



DEPARTMENT OF CIVIL, ENVIRONMENTAL AND GEOMATIC ENGINEERING

Semester Project Report

Data-driven identification and classification of rail surface defects

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Acknowledgements

This semester project would not be possible without the help of my supervisors, Cyprien Hoelzl and professor Eleni Chatzi. I first reached out to Eleni for a semester project opportunity during ETH week – for the purpose of improving my skills in doing research. Shortly thereafter, I was introduced to her PhD student, Cyprien Hoelzl, about a project revolving around identifying and classifying defects on train tracks.

Cyprien has been an exceptional mentor throughout this entire project. I received all the academic guidance necessary and whenever I had issues, I could always drop by his office or text him, after which helpful answers would promptly ensue. From the beginning, I could tell that he is down-to-earth, hard-working, very intelligent and possess great specialization in the field of train maintenance and monitoring. He is very good at explaining difficult concepts (with his quick and intuitive hand-drawings) and provided me with many informative resources. Furthermore, he truly cared about my progress, goes out of his way to aid me, and provides constructive feedback for everything I present to him.

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Finally, I greatly appreciate the help that I have received from Eleni's other PhD student, Harry (Mylonas Charilaos). He has provided me with very informative tools/feedback for my work with neural network architectures. Although interactions were few, one can immediately tell that he is very knowledgeable about the field of machine learning.

I have great gratitude for this opportunity working alongside Eleni and her multi-talented team. It has been a pleasant and educational experience. I sincerely could not ask for better supervisors.

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Chapter 1

Introduction

Railway companies need to continuously and sufficiently maintain the train tracks and optimally detect defects in order to have a more punctual and more effective train system. However, the current system is expensive, time consuming and ineffective. That is, maintenance agents need to walk along tracks and check them for defects. For visualisation purposes, there is roughly 5200 km of rails in Switzerland which needs to be inspected by 40 experienced inspectors.

In order to cope with this issue, Swiss Federal Railways (SBB) has specifically built two new special diagnostic vehicles (SDV) designed for defect identification among other purposes. For this, accelerometers have been installed at the front and back of the vehicle to collect the signal responses from the wheel and the train track (see appendix A.1).

A defect in train tracks can be seen as a discontinuity. As a train passes over this discontinuity, it will result in a perturbation that can be detected by sensors. It is our main assumption that each type of defect will have a specific signature that will allow its identification and classification. This is similar to the idea presented in [1] about human activity recognition.

1.1 Objective

As the title implies, the objective of this project is to identify and classify rail surface defects. To do this, we aim to build an effective pipeline that takes information about defects as input and outputs a classification confidence for these defects. By successfully identifying and classifying the defects, we take one step further towards reducing delays and making trains more punctual and reliable. The first step in this development consists of identification and classification, while the second step ultimately consists of future defect prediction.

1.2 Defects

Evidently, a defect can be seen as a deviation from the standard train track. For the exact defect type, SBB has self-constructed a database for the individual defect definitions. See appendix A.2 for an example as to how this is done.

Generally, a defect is separated into two overarching types: range- and point-defects. I.e. a defect that is detected at a single point versus a defect that is detected at varying lengths.

is this
a rec-
ognized
system?

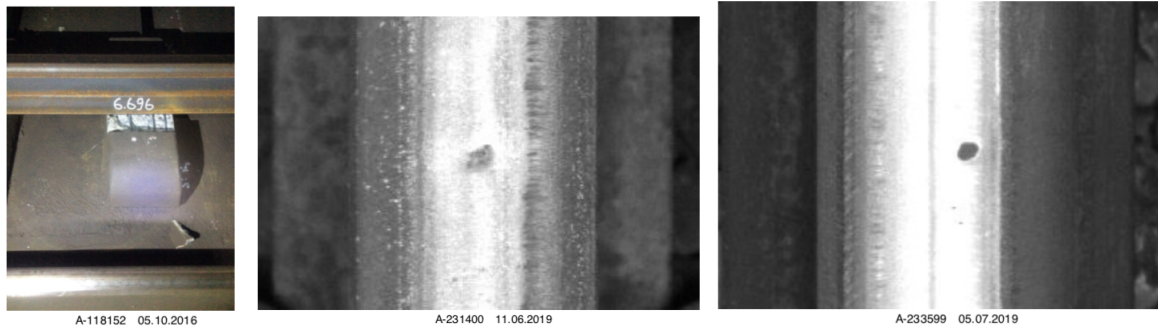


Figure 1.1: Left, middle, right: Schwellen (A-118152), Fahrbahn (A-233599), Vignolschiene (A-231400). These have all been reported as defects (with subcategories) with a length equals to zero, and thus have been classified as point defects using our terminology. Parenthesis signifies defect ID and all pictures comes from SBB defect report set ID: 400





A-103213 25.03.2017

Figure 1.2: Top, middle, bottom: Gleis-149.8m (A-184063), Schienenzwischenlage-5.0m (A-146358), Bankett-1169.5m (A-231400). These have all been reported as defects (with subcategories) with a length strictly greater than zero, and thus have been classified as range defects using our terminology. Parenthesis signifies defect ID and all pictures comes from SBB defect report set ID: 400. Most of these range defects have two pictures likely to give more detail

For this project, we have solely focused on the point defects for analysis, as this simplifies the problem statement. A point defect is perceived as a sharp signal response, whereas a range-defect is perceived over a greater time period. We thus disregard range-defects such that we do not have to deal with the extra, associated factors.

See list of defect types in appendix?

1.3 Data

The data has been collected and provided by SBB. Using their SDV, SBB has made trips back and forth to different cities in Switzerland in order to collect various data including but not limited to accelerometer data. After getting the data from SBB, it then goes through a processing pipeline (designed by Cyprien), after which the data can be manipulated with `python` dataframes (from `pd.DataFrame`). The accelerometer captures the accelerations at the XYZ-axes (along with the timestamps at each recording), of which we are only concerned with the Y-axis for the vertical perturbations for the accelerometer at the axle. See appendix A.1 for visualisations of the accelerometer placements on the SDV.

Furhtermore, the locations of the defects have to be retrieved from SBB's database. which were retrieved by Cyprien.

We need to define terminology of these: defects, ins joints, switches. In the following we will use entities as an umbrella term for the aforementioned track phenomenons.

Which data was worked on, put in tables, switches, ins joints and defects

1.4 Code

The code is written purely in python. To create neural network architectures, we are using: `keras` along with `tensorflow`. `keras` is essentially a high-level neural networks library which runs on top of `tensorflow`. It has consistent, a simple API and provides clear and actionable feedback upon user error. Models are easily made by connecting configurable building blocks together, with few restrictions [2]. The models were trained in Google Colab, which is a web application provided by Google that enables users to run python code in the web browser with access to GPUs¹. It is very similar to Anaconda's Jupyter Notebooks, except that Colab runs in the browser, is collaborative and provides free usage of GPUs (meaning model training goes faster).

All the code can be found on github:

<https://github.com/Aiyualive/SemesterProject2.0>.

The specific model execution workflow can be found Colab:

https://colab.research.google.com/drive/12VBz_KrJxeyR_pjpkC87fewv5aMSEI5_

¹<https://colab.research.google.com/notebooks/intro.ipynb>

Chapter 2

Design and Implementation

For the process of defect classification we designed the pipeline in 2.1. In the next sections, I would like to give an overview of how each step was implemented.

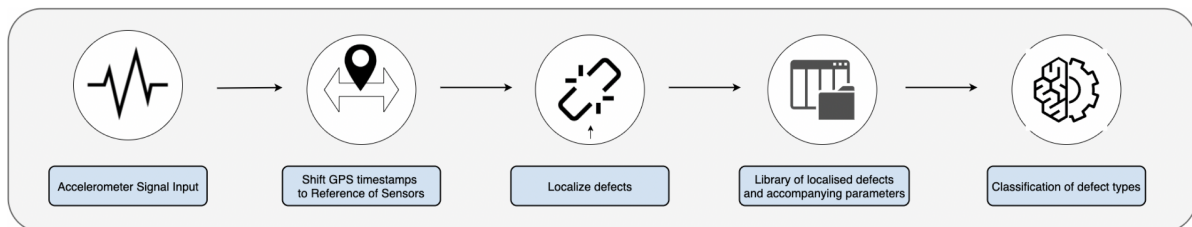


Figure 2.1: Primary pipeline

2.1 Shift of GPS timestamps

The SDV has its GPS sensor installed at a specified location on the vehicle body. However, what we need to achieve is the position (covered distance) at each accelerometer at either sides of the GPS. Since the GPS sensor is sampled at a lower frequency compared to the accelerometers (20kHz vs 24kHz respectively), we first need to get the corresponding positions for each accelerometer sample. This is done by interpolation using the timestamps of the accelerometers and GPS.

Depending on the direction of the vehicle we then subtract/add the offset between the accelerometers and the GPS sensor with regard to the position of these sensors on the vehicle body.

2.2 Peak windows

Retrieving the signal response around the defect location forms a crucial aspect in the overarching pipeline. The goal of this step is to, around each defect, create a "window" containing accelerometer accelerations of a specified time length – wherein Within the highest acceleration recording around is found in the center. As a result, all of these windows would be uniform in the sense that they are all centered according to the highest recording of a defect. It is then assumed that each window forms the signature of each track entity.

insert
drawing
of how
it is cal-
culated?

Since we are assuming that each track entity is identified by a well-formed peak, we first need to find this peak within a reasonable offset from the defect location, after which we center around that within another reasonable offset.

In the code, this is done by defining two parameters: `find_peak_offset = 1` and `window_offset = 0.5`. I.e. given a defect timestamp, we search for the highest acceleration recording that has occurred 1 second after and 1 second before the defect timestamp. Once the peak has been found, we then center it in a 1 second window (0.5 sec on each side).

insert a drawing of how this works?

2.3 Entity library

The peak windows arguably forms the central feature of the defect library. However, from domain knowledge, other features like speed also needs to be considered for our neural network. Apart from the peak windows, we have also extracted a variety of relevant features that might be useful for classification. These include .

list, and how was it implemented

- some can be extracted directly by the original dataframe, some needs some processing.
- talk about only analysing point defects
- show a few entity signals and their features, appendix for more signals?
- refer to the defects presented in introduction

2.4 Classification

We have created a primary **NN** class (short for neural network) along with a **ModelMaker** class. The former does everything from pre-processing the data to evaluating the used model. The latter, as the name suggests, is utilised for creating and using different models, which is useful as we can keep track of how the models have been modified and improved.

2.4.1 NN class

To make a classification, we first need to select the relevant features. Then we simply feed the features into an **NN** object, where the API of the **NN** class can be called for classification. The usage of the **NN** class is demonstrated below in 2.1.

API of NN class	
<code>__init__()</code>	initialises a NN object
<code>prepare_data()</code>	pre-process data, this includes standardisation of data
<code>make_model()</code>	uses ModelMaker class to select a model
<code>fit()</code>	trains the model
<code>classify()</code>	trains the model

Table 2.1: To train a model, these functions needs to be called sequentially

Other useful API functions	
<code>measure_performance()</code>	currently only done on validation data
<code>plot_metrics()</code>	plots the metrics
<code>plot_confusion_matrix()</code>	plots the confusion matrix
<code>load_weights()</code>	
<code>load_model_()</code>	
<code>save_history()</code>	
<code>save_model()</code>	
<code>save_classification_to_csv()</code>	
<code>run_experiment()</code>	evaluates the given model for a number of repetitions

Table 2.2: f

2.4.2 ModelMaker class

See example of this in next chapter.

Explain each layer?

todo

2.5 Visualisation

Finally, after evaluating the results (results can be seen in the next section) from the neural network, we have not achieved any significant results. Arguably, the visualisations of class separability should have been handled first. However, the previous steps took the majority of the time.

todo

Chapter 3

Evaluation

Here we will present the results and discuss the findings herein.

3.1 Models

Table 3.1: Table Title

Layer	Output Shape	Number of params
Synthetic data	2000	9

Dataset formats

<http://alexlenail.me/NN-SVG/AlexNet.html>

3.2 Model evaluation

In this section we evaluate our model with regard to a variety of metrics:

- loss
- accuracy
- true positives
- false positives
- true negatives
- false negatives
- precision
- recall
- auc

Insert explanation of each metric

just do one model at a time and show their metrics

run # \ Metrics	Model1	ClaveVectors	MNIST-bin-digits	MNIST-all-digits
1		61.355	3212.497	2454.585
2	16.568	62.396	3346.047	2782.271
3	14.362	59.282	2908.446	2618.519
4	13.85	62.193	3043.189	2600.233
5	13.755	61.024	3309.422	2470.139
6	12.218	58.531	3192.178	2823.685
7	12.232	60.187	3287.289	2452.566
8	13.346	59.398	3026.486	2810.943
9	11.433	61.892	3127.583	2528.202
10	11.63	60.925	3018.402	2746.729

Table 3.2: Experiment result

Defect Type	2
-------------	---

Table 3.3: Entity distribution, different defect types and class distributions

3.3 Visualisation of class clustering

insert the pca plots

3.4 Discussion

Data amount, could self-engineer data.

should have done visualisation first, if we have clear cluster separation, applying a neural network would be a bit exaggerated. And in that case, we could opt for a simple multi class support vector machine from the `sklearn` library. However, using `tensorflow` was the plan from the get-go as it is more industrially-applicable, so we disregarded simpler methods.

Chapter 4

Conclusion and future work

4.1 Conclusion

Results were quite mediocre, but has a lot of room for improvement. I am sure that given more time I would be able to explore and evaluate the results further.

how good is the foundation to move onwards with further research

4.2 Future work

- Might be interesting to also consider the XZ-axes.
- range defects
- tune the peak finding parameters
- track entity dependent/specific window offsets
- we must not set the findpeakoffset too high
- Questions, what if you want to use multiple features with 1 CNN
- I have participated in ETH Hatchery (ref), where our team build a prototype with a model train. We let the model train drive on the track with self-engineered defects.

4.3 TODO

- get percentage of each class in the validation set
- create an average of the model ie run model for more times
- add speed as a feature
- what does each filter do? what is kernel size?
- very fast speed, overlap between switch and ins, old vs new rail, ax1 arrow 2 arrow 3 arrow 4
- 3D plots?
- change the defect library to use pandas instead?
- visualise what the network is doing using Harry's code
- use speed as a feature also
- be consistent with function naming and variable names: function names with underscore and variable names with camelcase
- Which type of defects are we actually working with, we can see that it does good at the switches and ins joints, but no chance with the defects
- we should instead call it an entity library – make up your mind
- try only with defects and no ins and switches
- separate all the axle channels and train on them
- try to use low pass filter
- get better results
- we dont need non-defects for defect classification, we could just input something else and make sure that it is not a defect
- a specfic defect type vs ins joint vs switch
- we did not consider severity
- which track entities are we actually analysing

Bibliography

- [1] Introduction to 1d convolutional neural networks in keras for time sequences. <https://blog.goodaudience.com/introduction-to-1d-convolutional-neural-networks-in-keras-for-time-sequences-3a7ff801a2cf>. (Accessed on 02/11/2020).
- [2] Tensorflow vs keras: Which one should you choose. <https://analyticsindiamag.com/tensorflow-vs-keras-which-one-should-you-choose/>. (Accessed on 02/10/2020).

Appendix A

Introduction

A.1 Vehicle and accelerometer placements

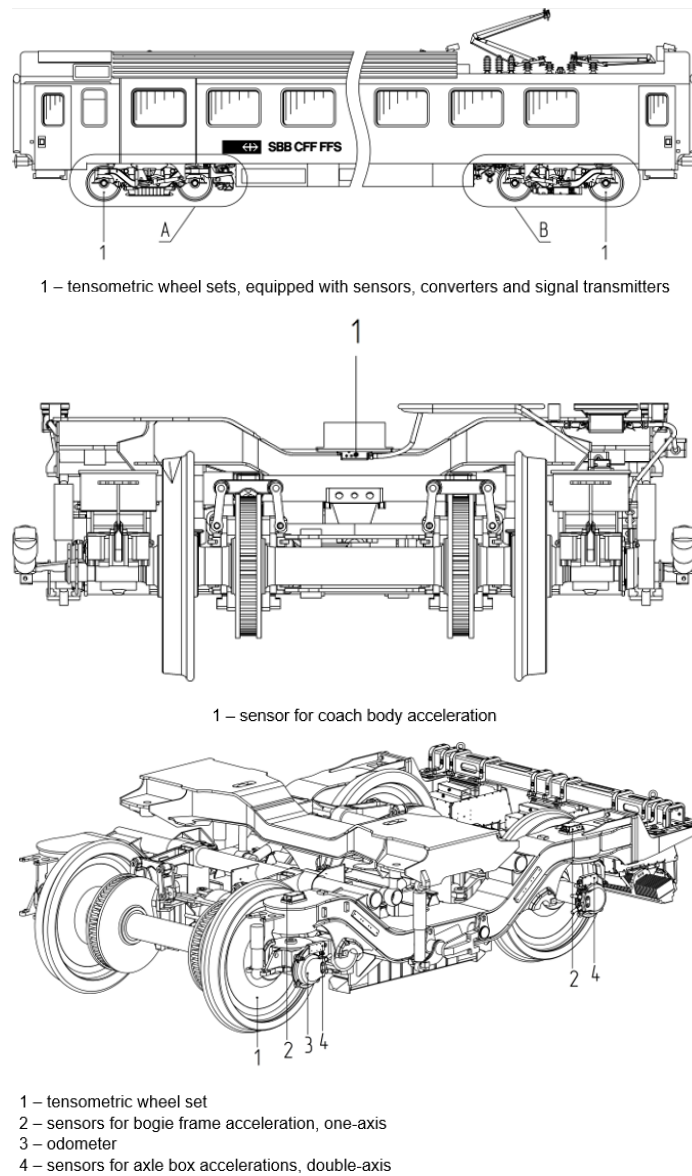


Figure A.1: These figures have been provided by Cyprien's folder of SBB documents. They show the accelerometer placements. For this project we have only considered axle number 4 in the third figure.

A.2 SBB defect report example

A-103213 (Offen ohne Massnahme)		Exportdatum: 26.09.2019 10:50	
Objekt-Infos		Av-Region:	RME-FB-Lyss
Inspektionsobjekt:	AESP 284.2 - WANZ 112.2	Massnahmen-ID:	
Anlagenstrukturelement	Bankett		
Position der Abweichung		FS-spezifische Positionsfelder	
Linie:	400 Löchlüt - Wanzwil - Rothrist West	Gleis:	
km von:	17.2 km bis: 18.4	Weiche:	
Positionierung:	Keine Positionierung	Mast:	
Position:		FL-Sektor:	
Informationen zur Abweichung			
Abweichungstyp (DE):	Ungenügendes Schotterprofil	Entdeckungsart:	Av - Anlagenverantwortlicher
Schweregrad:	6	Erste Feststellung am:	30.04.16 07:09 durch: Christian Schärli
Dringlichkeit:	4	Letzte Feststellung am:	14.10.18 11:53 durch: Christian Schärli
Bemerkung:	Fast die ganze Länge am tiefen Strang	Massnahmenidee:	
FB-spezifische Informationen zur Abweichung		Ausführung durch	
SCDE Relevant:	Nein	U-Nummer:	
Ultraschallfelder		Datum:	
Notverlaschen:	Nein	Unterschrift:	
In Garantie:	Nein		
Qualität:			
Schienenprofil:	SBB VI bzw. EN 60 E1/E2		
Frist:			
Radius:	3197.9		
Prüfungsart:			
Hersteller:			
Jahr:			

Figure A.2



A-103213 25.03.2017

Figure A.3: A typical report for an arbitrary defect usually contains one description page followed by its picture(s)

Appendix B

Implementation

Functions in NN class
prepare data

Appendix C

Results

Latent Dimension	2	RBF Dimension	2
Shape	8×8	RBF grid	4×4
Latent Points	64	RBF centres	16
Dist. Mixtures	Bernoulli	Basis function	Gaussian
Regularisation α	0.001	Widths σ	1.0

Table C.1: The parameters for the latent model and the RBF neural network. Distribution mixtures and basis functions cannot be altered as our implementation is specific for the Bernoulli GTM version