

Advanced Rail Infrastructure Mapping Technologies for Train Derailment Mitigation

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1. Introduction

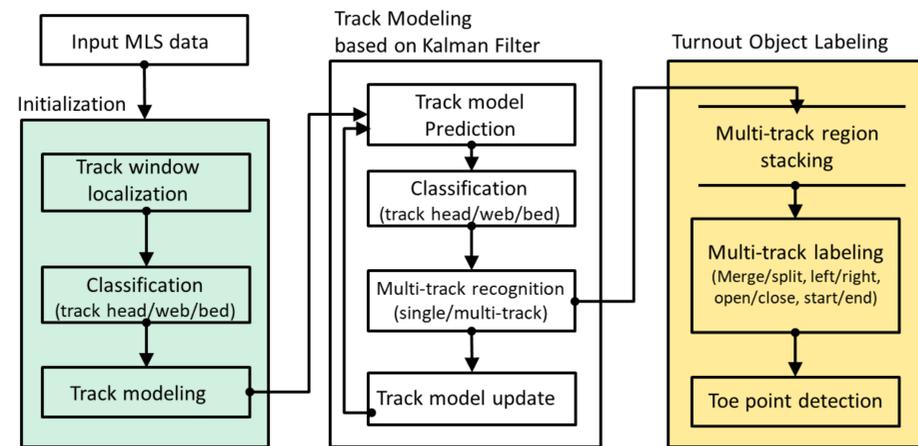
Backgrounds

- More than 60% of rail accidents were reported due to derailments. The most significant causes of derailment accidents are related to defects of track/wayside elements and impacts of environmental factors.
- Mobile LiDAR (Light Detection and Ranging) System (MLS)** is an emerging technology enabling rapid engineering grade mapping and virtual surveying over railway infrastructure.
- Despite its large potential, MLS has been only used for rail track condition assessment. Its potential for railway asset management has not been exploited yet.

Research Objectives

- Developing an end-to-end computer vision pipeline, called **ADE (Automatic Data Extraction)** for detecting multi-scale and multi-attributes rail asset detection using MLS.
- Automatically detecting and modeling: **1) rail track head/web/head, 2) single track regions, 3) multi-track regions, 4) turnout regions, 5) multi-track categories (merge/split, left/right, open/close, start/end), 6) switch boxes.**
- Developing “**Frontend Perception**” for detecting objects using binary string template matching with contextual energy minimization algorithm and “**Backend Optimization**” using Kalman Filter (EKF).

2. Workflow

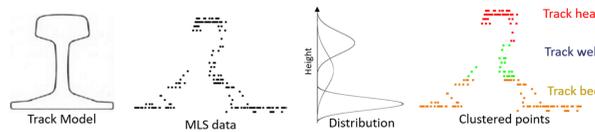


ADE (Automated Data Extraction) System Workflow

3. Methodology

Frontend Perception

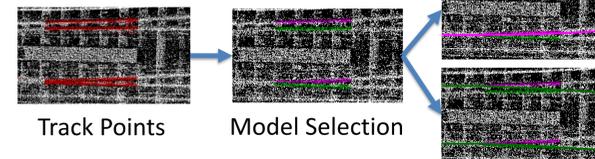
Track Detection



$$p(x) = \sum_{k=1}^3 \alpha_k N(x|\mu_i, \sigma_i)$$

EM-GMM

Single/Multi-track Recognition

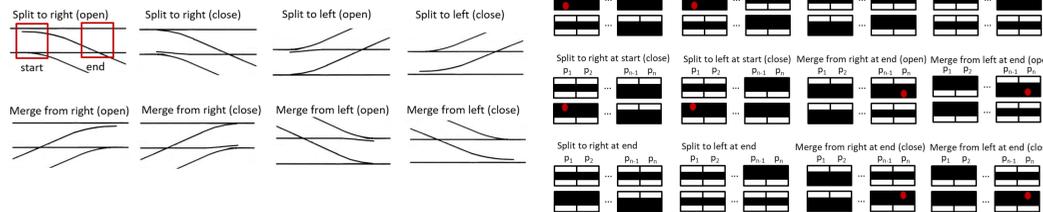


$$DL = \lambda L(D|H) + (1 - \lambda)L(H)$$

$$= \lambda \left(\frac{\Omega}{2 \ln 2} \right) + (1 - \lambda) \log_2(N + 1)$$

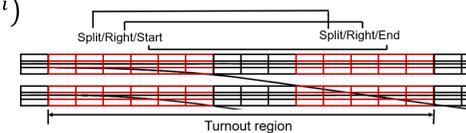
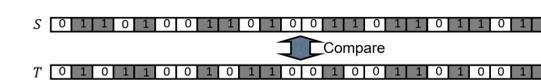
MDL (Minimum Description Length)

Binary String Templates

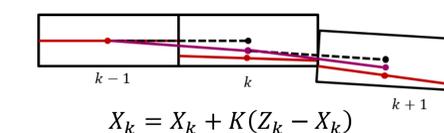


Multi-scale Context Matching

$$Score(S^i, T^j) = w \cdot U(S^i, T^j) + (1 - w) \cdot C(S^{i-1}, S^i)$$



Backend Extended Kalman Filter



$$\begin{bmatrix} X_x \\ X_y \\ X_z \end{bmatrix}_k = \begin{bmatrix} X_x \\ X_y \\ X_z \end{bmatrix}_{k-1} + \Delta L \begin{bmatrix} \sin\theta \\ \cos\theta \\ 0 \end{bmatrix}$$

Where, X: state vector, ΔL: distance, θ: orientation

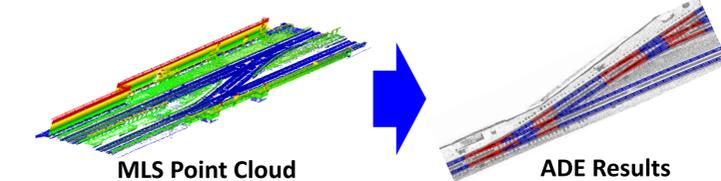
4. Experimental Results

Rail Track Modeling Accuracy

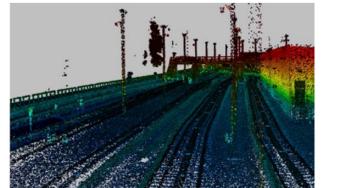
Path	Length	Point-to-model distance (m)				Recall (%)	Description
		Horizontal		Vertical			
		Ave.	Std.	Ave.	Std.		
1	1,581	0.019	±0.013	-0.002	±0.010	99.95	Main track
2	1,578	0.019	±0.029	-0.003	±0.010	99.92	Main track
3	338	0.028	±0.024	-0.003	±0.005	99.23	Parking lot
4	181	0.028	±0.025	-0.004	±0.010	99.34	Parking lot
5	213	0.026	±0.023	-0.004	±0.010	99.52	Parking lot
6	240	0.025	±0.020	-0.004	±0.011	99.90	Parking lot
7	264	0.020	±0.016	-0.003	±0.008	99.97	Parking lot
8	47	0.030	±0.025	-0.002	±0.002	99.19	Sub-track connecting between path 1 and path 3
9	47	0.031	±0.028	-0.002	±0.005	98.15	Sub-track connecting between path 2 and path 3
Total	4,489	0.025	±0.023	-0.003	±0.008	99.46	-

Rail-track Type Recognition

	Multi-track Detection (Detection rate)	Multi-track Type Recognition			
		Correct	Multiple Solution	Incorrect	Success rate
Unary term only (w = 1)	100 %	69	28	3	69 %
Unary term and contextual term (w = 0.9)	100 %	97	3	0	97 %



Teledyne Optech LYNX



MLS Point Clouds

5. Conclusions

- ADE system achieved 0.025m (RMSE ±0.023m) and -0.003m (RMSE ± 0.008m).
- ADE system achieved 99.46% recall (object detection rate).
- Our experiments proved that context-based template matching increased 28% success rate of track type recognition.

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