Railway electrification system classification from mobile laser scanning data using hierarchical CRF

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Introduction

Railways have been used as one of the most crucial means of transportation in public mobility and economic development. The electrification system in the railway infrastructure is an essential facility for stable train operation. Due to its important role, the electrification system needs to be rigorously and regularly inspected and managed.

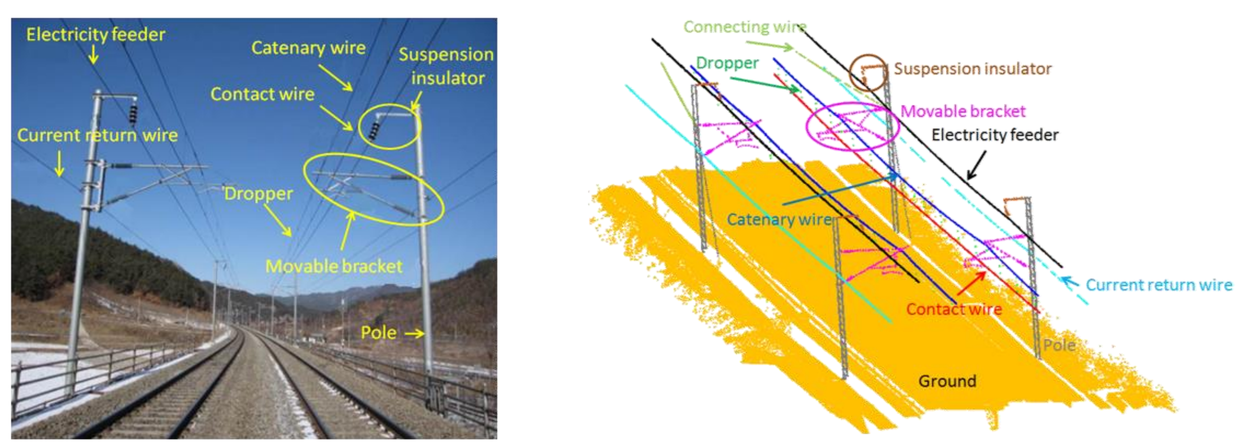


Fig .1 Electrification system configuration and object class definition

We present a supervised learning method to classify Mobile Laser Scanning (MLS) data into ten target classes representing overhead wires, movable brackets and poles, which are key objects in the electrification system. The method focuses on learning multi-scale relative spatial regularities under a probabilistic graph framework. Both local smoothness, relative object location and relative displacement are learnt in both short range, middle range and full range respectively.

Dataset

The MLS data for experiment was taken at the Honam high-speed railway in South Korea. The MLS data were acquired in 2014 using the Trimble MX8 system, which was mounted on an inspection train with a speed of 50 km/h to 70 km/h. The average density varies on the position of the laser scanner ranging from 100 points/m^2 to 800 points/m^2. The whole railway length is approximately 1 km and is divided into six subsets.

Fig. 2 Trimble MX8 mounted on a train.

Table.1 Specification of Trimble MX8

Parameter	Values
Accuracy	10 mm
Precision	5 mm
Maximum effective measurement rate	600,000 points/second
Line scan speed	Up to 200 lines/second
Echo signal intensity	High resolution 16-bit intensity
Range	Up to 500 m

Multi-Scale Line Extraction

❖ Line representation is computational efficient to avoid massive data size .

❖ Line merging through seed-filling based method to reserve geometry.

❖Multi-scale spatial learning in both local, second and object scale.

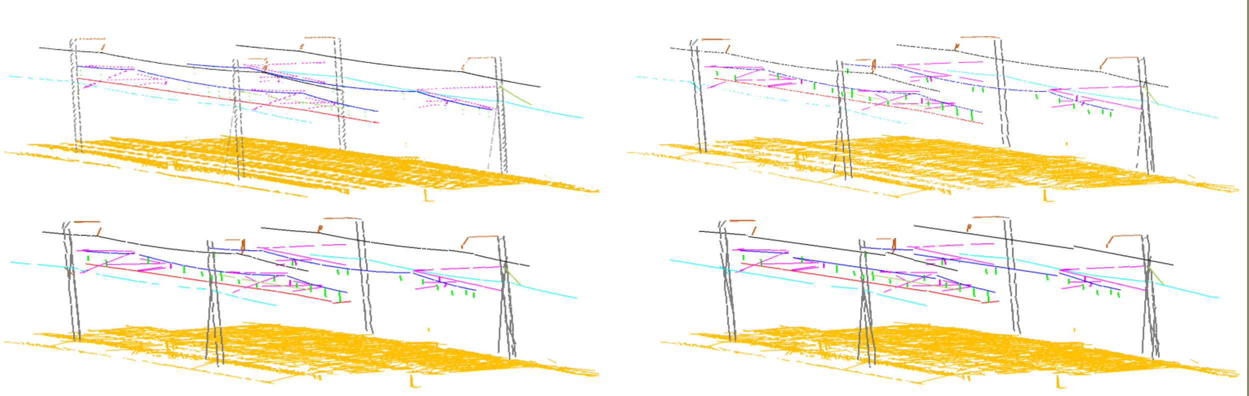


Fig .3 Three-scale line representation of original MLS data,

Hierarchical Conditional Random Field

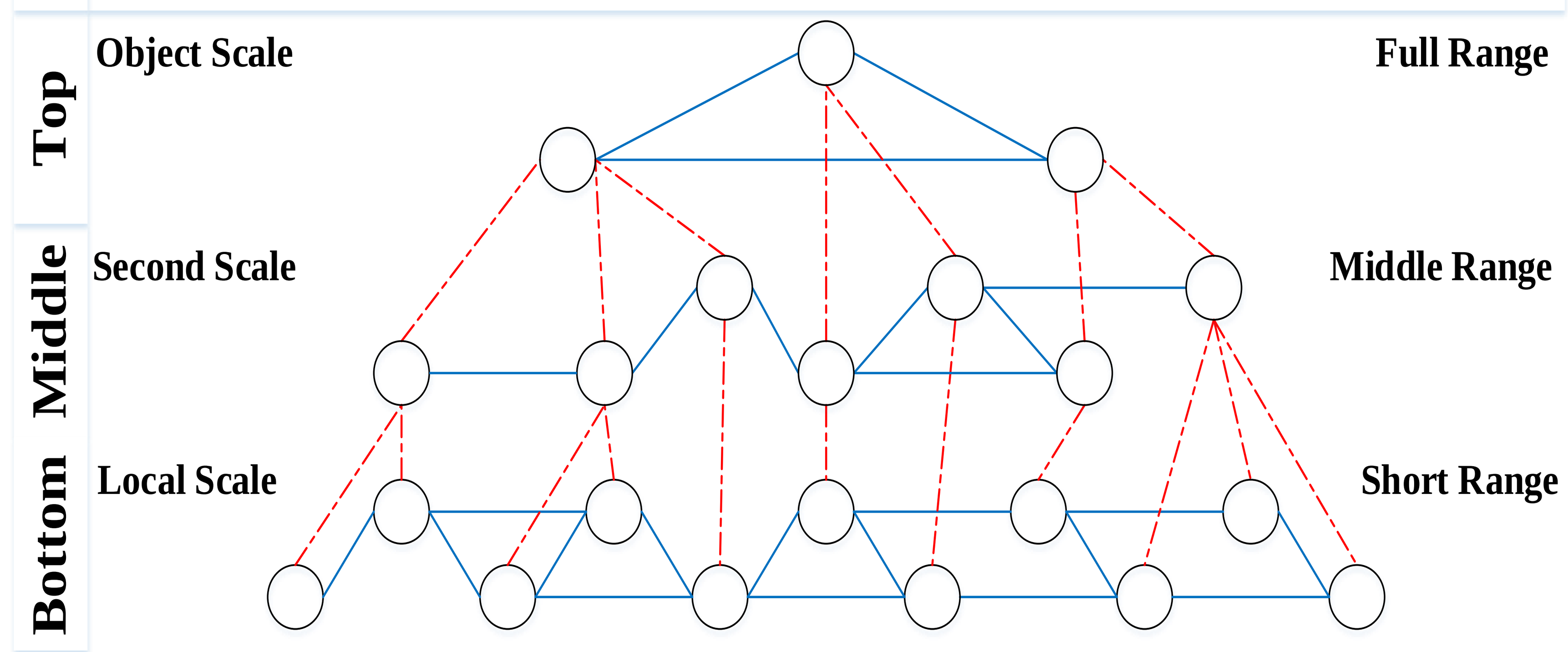


Fig. 4 Hierarchical CRF graph structure

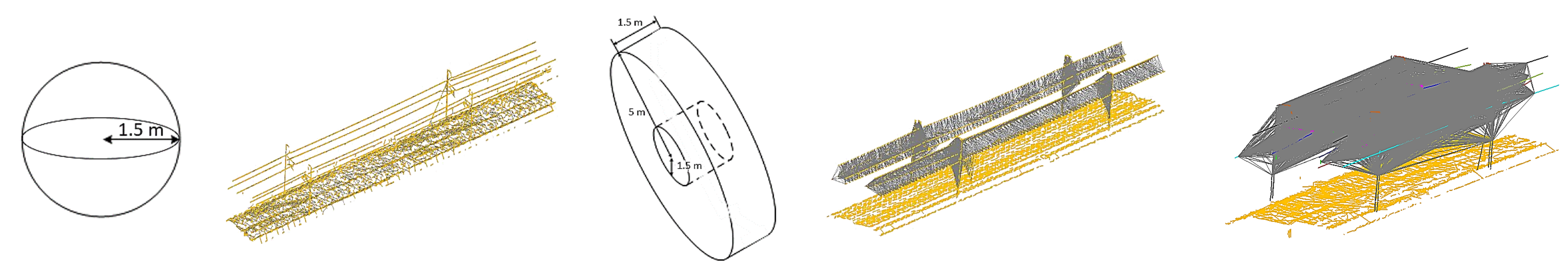


Fig. 5 Graph structure for short range, middle range and full range respectively.

1 Conditional Random Field

Conditional Random Field (CRF) is an undirected probabilistic graphical model to encode relational information between nodes in the graph. A CRF G is composed of a set of nodes n and edges e which connect nodes. As a discriminative classifier, CRF directly computes posterior probability $p(Y|X)$ between hidden variable Y and observed data X into a multiplication of potential factor.

$$p(Y|X) = \frac{1}{Z(X)} \prod_{i \in S} \varphi_i(y_i, X) \prod_{h \in H} \varphi_h(y_h, X) \quad (1)$$

2 Short Range Smoothness

Local smoothness assumes that neighboring entities such as pixel or individual point prefer to belong with same object. A contrast-sensitive Potts model was introduced to compromise between data feature and smoothness degree dependent on the Euclidean distance difference.

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

3 Middle Range Relative Location

Relative location prior is a two-dimensional vector in which the first element is the height difference of line primitives while the second element is the difference of line primitives' horizontal distance to its corresponding railway track. A RBF function is used to measure the similarity.

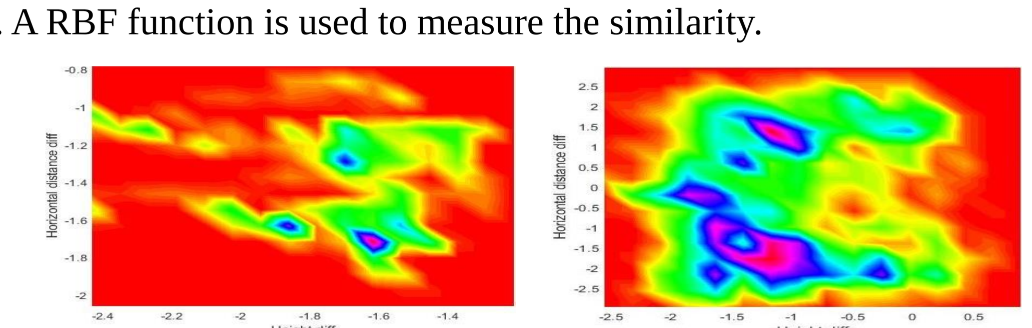


Fig. 6 Example of relative displacement prior.

$$\varphi_{ij}^{M}(y_i, y_j, X) = \log\left[\frac{1}{m}\sum_{n=1}^{m} f_{l|k}(d_{lk}^{n}, d_{ij})\right] \quad (3)$$

4 Full Range Displacement

Any contextual relation will be learnt at object scale because all nodes are connected and the relative displacement will be considered as similar as training data. This representation on the object scale can help us learn the instance-based relative spatial regularities.

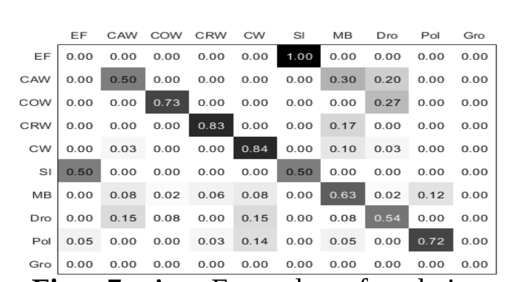


Fig. 7 An Example of relative displacement probability map.

$\mathrm{M}_{y_j|y_i}(d_{ij})$ is a relative displacement probability map encodes the conditional probability that the line primitive j with a label l given a line primitive i with the label k at a relative displacement vector d_{ij} for any class-pair.

$$\varphi_{ij}^{TF}(y_i, y_j, X) = \log\frac{1}{2}\left(\mathrm{M}_{y_j|y_i}(d_{ij}) + \mathrm{M}_{y_i|y_j}(-d_{ij})\right) \quad (4)$$

Experiment Result

❖Visualization of the best and the worst subsets classification result

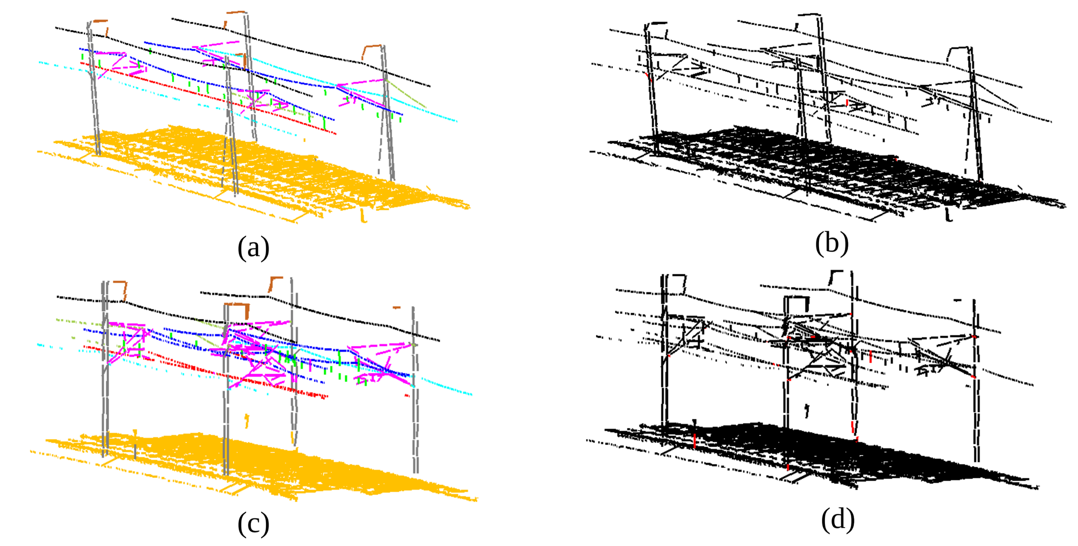
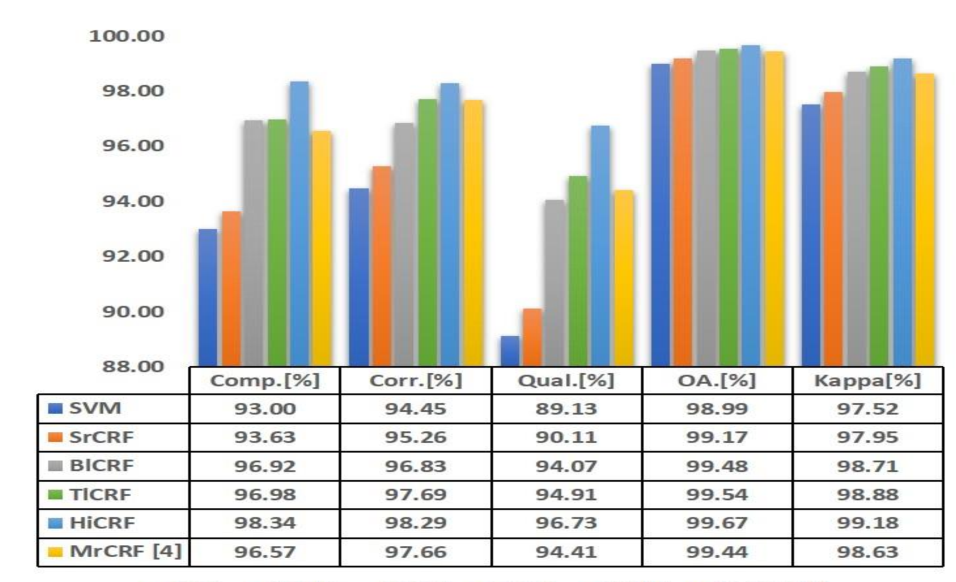


Fig. 8 (a),(c) is the classification result of subset 1 and 5. (b),(d) shows corresponding correct and misclassification.

❖Quantitative classification result of proposed model and standard SVM

	SVM (Without context)			HiCRF (With context)		
	Comp.[%]	Corr.[%]	Qual.[%]	Comp.[%]	Corr.[%]	Qual.[%]
EF	99.84	100.00	99.84	100.00 (+0.16)	100.00 (0.00)	100.00 (+0.16)
CAW	99.63	99.42	99.06	99.56 (-0.07)	99.34 (-0.08)	98.91 (-0.15)
COW	99.42	100.00	99.42	99.71 (+0.29)	100.00 (0.00)	99.71 (+0.29)
CRW	99.90	99.28	99.18	99.90 (0.00)	99.18 (-0.10)	99.08 (-0.10)
CNW	93.97	96.14	90.56	96.73 (+2.76)	96.73 (+0.59)	93.67 (+3.11)
SI	64.86	79.12	55.38	95.50 (+30.64)	96.36 (+17.24)	92.17 (+36.79)
MB	89.71	91.24	82.60	96.89 (+7.18)	97.36 (+6.12)	94.41 (+11.81)
Dro	92.36	92.36	85.81	97.90 (+5.54)	97.90 (+5.54)	95.89 (+10.08)
Pole	90.65	87.30	80.09	97.31 (+6.66)	96.08 (+8.78)	93.60 (+13.51)
Gro	99.69	99.68	99.38	99.88 (+0.19)	99.96 (+0.28)	99.85 (+0.47)
OA (%)	98.99			99.67 (+0.68)		
Kappa (%)	97.52			99.18 (+1.76)		

❖Comparison between other classification methods



	Comp.[%]	Corr.[%]	Qual.[%]	OA.[%]	Kappa[%]
SVM	93.00	94.45	89.13	98.99	97.52
SrCRF	93.63	95.26	90.11	99.17	97.95
BlCRF	96.92	96.83	94.07	99.48	98.71
TlCRF	96.98	97.69	94.91	99.54	98.88
HiCRF	98.34	98.29	96.73	99.67	99.18
MrCRF [4]	96.57	97.66	94.41	99.44	98.63

Fig. 9 The comparison of our method (HiCRF) with other typical classifiers.

Conclusions

❖ We proposed a new hierarchical CRF model to classify railway electrification scenes, which can consider both local smoothness and object spatial regularities. This spatial regularities are learnt at multi-scales in the whole scene.

❖ The results showed that the can effectively classify individual railway elements, representing an average recall of 98.34% and an average precision of 98.29% for all classes.

❖ Learning spatial regularities at multi-scales caused classification difference for individual objects and full-range displacement learning can significantly improved classification result.