Project report

Vilmos Szirmai

May 2024

1 Introduction

The topic of my project is related to the automotive industry and is done in a fellowship program at Bosch. In automotive manufacturing, it is critically important to detect both design flaws and faulty components. One approach is to listen to the noise: undesirable noise in a car component can be used to infer various manufacturing or design defects. The aim of the project is to develop machine learning models to localize the source of noise from measurements of vibrations in order to locate the errant parts. To get signals for modeling purposes, we excited parts with an automatic hammer and recorded time signals at several points. The noise is measured with a laser vibrometer, resulting in a signal of velocities as a function of time.

In this report, several approaches are presented to the above problem, discussing modeling choices, metrics of error, model performances, and also different scopes of generalizations.

2 Approach

The approach is to find out where the measurement was made. This is because it is equivalent to localizing the excitation. We went around this using two methods:

- A regression approach to estimate distance from the excitation point
- Discretizing by dividing the component into parts

The first method aims to (relatively) precisely determine the location of the measurement point. In this case, the error-measuring metric is the Euclidean distance. The second approach may be somewhat more practical. However, the problem here arises from merely considering how accurately the model is able to predict the label of the range. In this scenario, we might also count as an error when the model misclassifies a point that was located on the boundary of the range.

3 Formal description of the task

Since our task in both approaches is to predict where the measurements have been taken, we need to take a coordinate system. The origin of this coordinate system should be placed at one of the corners of the plate or part, and in addition a positive x- and y-direction should be taken. This is an absolute system, after taking them together with the measurement and excitation points, then retaining them for each measurement. Both the excitation and measurement points are stored with coordinates, plus they have a point index assigned to them by the measurement software.

In case of coordinate estimation of a measurement point, it is given what we are referencing and what will provide the labels for our supervised learning task. But when we discretize, we need some kind of system by which to group the points.
To do this, we have several built-in algorithms in Python, such as K-means or Gaussian Mixture, both of which divide the points into a fixed number of clusters based on the planar coordinates. Now let us move on to possible generalizations.

4 Generalizations

- **Generalization over different forces (measured in Newton)**
  We investigated whether the models can generalize between different forces. The result was that they can if they have to predict from smaller forces to bigger ones. We got much different accuracy scores when we used nearest neighbor interpolation and simple feedforward neural networks (this will be shown in the last paragraph).

- **Generalization over different excitation shapes**
  Models are not too sensitive to this, so this generalization seems to be solved.

- **Generalization over distance prediction from different excitation points**
  A harder instance, models only achieve from 1 cm to 7 cm mean error.

- **Generalization over distance estimation on different automotive parts**
  It looks almost impossible to solve. Models had from 18 cm to 77 cm mean error.

- **Generalization by finding an appropriate embedding**
  It is thought to be a valid approach to use self-supervision to find a proper embedding. It is by exploiting the inner structure of time signals to predict both discrete clusters and distances.

5 Elements of the measurement setup

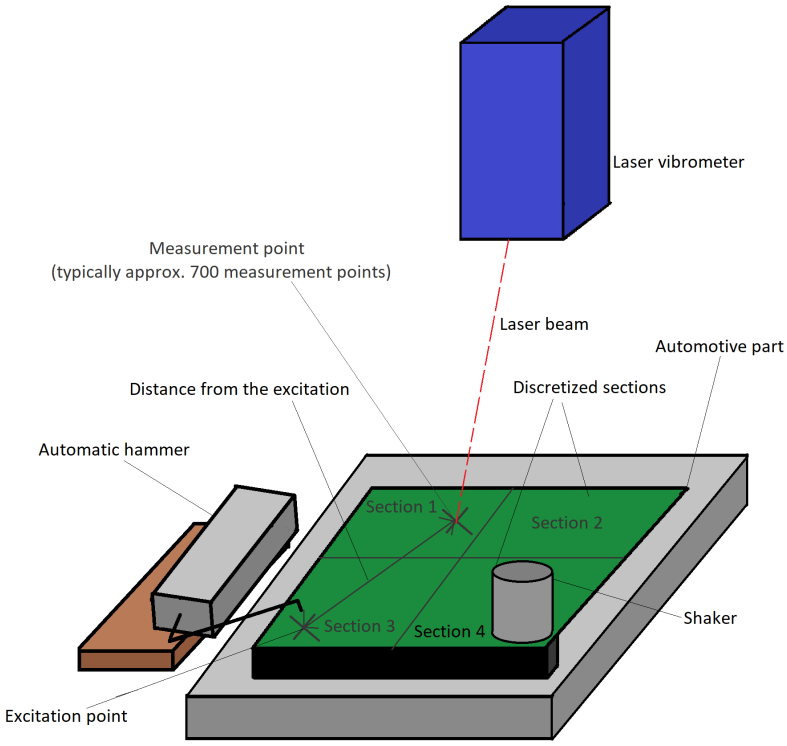


Figure 1: Schematic figure of the measurement setup

Figure 1 depicts the measurement setup. As the hammer strikes the component, a wave is generated. The laser vibrometer calculates from the temporal changes in the laser beam how fast the component vibrates at a given point at each moment in time. These temporal signals are later utilized to solve both classification to predict the label of the part of the measurement point, and regression tasks to estimate distance.

6 Categorization

There are four categorization aspects for the data.

- **Excitation shape**: There are various excitation shapes, including single, double, triple and multiple, among others. Figures illustrating single and double hits, along with explanations of the phenomena, can be found in the appendix.
- **Force applied**
- **Direction of the excitation**: This is a very simple one, because it has only two versions: +Z and -Z depending on the direction in which the hammer strikes in the coordinate system.

- **Location of the excitation**: This aspect serves the purpose of logically associating the estimated distances with the points of excitation.

7 The prediction

7.1 Distance estimate by interpolation

The current main estimation method, interpolation, employs a nearest neighbor approach. This method assumes that closely located measurement points will yield similar time signals. It utilizes Euclidean distances between points in a matrix to assign values to new points. Initially, there was a notable improvement in accuracy, with average error dropping from 5 cm to 1 cm. Though some challenges have arisen, this progress indicates a promising new direction.

7.2 Triangulation

This method utilizes three excitation points, each estimating the distance to a given measurement point. The predicted measurement point is determined by the common intersection of the circles drawn from these excitation points. While theoretically sound, numerical errors and their accumulation can lead to deviations. To address this, a straightforward approach was adopted: if circles should intersect but do not due to distance estimate errors, the midpoint between the intersections of the segments connecting their centers with the circles will be the predicted point. This method ensures robustness by providing estimates even in cases where direct intersection is not feasible, initially discarded to avoid ambiguity.

7.3 Working with triggered signals

At this point, it should also be mentioned that we abandoned the idea of working with the whole time series, as we realized that the resting phase at the beginning contains a lot of information about the distance from the excitation point, but this is due to the fact that the measurements were always made in a predefined time window. In reality, the excitation will hit the sensor unexpectedly, so we have switched to working with triggered signals, which are generated by cutting off the portion of the signal at the beginning that does not reach a given level in absolute value (usually set to 0.01).

7.4 Discretization

This approach involves decomposing the component into clusters based on x-y coordinates. Future adaptations aim to discretize potential error sources into clusters. The program code resembles previous distance estimation methods but operates on cluster labels instead. A strong correlation between the number of clusters (varied between 3 and 8) and model accuracy was observed.

8 Models and their performance

8.1 Triangulation

Method	Min error	Max error	Mean error	Std	Number of estimations	Under 0.5 cm
Interpolation	0.0	0.38	0.003	0.03	174	172
Pol. regression	$4.58 \cdot 10^{-17}$	0.0016	0.0002	0.0004	542	542

Table 1: Performance of triangulation

The minimum error, maximum error, mean error, and standard deviation (std) are all measured in meters. It is important to note that the second set of measurements is significantly superior to the first. This improvement stems from its application to automotive parts, which are smaller in scale compared to the metal sheet. As a result, all the data exist within a smaller range, contributing to a more precise assessment.

8.2 Cluster prediction

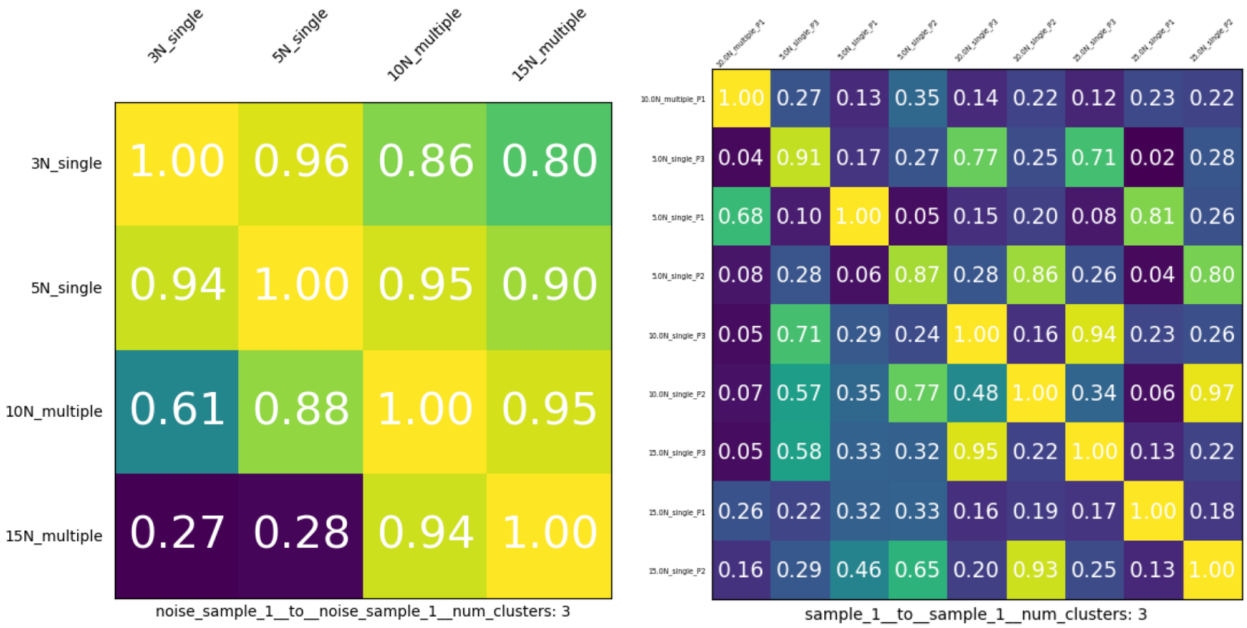
As it was mentioned before, a correlation was observed between the number of clusters and the accuracy score. However, it is evident that this model struggles to generalize across distinct excitation points and various automotive parts. This limitation arises from the diverse signal shapes generated by different excitation points and the considerably varied discretizations present in different automotive components. Figures of performances can be found in the appendix.

8.3 Summary and further concepts

Overall, we observe that interpolation distance estimation works relatively well, particularly when providing estimates for identical components and even more so when the time signals are captured from the same excitation point. Consequently, triangulation also yields relatively good results. Polynomial regression offers slightly better estimates, but its drawback lies in the slow fitting to data and considering too many variables. To circumvent this, in the future, we will prefer using Lasso, Forward Selection or Elastic Net.

Interpolation may also be suitable for discretization label estimation; however, this cannot be generalized as it depends on the nature of the component. Furthermore, neural networks significantly outperform interpolation in terms of accuracy scores, so we will lean towards this direction in the future.

A Figures of cluster prediction accuracy scores

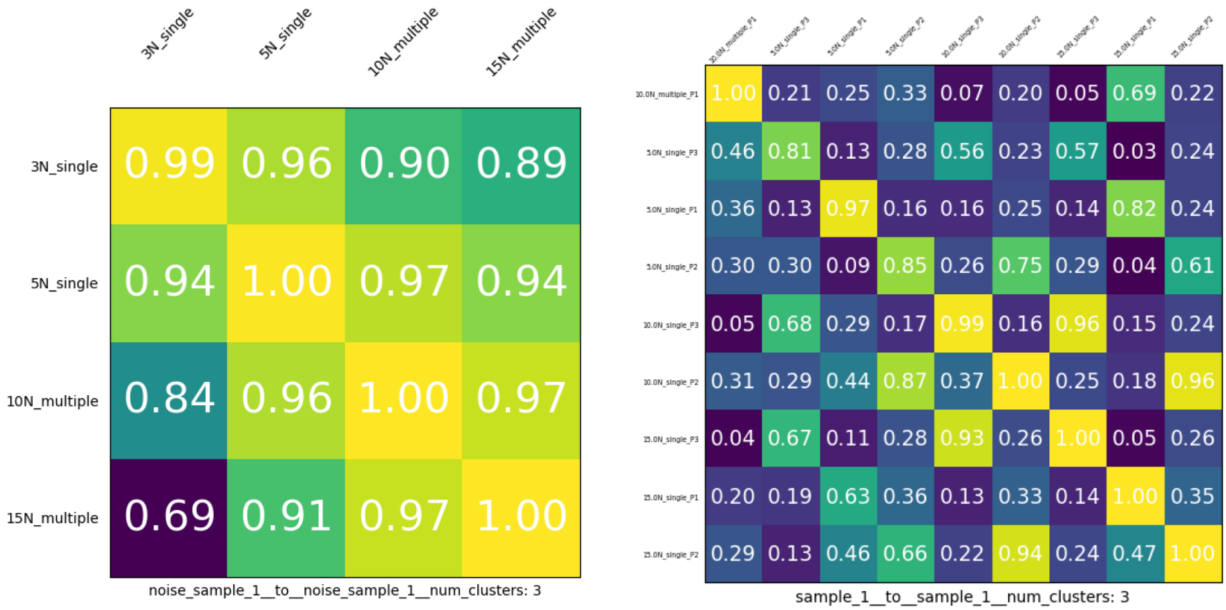


(a) Accuracy scores with one excitation point

(b) Accuracy scores with different excitation points

Figure 2: Accuracy matrices with different generalizations using interpolation

In Figure 2 rows of the matrices correspond to training sets i.e. which set the nearest neighbor method used as a reference, and the columns correspond to test sets i.e. to which signals the method had to predict.
On the next page we can also see a similar pair of figures corresponding to accuracy scores achieved by a feedforward neural network. It had only two hidden layers with sizes 32 and 64 respectively.



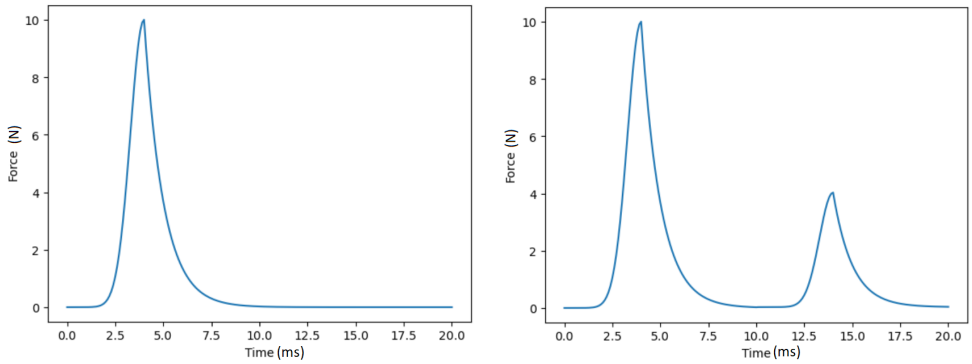
(a) Neural network accuracy scores

(b) Neural network accuracy scores, different excitation points

Figure 3: Accuracy matrices with different generalizations using neural network

B Excitation shapes

Since there are various excitation shapes, which is one of the categorization aspects, below we can see what they look like.



(a) Single hit

(b) Double hit

Figure 4: Schematic figures of different excitation shapes

In Figure 4, on the left-hand side, we can see the single hit, in which case, the hammer excites the component only once. The resting phase is when the wave has not yet reached the measurement point, followed by an elevation, and then the force diminishes. On the right-hand side, the double hit is depicted. In this case, as the hammer excites the component, it rebounds, hitting the hammer again, thus receiving excitation twice, hence the two elevation phases in the applied force.

C Further modeling techniques

C.1 Logistic regression

The first was the attempt to predict the indices of points using logistic regression. To do this, we simply took the time signals, and the corresponding label was the point index. The problem with this was that we did not have enough data to create a distinct training and test set. So, they were the same, thus the model could trivially predict unseen labels. We tried to solve this by repeating the measurements, but then the signal shapes were extremely similar, so it was trivial to predict the label again. Furthermore, this model was extremely sensitive to the time shift of the signal shapes. When we shifted the signals in time, accuracy score dropped to 0.02. Thus, this approach was quickly discarded.

C.2 Coordinate prediction by linear regression

Next came a model that attempted to predict the coordinates straight away, and this was linear regression. This did not seem so bad at first, but it was off by an average of 5 cm in absolute deviation for the x-coordinates and 1 cm on average for the y-coordinates, making it almost impossible to predict the measurement point correctly.

C.3 Distance estimate by linear regression

Then came the approach that is still one of the main directions of the project, that is, estimating the distance from the excitation point. Here again, we initially tried linear regression, which was also off by an average of 5 cm.

C.4 Predicting the excitation point

This method is based on trying to estimate the angle of the line connecting the measurement and the excitation point with the x-axis, and then to obtain the coordinates of the excitation point by writing the equations of two lines and determining their intersection. Yes, but while in theory this method works perfectly, in practice it was not as easy to estimate the angle as we thought, so the model did not predict the excitation point very well.