iVRIDA: intelligent Vehicle Running Instability Detection Algorithm for high-speed rail vehicles using Temporal Convolution Network – A pilot study

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Outline

- Introduction
- iVRIDA
- Results
- Conclusion and Future Work

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Introduction

- Introduction
- iVRIDA
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- Conclusion and Future Work

Introduction

- Intelligent fault identification of rail vehicles is of utmost importance to reduce the operating and maintenance cost.
- Early identification of vehicle faults responsible for an unsafe situation, such as the instable running of high-speed vehicles, is very important

[1] https://www.youtube.com/watch?v=5sVbCRLEZCE&ab_channel=TravelingTom

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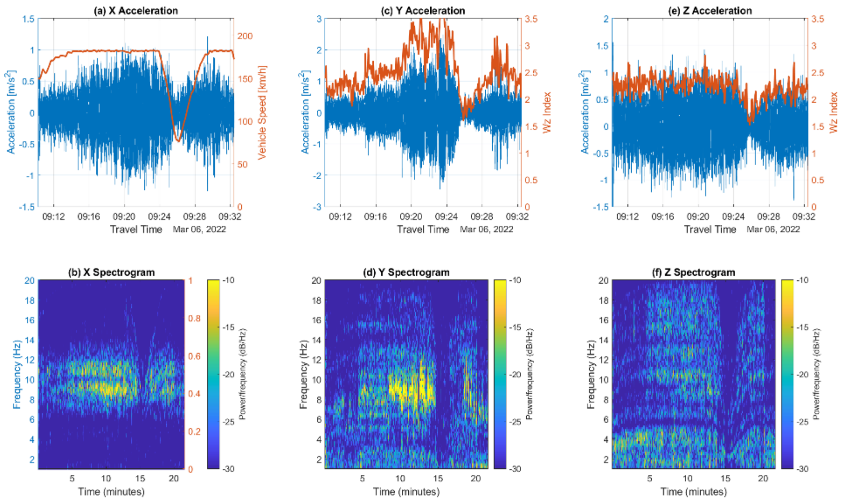
Introduction

- A new 8.7 km tunnel opened for traffic on Swedish main line connecting Gothenburg and Malmö
- Poor media publicity for train operators[1] due to poor ride comfort




NyTeknik

Premium / Automation / digitization / Energy / Vehicle / Startup / engineering Career / Free jobs

VEHICLE

Hallandsåsen

More train types are shaking through Hallandsåsen

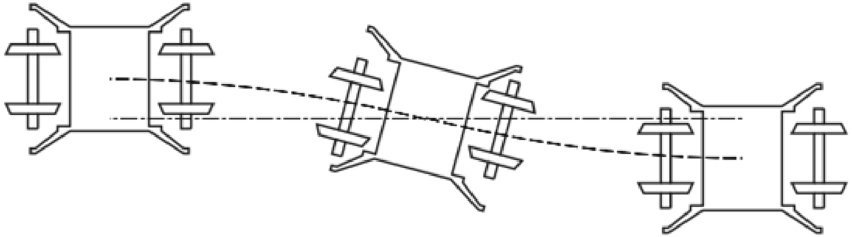
2016-02-08 09:34 Av: Linda Nohrstedt 0 kommentarer

It is not only SJ 3000 that has been affected by vibrations through the Halland saw tunnel. Powerful shaking has also been experienced on board the Öresund train and freight trains.

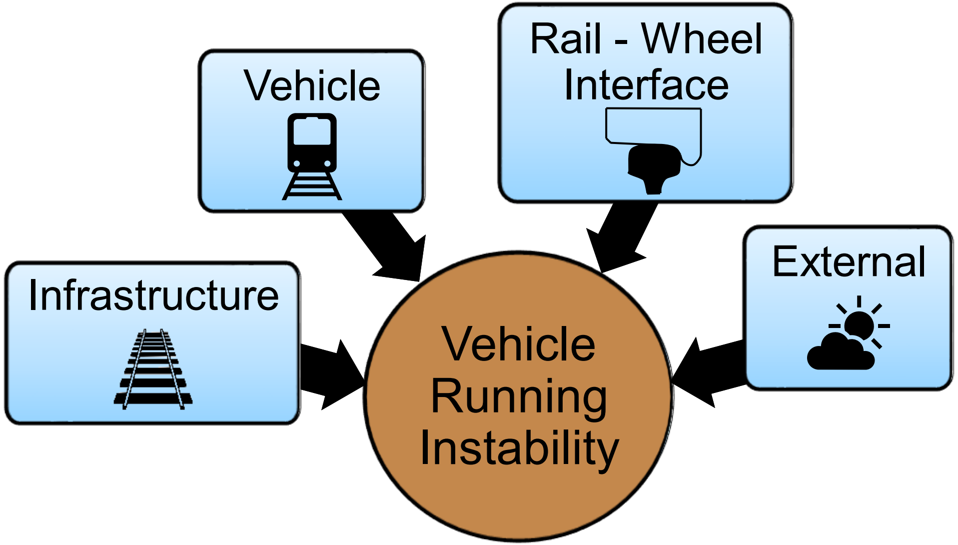
[1] https://www.nyteknik.se/fordon/fler-tagtyper-skakar-genom-hallandsasen-6336179 accessed on 20th Aug 2019 (Swedish to English google translation)

Introduction

- An intrinsic behavior of wheelset [1]
  - At high speed and on tangent track
  - Bogie hunting (3-9 Hz)
  - Carbody hunting (< 2Hz)



- Many parameters influences



- Research Question
  - How to identify root cause from onboard measurements?

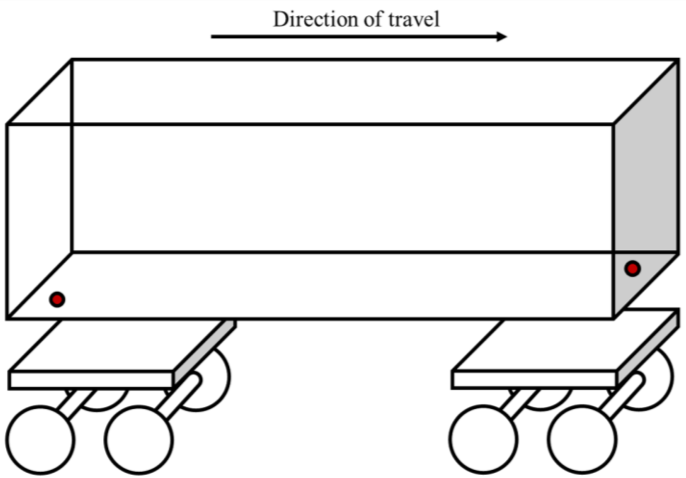
[1] Knothe K, Stichel S. Rail vehicle dynamics. Rail Vehicle Dynamics. 2016.

Introduction

- The task is challenging
  - The nonlinear dynamics associated with multiple subsystems
  - Multiple components may trigger running instability

- Using only carbody floor accelerations
  - Task is more challenging
  - However, maintenance is significantly lower compared to axlebox accelerometers.

- iVRIDA
  - A Temporal Convolution Network (TCN)-based algorithm to detect rail vehicle faults.



iVRIDA

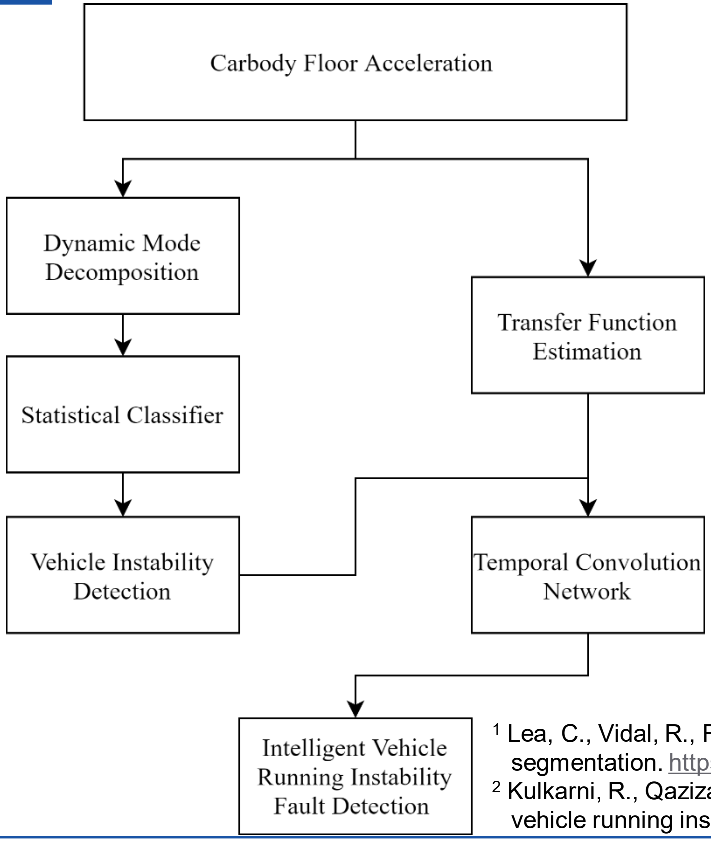
Introduction

iVRIDA – Schematic

Results

Conclusion and Future Work

iVRIDA – Schematic



- The proposed iVRIDA algorithm utilizes two data-driven methods
  - Dynamic Mode Decomposition (DMD) Algorithm for vehicle instability detection
    - > *Features extracted from carbody floor acceleration*
    - > *Binary classification problem*
  - Temporal Convolutional Network [1] (TCN) for identifying root causes of observed vehicle instability.
    - > *Transfer function[2] between carbody floor and track is calculated*
    - > *Multiclass classification problem*

[1] Lea, C., Vidal, R., Reiter, A., & Hager, G. D. (2016). Temporal convolutional networks: A unified approach to action segmentation. https://doi.org/10.1007/978-3-319-49409-8_7
[2] Kulkarni, R., Qazizadeh, A., & Berg, M. (2022). Identification of vehicle response features for onboard diagnosis of vehicle running instability. Proceedings of the IEEE Conference on Prognostic Health Management 2022, Detroit, USA.

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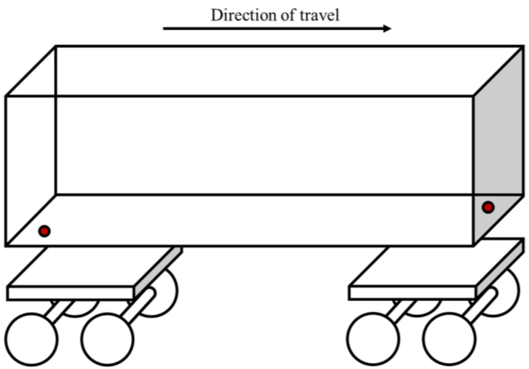
iVRIDA – Vehicle Running Instability Detection with DMD

- The DMD [1] algorithm is chosen because it is a fast and accurate algorithm suitable for detection of the eigenfrequencies and eigenmodes of the system.
- It is convenient for vehicle running instability detection due to the order in which the results are sorted, namely by energy content.
  - In fact, during hunting motion, essentially only one mode will be excited. This mode will be the one with the highest energy content.



X & Y acceleration at two ends of coach → Dynamic Mode Decomposition → Running Instability Frequency & Instability Mode

[1] Brunton, S. L., & Kutz, J. N. (2019). Data-Driven Science and Engineering. In Cambridge University Press. Cambridge University Press.

iVRIDA – Intelligent Fault Detection of Vehicle Running Instability with TCN

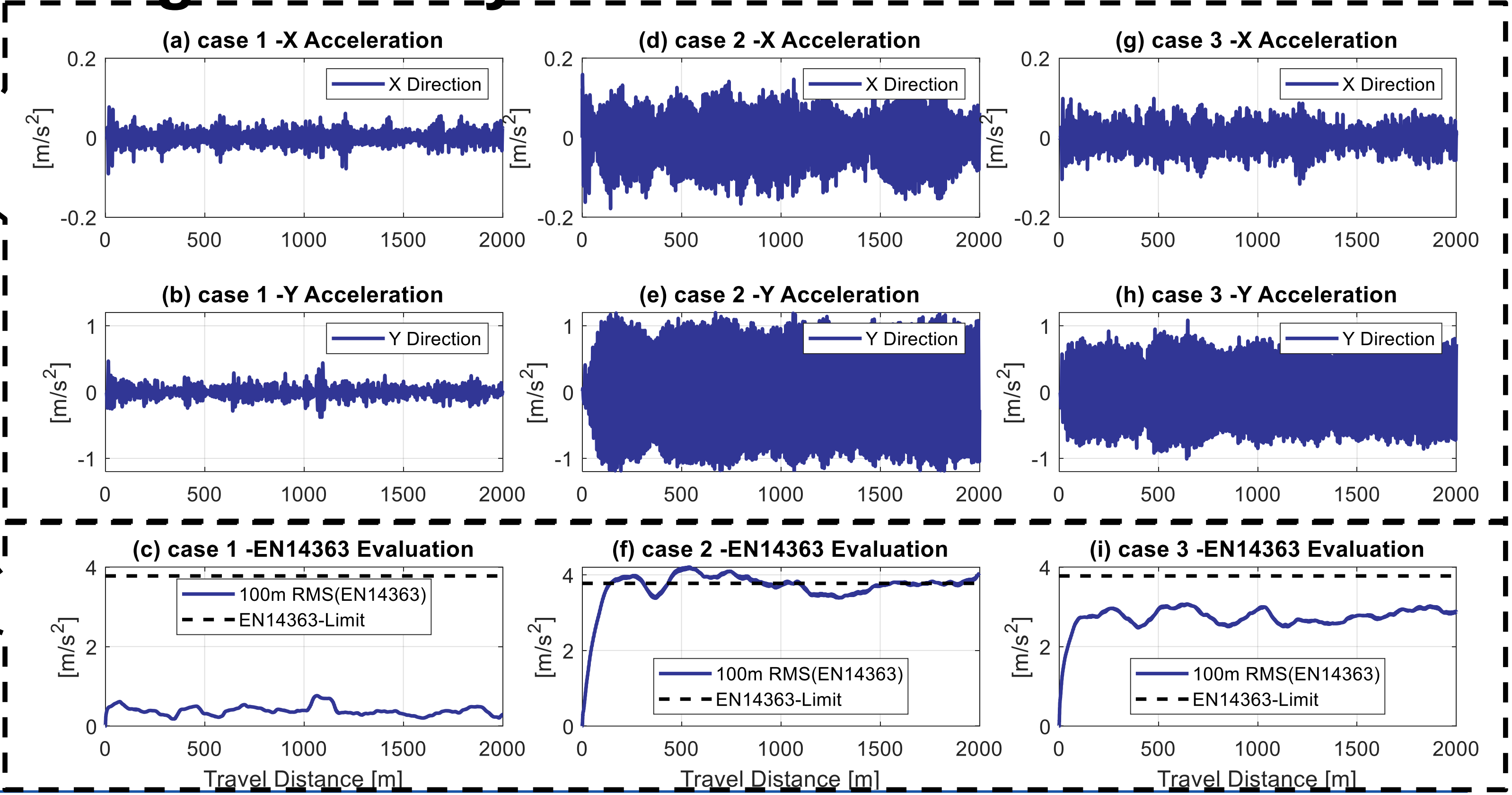
- Estimation of Transfer Functions [1]
  - A rail vehicle running on track in presence of track irregularities can be considered a MIMO system.
    - *Inputs are Alignment Level (AL), Track Gauge (TG), and Cross Level (CL) irregularities*
    - *Outputs are vehicle accelerations in Y direction.*
  - Thus, the transfer functions between carbody floor accelerations and track irregularities are estimated according to principals of MIMO system identification.
  - The simplified relationship between the input and output signal is modelled by linear, time-invariant Transfer Functions.

[1] Kulkarni, R., Qazizadeh, A., & Berg, M. (2022). Identification of vehicle response features for onboard diagnosis of vehicle running instability. Proceedings of the IEEE Conference on Prognostic Health Management 2022, Detroit, USA.

iVRIDA – Intelligent Fault Detection of Vehicle Running Instability with TCN

Carbody Floor Acceleration

Bogie Frame Acceleration



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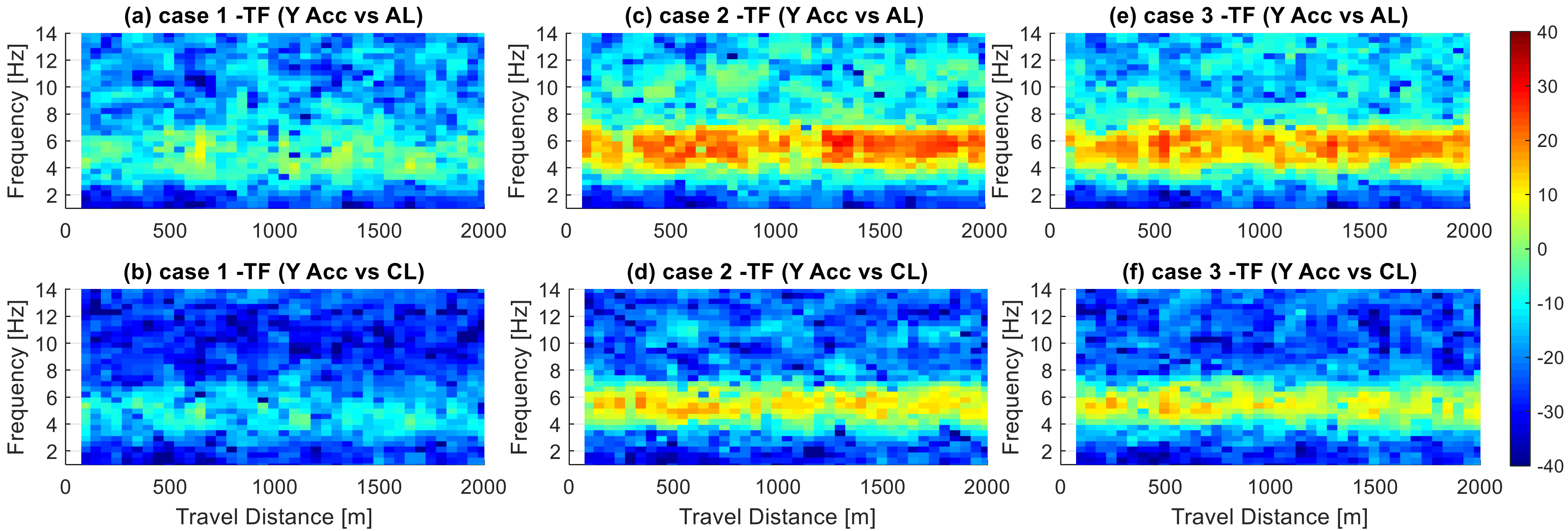
iVRIDA – Intelligent Fault Detection of Vehicle Running Instability with TCN

- Transfer Function Estimation Case Study



iVRIDA

Introduction

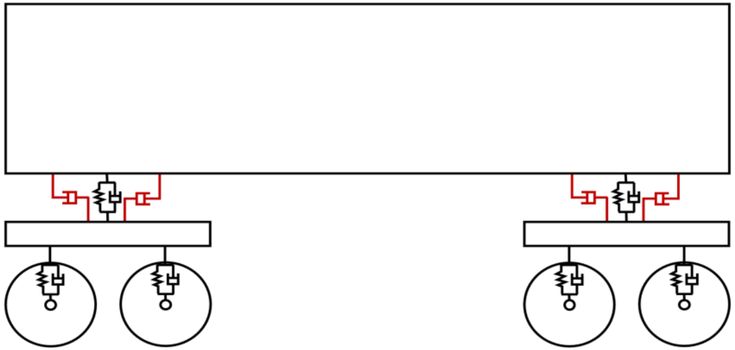
iVRIDA – Vehicle Response (VR) Database

Results

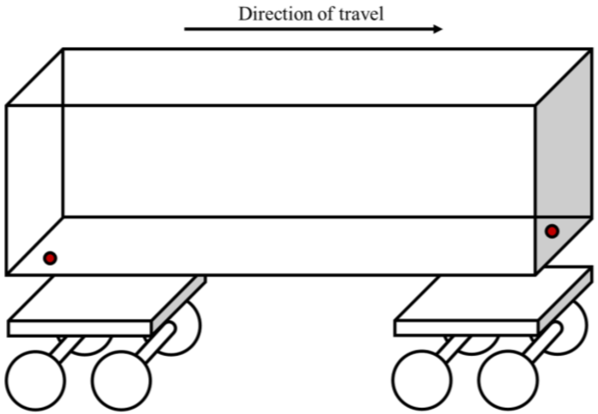
Conclusion and Future Work

iVRIDA – Vehicle Response (VR) Database

- X2000 Vehicle Model [1]



- Nonlinearities included in vehicle model
  - Wheel-Rail Interface
  - Primary and secondary suspension elements



- 1 km tangent track section with measured irregularities
- Simplified measurement scheme
  - Carbody floor acceleration at two points

[1] Dirks, B. (2003). Vehicle Dynamics Simulation of Wheel Wear for Swedish High-Speed Train X2000. KTH Royal Institute of Technology, Stockholm, Sweden.

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iVRIDA – Vehicle Response (VR) Database

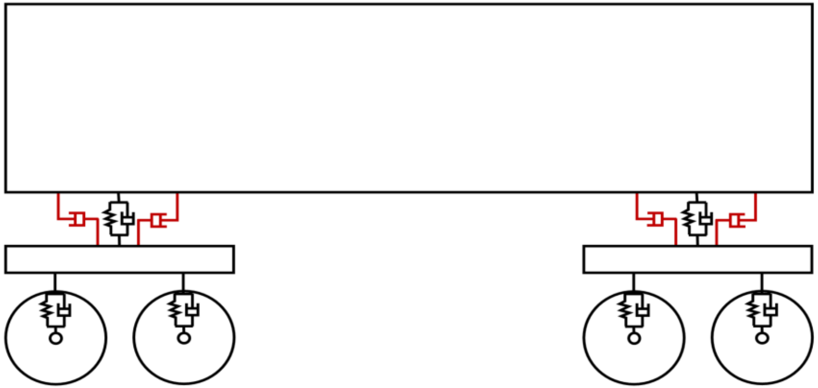
Key parameters for vehicle instability

1. Coefficient of Friction = 0.1 to 0.6 (6 steps each of 0.1)
2. Equivalent Conicity = 0.1 to 0.6 (6 steps each of 0.1)
3. Yaw Dampers Failure Rate (One at a time) = [0.1, 0.3, 0.5, 0.7, 0.9, 1]
4. Speed = 180, 200, 220

15552 Simulations

Other Parameters

1. Gaussian Distribution of other parameters around nominal value:
   i. Primary suspension (X,Y,Z) : Stiffness and damping
   ii. Secondary Suspension (X,Y,Z) : Stiffness and damping



iVRIDA

- Introduction
- iVRIDA – Machine Learning Problem Formulation
- Results
- Conclusion and Future Work

iVRIDA – Machine Learning Problem Formulation

- Vehicle Running Instability Detection with DMD
  - 15552 simulation cases i.e. 15552 observations
  - 5 features extracted from carbody floor acceleration with DMD
    - > *Instability frequency*
    - > *Normalized mode shapes (X&Y direction at two sensor locations)*
  - The true labels of stable/instable are generated with the running instability evaluation scheme defined in EN14363.
  - This is a typical binary classification problem, and any typical statistical classifier can perform the classification task.
  - Linear SVM (L-SVM) is deployed.
    - > *Database of 15552 cases*
    - > *87.5% database for training (7-fold crossvalidation)*
    - > *12.5% cases for testing*
    - > *Hyperparameters are optimized*

iVRIDA – Machine Learning Problem Formulation

- Intelligent Fault Detection of Vehicle Running Instability with TCN[1]
  - Database labelling strategy
    > *Faulty wheel-rail profile pair*
      - **λ_{3mm} >= 0.4**
    > *Faulty yaw damper*
      - One damper failing at a time
      - **Loss of performance >= 50%**
  - There are 10 fault classes/labels

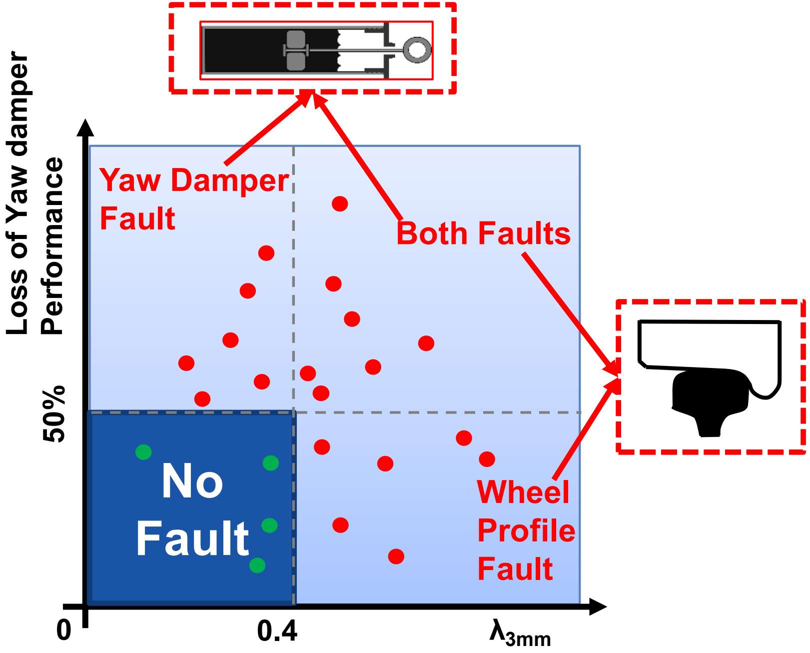
    No Fault + No Fault; Worn Wheel + No Fault

    No Fault + R BF 11; Worn Wheel + R BF 11

    No Fault + L BF 11; Worn Wheel + L BF 11

    No Fault + R BF 12; Worn Wheel + R BF 12

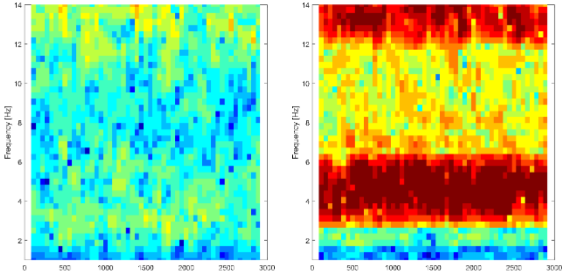
    No Fault + L BF 12; Worn Wheel + L BF 12



[1] Lea, C., Vidal, R., Reiter, A., & Hager, G. D. (2016). Temporal convolutional networks: A unified approach to action segmentation. https://doi.org/10.1007/978-3-319-49409-8_7

iVRIDA – Machine Learning Problem Formulation

- Intelligent Fault Detection of Vehicle Running Instability with TCN[1]
  - The time-series form of transfer functions [2] are horizontally stacked together



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  - Fault Detection is typical multiclass classification problem
    > *Database of 15552 cases*

    > *87.5% database for training (7-fold crossvalidation)*
      - 6 folds are used for batchwise training of the network
      - 7th fold is validation set

    > *12.5% cases for testing*

[1] Lea, C., Vidal, R., Reiter, A., & Hager, G. D. (2016). Temporal convolutional networks: A unified approach to action segmentation. https://doi.org/10.1007/978-3-319-49409-8_7
[2] Kulkarni, R., Qazizadeh, A., & Berg, M. (2022). Identification of vehicle response features for onboard diagnosis of vehicle running instability. Proceedings of the IEEE Conference on Prognostic Health Management 2022, Detroit, USA.

iVRIDA – Machine Learning Problem Formulation

- Intelligent Fault Detection of Vehicle Running Instability with TCN[1]
  - TCN is Deep learning algorithm proposed in 2018 for regression/classification of time series data.
  - TCN shows excellent abilities in solving sequential problems such as analyzing time series data and outperforms RNN/LSTM models.

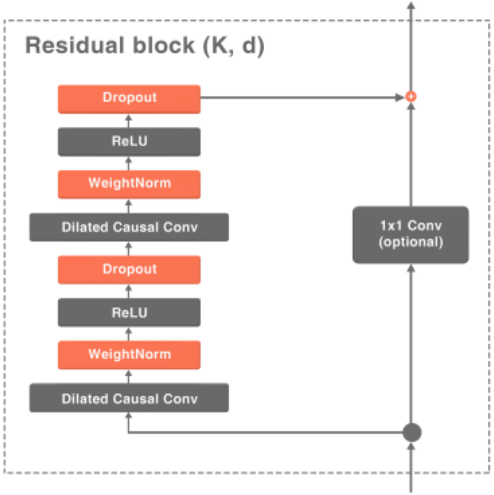

Table 1. Evaluation of TCNs and recurrent architectures on synthetic stress tests, polyphonic music modeling, character-level language modeling, and word-level language modeling. The generic TCN architecture outperforms canonical recurrent networks across a comprehensive suite of tasks and datasets. Current state-of-the-art results are listed in the supplement. ^{h} means that higher is better. $^\ell$ means that lower is better.

Sequence Modeling Task	Model Size (≈)	Models			
		LSTM	GRU	RNN	TCN
Seq. MNIST (accuracy^h)	70K	87.2	96.2	21.5	**99.0**
Permuted MNIST (accuracy)	70K	85.7	87.3	25.3	**97.2**
Adding problem T=600 (loss$^\ell$)	70K	0.164	**5.3e-5**	0.177	**5.8e-5**
Copy memory T=1000 (loss)	16K	0.0204	0.0197	0.0202	**3.5e-5**
Music JSB Chorales (loss)	300K	8.45	8.43	8.91	**8.10**
Music Nottingham (loss)	1M	3.29	3.46	4.05	**3.07**
Word-level PTB (perplexity$^\ell$)	13M	**78.93**	92.48	114.50	88.68
Word-level Wiki-103 (perplexity)	-	48.4	-	-	**45.19**
Word-level LAMBADA (perplexity)	-	4186	-	14725	**1279**
Char-level PTB (bpc$^\ell$)	3M	1.36	1.37	1.48	**1.31**
Char-level text8 (bpc)	5M	1.50	1.53	1.69	**1.45**

[1] Lea, C., Vidal, R., Reiter, A., & Hager, G. D. (2016). Temporal convolutional networks: A unified approach to action segmentation. https://doi.org/10.1007/978-3-319-49409-8_7

Results

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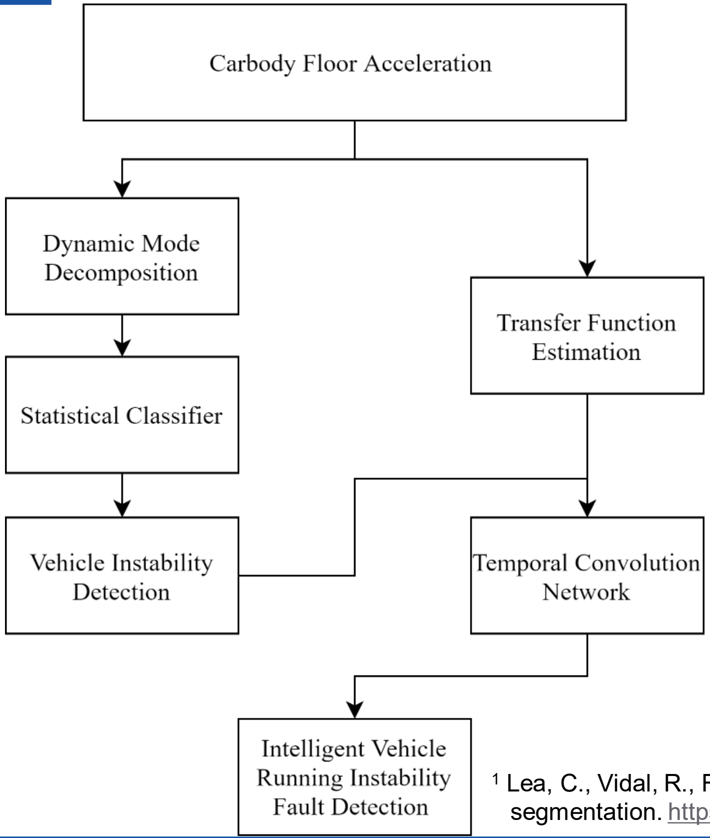
iVRIDA – Results



- Results
  - Dynamic Mode Decomposition (DMD) Algorithm for vehicle instability detection
  - Temporal Convolutional Network [1] (TCN) for identifying root causes of observed vehicle instability.

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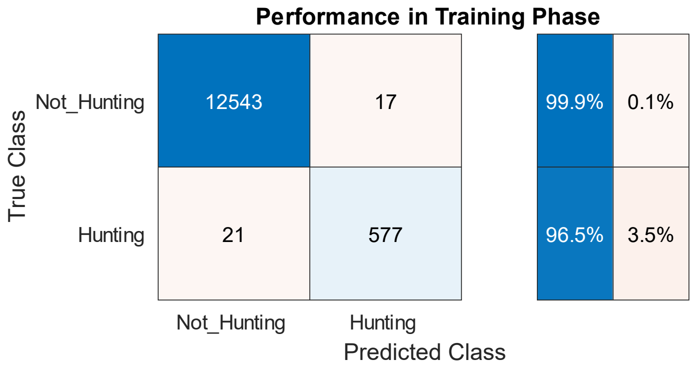
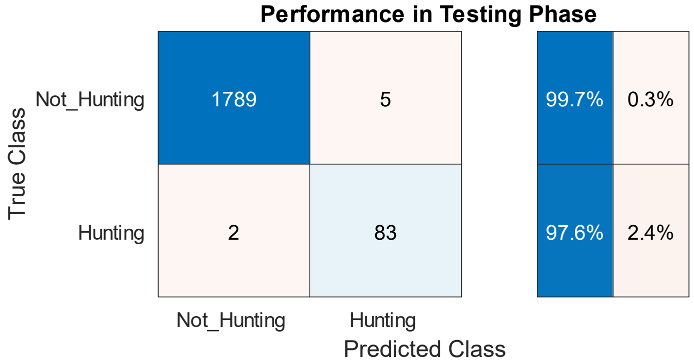
Results – Vehicle Running Instability Detection





- Performance in Training Phase
  - Overall classification accuracy of 99.7%
    - *99.9% cases of non-hunting are correctly classified*
    - *96.5% cases of hunting are correctly classified*
- Performance in Testing Phase
  - Overall classification accuracy of 99.6%
    - *99.7% cases of non-hunting are correctly classified*
    - *97.6% cases of hunting are correctly classified*

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Results – Intelligent Fault Detection

Confusion Matrix in Training Phase

True Class \ Predicted Class	Worn-Wheel_&_R-BF12	Worn-Wheel_&_L-BF12	No-Fault_&_L-BF12	No-Fault_&_R-BF12	Worn-Wheel_&_R-BF11	Worn-Wheel_&_L-BF11	Worn-Wheel_&_No-Fault	No-Fault_&_L-BF11	No-Fault_&_R-BF11	No-Fault_&_No-Fault		
Worn-Wheel_&_R-BF12	95.7%	0.1%		2.9%	0.3%	0.2%	0.8%		0.0%	0.1%	95.7%	4.3%
Worn-Wheel_&_L-BF12	0.1%	94.8%	2.5%	0.0%	0.1%	0.1%	2.1%	0.0%		0.2%	94.8%	5.2%
No-Fault_&_L-BF12	0.0%	3.3%	94.2%	0.1%			0.1%	0.1%	0.1%	2.1%	94.2%	5.8%
No-Fault_&_R-BF12	4.7%		0.0%	93.7%	0.0%	0.0%	0.1%	0.1%	0.1%	1.2%	93.7%	6.3%
Worn-Wheel_&_R-BF11	0.0%	0.0%			93.0%	0.5%	4.2%		2.0%	0.3%	93.0%	7.0%
Worn-Wheel_&_L-BF11	0.1%	0.0%			0.7%	92.7%	3.6%	2.1%	0.2%	0.6%	92.7%	7.3%
Worn-Wheel_&_No-Fault	0.9%	1.7%	0.0%	0.0%	1.6%	2.0%	92.2%	0.1%	0.1%	1.4%	92.2%	7.8%
No-Fault_&_L-BF11		0.0%	0.1%	0.0%	0.0%	3.2%	0.0%	92.0%	0.3%	4.2%	92.0%	8.0%
No-Fault_&_R-BF11			0.0%	0.0%	2.7%	0.1%	0.2%	0.4%	91.6%	4.9%	91.6%	8.4%
No-Fault_&_No-Fault	0.0%	0.1%	1.1%	0.9%	0.1%	0.3%	2.0%	2.7%	1.8%	90.9%	90.9%	9.1%
	93.5%	93.2%	95.1%	95.1%	92.9%	91.4%	92.2%	91.9%	93.5%	91.6%		
	6.5%	6.8%	4.9%	4.9%	7.1%	8.6%	7.8%	8.1%	6.5%	8.4%		

- Performance of iVRIDA in Training Phase
  - Overall classification accuracy of 92.9%
  - Lowest fault detection accuracy 90.9% for No Fault & No Fault class
  - Highest classification accuracy of 95.7% for Worn_Wheel_&_R-BF12 fault

Results – Intelligent Fault Detection

Confusion Matrix in Test Phase

True Class \ Predicted Class	Worn-Wheel_&_R-BF12	Worn-Wheel_&_L-BF12	No-Fault_&_R-BF12	Worn-Wheel_&_R-BF11	No-Fault_&_L-BF11	No-Fault_&_L-BF12	Worn-Wheel_&_No-Fault	Worn-Wheel_&_L-BF11	No-Fault_&_No-Fault	No-Fault_&_R-BF11		
Worn-Wheel_&_R-BF12	94.4%		3.6%	0.2%			1.5%	0.2%	0.1%	0.1%	94.4%	5.6%
Worn-Wheel_&_L-BF12	0.2%	93.6%	0.1%	0.1%		3.2%	2.6%	0.1%	0.2%	0.1%	93.6%	6.4%
No-Fault_&_R-BF12	4.5%		93.2%		0.1%	0.2%	0.1%		1.6%	0.3%	93.2%	6.8%
Worn-Wheel_&_R-BF11	0.1%	0.1%		92.6%		0.1%	4.1%	1.2%	0.1%	1.8%	92.6%	7.4%
No-Fault_&_L-BF11				0.2%	91.3%		0.1%	3.9%	3.9%	0.6%	91.3%	8.7%
No-Fault_&_L-BF12		4.4%	0.1%		0.2%	90.1%	0.1%		5.2%		90.1%	9.9%
Worn-Wheel_&_No-Fault	1.2%	3.1%	0.0%	2.2%			89.4%	2.6%	1.4%	0.0%	89.4%	10.6%
Worn-Wheel_&_L-BF11	0.2%	0.1%		0.7%	2.2%		6.6%	89.2%	0.9%	0.2%	89.2%	10.8%
No-Fault_&_No-Fault	0.1%	0.0%	1.5%	0.1%	3.4%	1.6%	2.8%	0.2%	88.5%	1.8%	88.5%	11.5%
No-Fault_&_R-BF11			0.1%	2.0%	0.4%		0.6%	0.1%	10.2%	86.7%	86.7%	13.3%
	92.6%	89.9%	93.2%	92.3%	90.6%	93.2%	89.1%	89.3%	87.3%	92.9%		
	7.4%	10.1%	6.8%	7.7%	9.4%	6.8%	10.9%	10.7%	12.7%	7.1%		

- Performance of iVRIDA in Testing Phase
  - Overall classification accuracy of 90.6%
  - Lowest fault detection accuracy 86.7% for No-Fault_&_R-BF11 Fault class
  - Highest classification accuracy of 94.4% for Worn_Wheel_&_R-BF12 fault

Conclusions and Future Work

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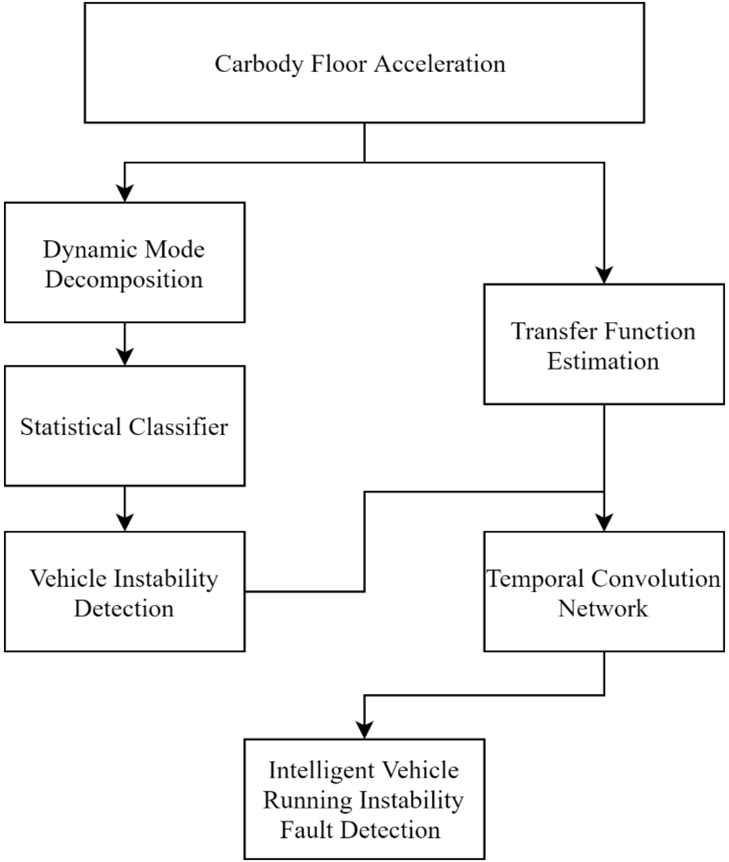
Conclusions and Future Work

- iVRIDA – intelligent Vehicle Running Instability Detection Algorithm
  - Only Carbody floor accelerations
  - Instability detection with SVM+DMD
  - Fault Identification with TCN

- Performance of iVRIDA
  - Extensive database of 15552 simulations
  - Overall accuracy more than 90%

- After summer break, the algorithm is undergoing validatation with onboard measurements of X2000 fleet.



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Thank You

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