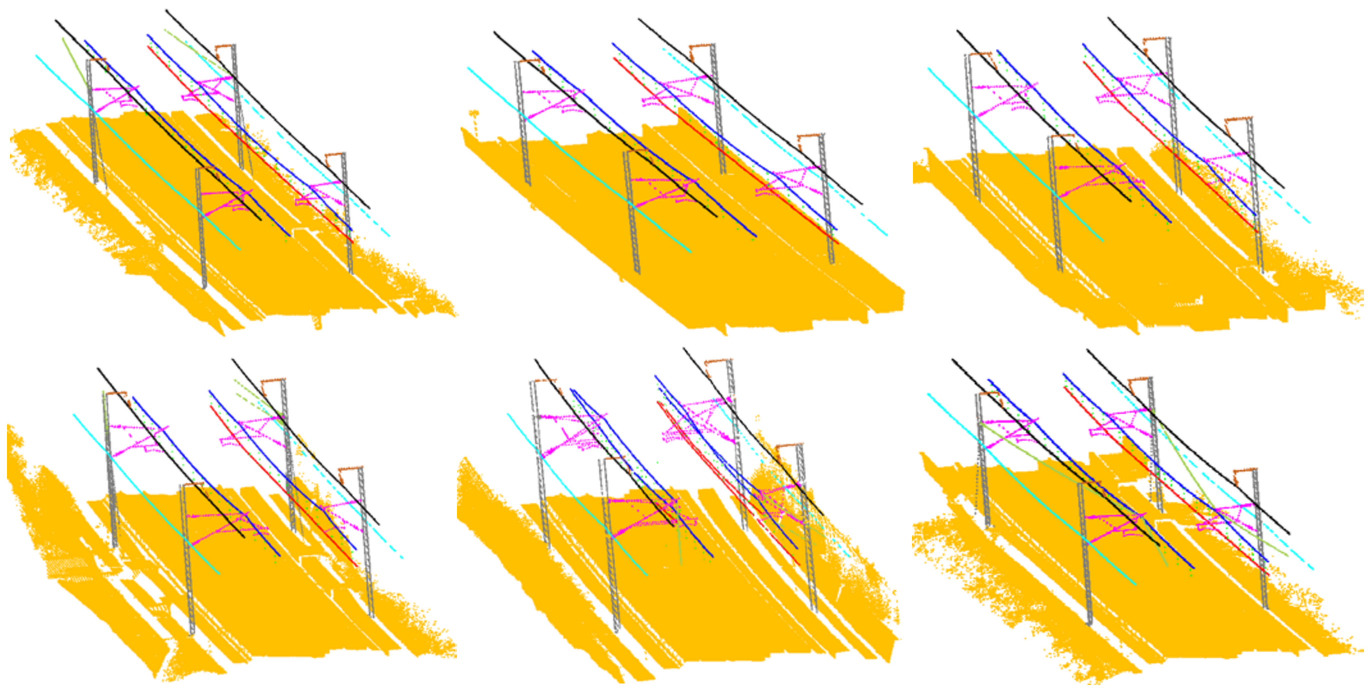
Inference

- Inference is the operation to find the most possible label configuration in the graphical model given the observation X
- **Approximation**

$$\begin{cases} \text{Loopy Belief Propagation} \\ \text{Multi−class graph−cut} \\ \text{Mean Field} \end{cases}$$

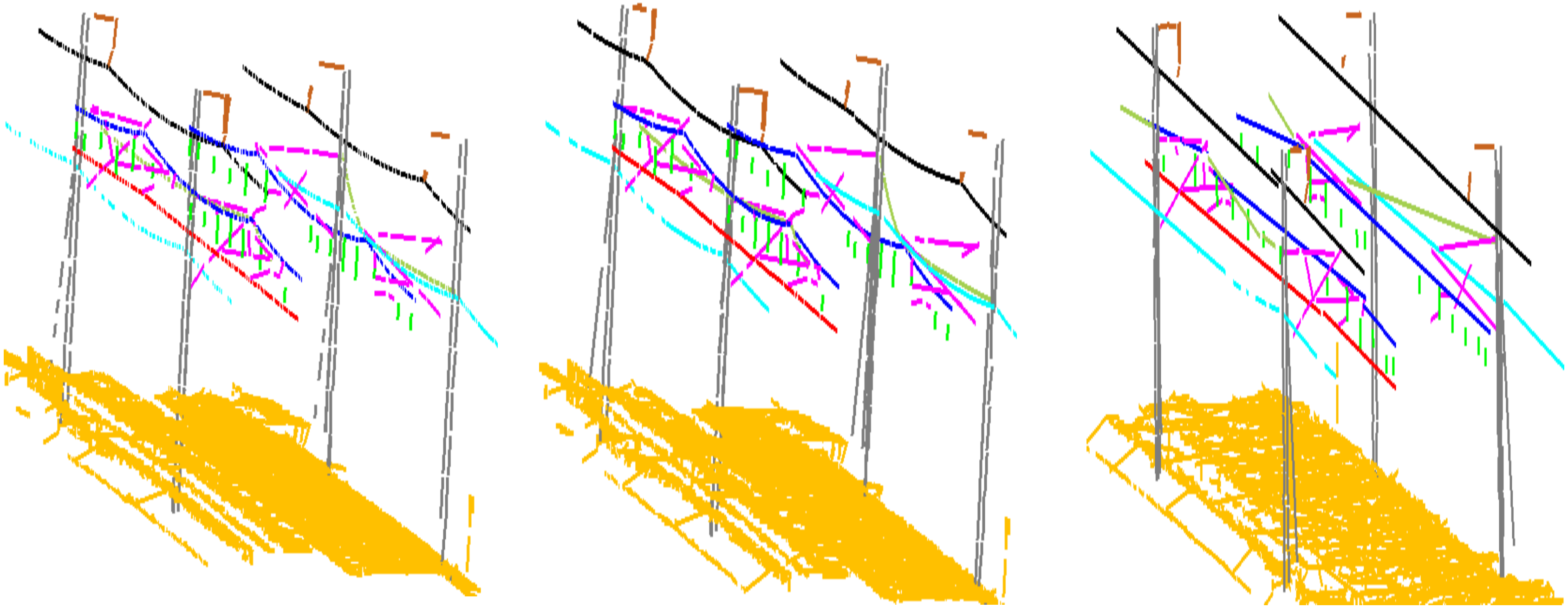
☑

Data Description



The length of the dataset selected for our study is approximately 1 km. There are two pairs of rail tracks and 24 poles at regular intervals. The dataset was divided into six sub-regions for evaluation purposes, each of which has four poles (two pole-pairs), and its length is approximately 160 m.

Line Merging Result



Scale1 Scale2 Scale3

Line Merging Result

Pole relative distance distribution to railway at primitive scale

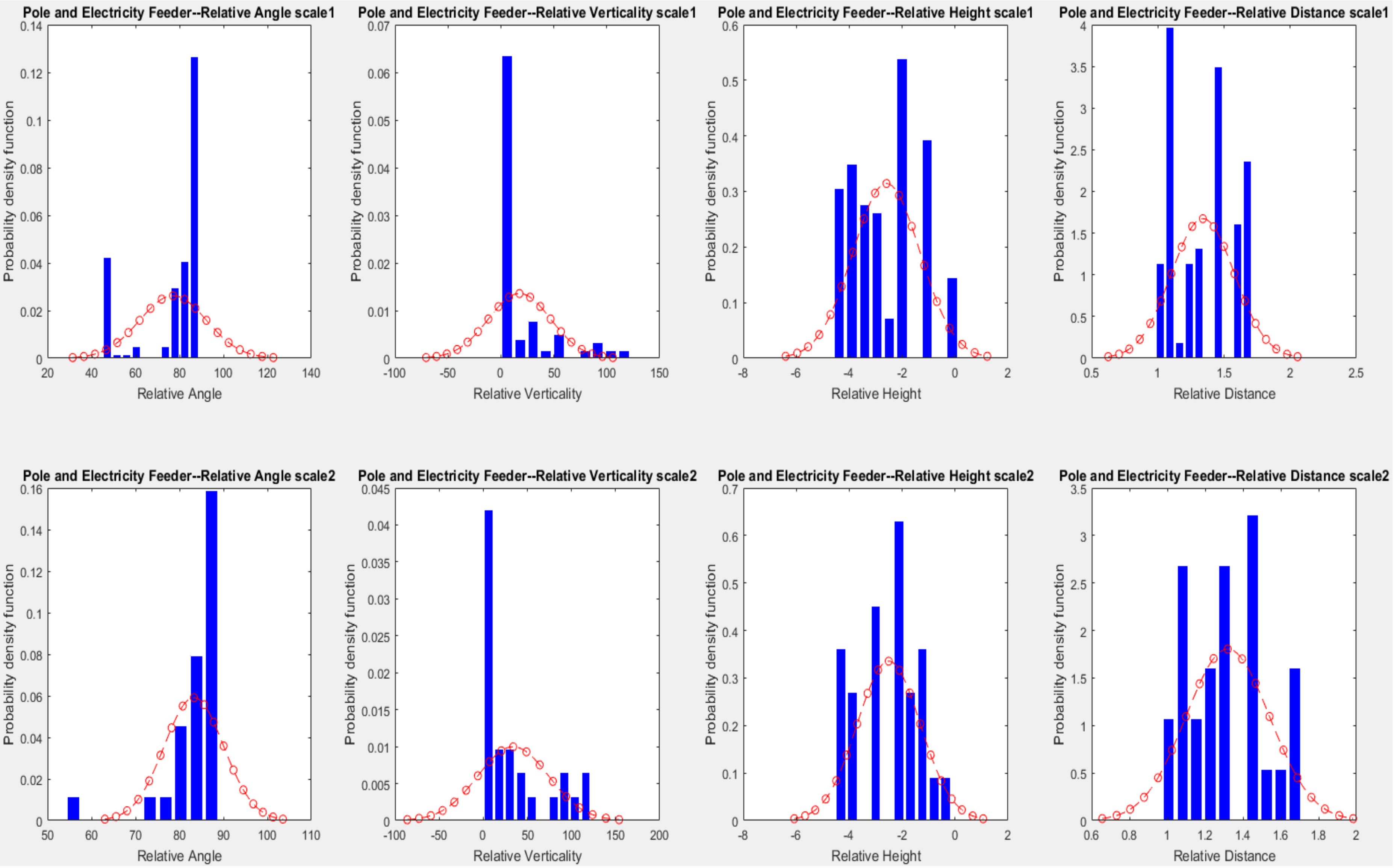
Pole relative distance distribution to railway at middle scale

Pole relative distance distribution to railway at top scale

Table 1 Average length and belonging points at each scale in training data

	Bottom		Middle		Top	
	Avg Len	Avg Pnt	Avg Len	Avg Pnt	Avg Len	Avg Pnt
EF	0.778	12.82	4.670	62.41	43.74	574.20
CAW	0.768	16.97	4.580	82.17	21.57	385.60
COW	0.740	8.30	4.047	28.69	18.32	124.33
CRW	0.695	8.05	4.455	26.77	14.39	82.21
CNW	0.732	13.61	4.933	66.53	15.35	213.33
SI	0.585	21.25	0.627	19.21	0.599	20.28
MB	0.668	24.56	0.897	34.58	1.048	39.77
DRO	0.519	9.44	0.505	4.56	0.505	4.56
Pole	0.852	29.13	1.370	45.24	1.904	57.47
GRO	1.009	56.82	1.265	76.73	1.911	118.18
AVG	0.735	20.10	2.738	44.69	11.93	161.99

Line Merging Result

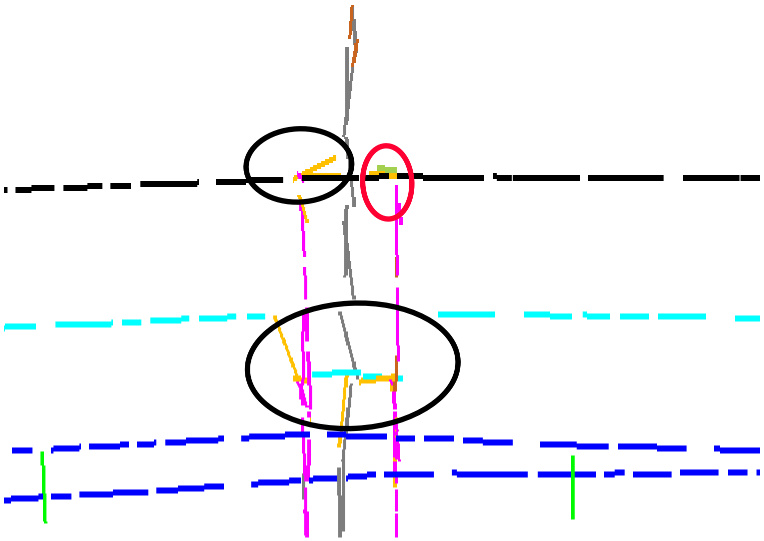


Classification Result

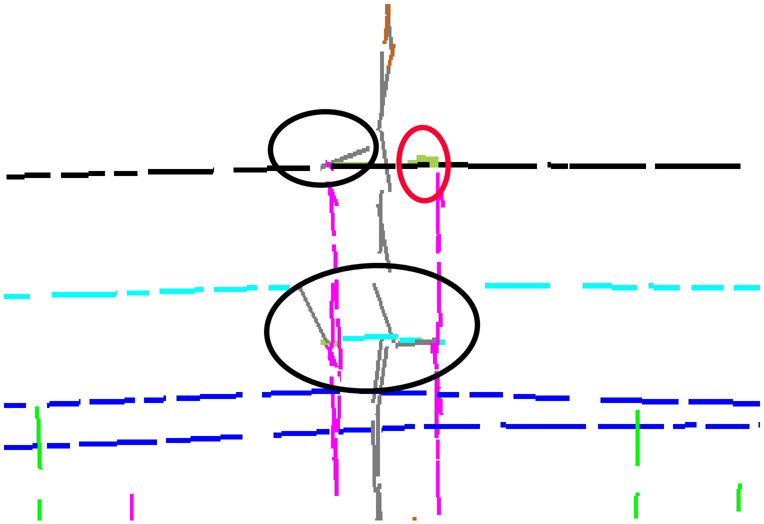
SVM

Multi-layer CRF

Classification Result



SVM



Multi-layer CRF

Quantitative Analysis

Table 2 A summary of four different classifiers performance (unit %)

Class	(a) SVM (98.05)			(b) One-Layer CRF (98.99,+0.94)			(c) Two-Layer CRF (99.05,+1.00)			(d) Multi-Layer CRF (99.21,+1.16)		
	Recall	Precision	F1	Recall	Precision	F1	Recall	Precision	F1	Recall	Precision	F1
EF	99.71	99.90	99.81	99.81	99.90	99.85	99.81	99.90	99.85	99.90	99.90	99.90
CAW	98.95	99.47	99.21	99.13	99.21	99.17	99.13	99.56	99.34	99.39	99.56	99.48
COW	98.10	100.00	99.04	98.96	98.62	98.79	98.79	100.00	99.39	99.13	99.83	99.48
CRW	99.87	99.23	99.55	99.87	99.87	99.87	99.87	99.23	99.55	99.87	99.23	99.55
CNW	90.36	95.74	92.98	87.55	94.78	91.02	90.76	96.58	93.58	90.76	96.17	93.39
SI	53.33	72.73	61.54	94.44	92.39	93.41	96.67	92.55	94.57	95.56	93.48	94.51
MB	77.07	92.93	84.26	80.80	92.10	86.08	86.93	97.60	91.96	91.47	95.54	93.46
Dro	68.97	91.95	78.82	73.28	96.59	83.33	70.69	97.62	82.00	82.76	96.97	89.30
Pole	75.35	84.96	79.87	97.65	82.28	89.30	94.98	82.65	88.39	94.66	86.89	90.61
Gro	99.73	98.43	99.07	99.74	99.91	99.83	99.74	99.76	99.75	99.75	99.82	99.78
Average	**86.14**	**93.53**	**89.41**	**93.12**	**95.57**	**94.07**	**93.74**	**96.55**	**94.84**	**95.33**	**96.74**	**95.95**

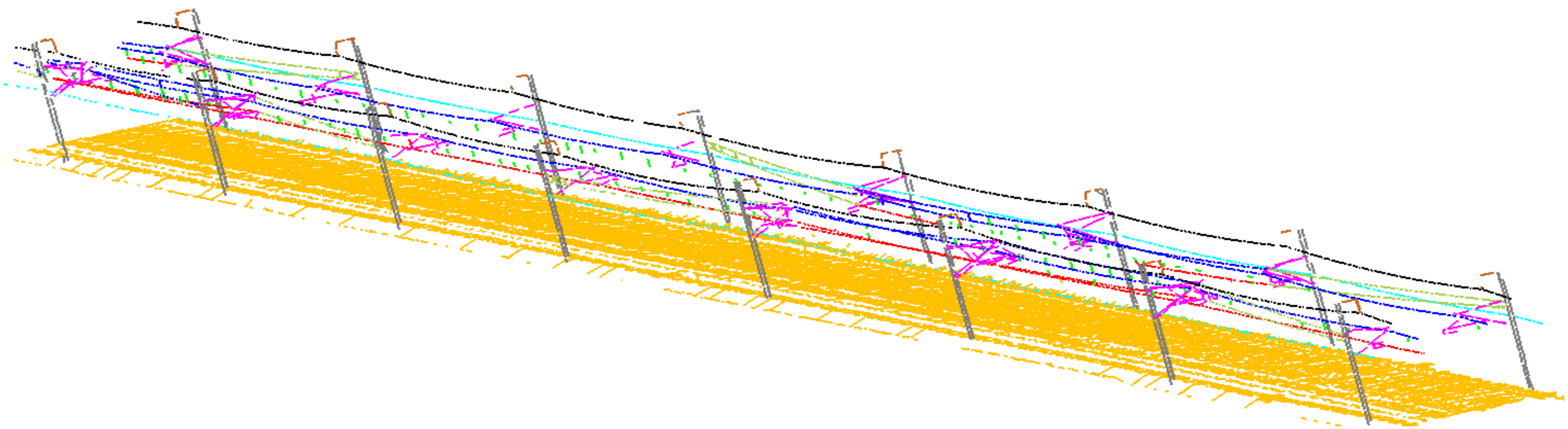
Quantitative Analysis

Table 2 A performance comparison between different classifiers(unit %)

Class	(a) SVM - One-Layer (+0.94)			(b) One-Layer - Two-Layer (+0.06)			(c) Two-Layer - Multi-Layer (+0.16)			(d) SVM - Multi-Layer (+1.16)		
	Recall	Precision	F1	Recall	Precision	F1	Recall	Precision	F1	Recall	Precision	F1
EF	+0.10	+0.00	+0.05	-0.00	-0.00	-0.00	+0.10	+0.00	+0.05	+0.19	+0.00	+0.10
CAW	+0.18	-0.26	-0.04	-0.00	+0.35	+0.17	+0.26	+0.00	+0.13	+0.44	+0.09	+0.26
COW	+0.87	-1.38	-0.25	-0.17	+1.38	+0.60	+0.35	-0.17	+0.09	+1.04	-0.17	+0.44
CRW	0.00	+0.64	+0.32	0.00	-0.64	-0.32	0.00	0.00	0.00	0.00	0.00	0.00
CNW	-2.81	-0.96	-1.95	+3.21	+1.80	+2.56	0.00	-0.41	-0.19	+0.40	+0.43	+0.41
SI	+41.11	+19.66	+31.87	+2.22	+0.16	+1.16	-1.11	+0.93	-0.06	+42.22	+20.75	+32.97
MB	+3.73	-0.83	+1.82	+6.13	+5.51	+5.88	+4.53	-2.06	+1.50	+14.40	+2.62	+9.20
Dro	+4.31	+4.64	+4.52	-2.59	+1.03	-1.33	+12.07	-0.65	+7.30	+13.79	+5.02	+10.48
Pole	+22.29	-2.68	+9.44	-2.67	+0.38	-0.92	-0.31	+4.24	+2.22	+19.31	+1.93	+10.74
Gro	+0.01	+1.49	+0.75	0.00	-0.15	-0.08	+0.01	+0.05	+0.03	+0.02	+1.39	+0.71
Average	**+6.98**	**+2.03**	**+4.65**	**+0.61**	**+0.98**	**+0.77**	**+1.59**	**+0.19**	**+1.11**	**+9.18**	**+3.20**	**+6.53**

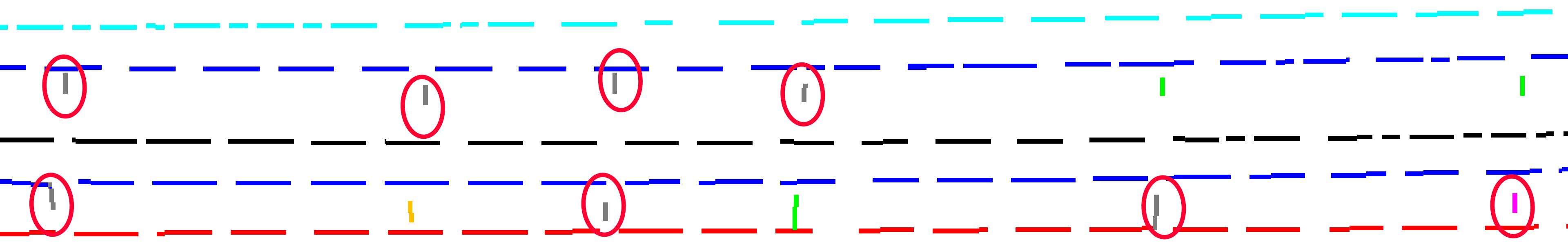
Additional Dataset

- Two more challenging dataset were also tested to evaluate the generalization of the algorithm.
- One test site contains 12 poles and the railway is not straight and another test site has 16 poles.
- Both these two test datasets have obvious spatial configuration difference between training data.



Additional Dataset

	Test Set 7			Test Set 8		
	Recall	Precision	F1	Recall	Precision	F1
EF	99.10	100	99.55	99.71	100	99.85
CAW	99.01	100	99.50	94.38	99.89	97.06
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MB	94.34	97.40	95.85	81.89	94.69	87.83
DRO	32.35	100	49.06	42.86	94.11	58.90
Pole	92.48	82.99	87.48	95.80	77.51	85.69
GRO	99.92	99.72	99.82	99.91	99.55	99.73
AVG	91.20	96.27	91.95	90.35	93.88	90.93



Conclusion

- Two-layer CRF slightly improves the classification quality of suspension insulator, pole and ground, compared with one layer CRF, by rectifying spatial irregularity.

- Fully connected layers especially improves the classification result of pole by reducing pole's commission error .

- Multi-layer CRF model can significantly refines misclassified errors in local classifier if there are strong regularity among railway elements.

- Multi-layer CRF model can only partly solved misclassified errors among object boundaries and misclassification mostly happens between pole& dropper and pole&movable bracket.

Future Plan

July-November, 2017

Indoor Reconstruction at INRIA

December-April, 2018

Paper & Thesis Writing

May-July, 2018

Thesis Defense

THANK YOU !