Evaluation of Head Toss Based on Sensor Data Collected from a Car on a Four-Poster Rig

A study in how to quantify, measure and replicate a subjective feeling in car ride in an objective manner using a four-poster rig

Master's thesis

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Cover: A Volvo placed on the four-poster rig at Volvo Hällered.

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Abstract

Comfort development in vehicles has been a factor for a long time. Recent research examines urban driving at low speed which causes jerking motion of the car that can be unpleasant for the passengers' necks and heads. These undesirable comfort disruptions are known as head toss. The report aims to find an objective way to measure and compare the occurrence and harshness of the subjective feeling of head toss between different cars and chassis setups. Furthermore, the aim is to measure the head toss on a 4-poster rig, commonly known as a shake rig. This was done through collection of chassis and head acceleration data and the rating of each head toss on a scale of 1-9. The relationship between head toss occurrence and chassis accelerations would show to be complex and non-linear. A design of models and tools that were able to accurately predict the occurrences and rating of head toss was therefore executed. The models that performed best was neural networks and ensemble learning models. Using these models, a program was developed which could predict the occurrence of head toss and its harshness accurately. The final result of this project thus became an experiment set up to execute a rig program in order to collect data, and a program that evaluated the collected data to display an objective evaluation of head toss.

Keywords: Head toss, subjective measurement, car comfort, objective testing, four-poster rig, non-linear model, ensemble learning, neural network, system identification, sensor data, time series.

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Introduction

Comfort has been a factor in the development of vehicles for a long time. One of the first signs of active measures taken to address comfort, was introduced in a form of suspensions on a cart during the roman times (Mastinu & Plöchl, 2014). The development of the car has seen a recent change of focus from ergonomics to comfort solutions. The development of comfort has been through adapting to its environment i.e. the roads and condition active at the time. Therefore, car comfort may have been different, in times where roads were often in bad condition, compared to modern day comfort. The roads are improving and more robust in terms of quality of the driving environment which pushes car comfort to adapt to those circumstances. This is one reason why older cars may display better performance regarding comfort, in benchmark tests for comfort (Mastinu, Pennati, Gobbi, Previati, & Ballo, 2017). Head toss can be categorized as a human mechanical impact which is the reaction of a body segment due to a measurable set of parameter such as accelerations, forces, and deflections (Human Biomechanics and Simulations Standards Committee, 2011).

This project realizes an objective measurement of the subjectively perceived head toss. By the usage of car testing on the proving grounds of Volvo Hällered, methods were established in order to use measurement systems to collect data and develop machine learning models to analyze the data.

1.1 Background

In daily driving, a lot of time is spent at low speed; on pedestrian streets, low speed zones, over speed bumps or cobblestone roads. This type of driving often causes a jerking motion of the car, which can be unpleasant to the driver's neck and head known as head toss. Car manufacturers try to find a good balance between this and other attributes. At Volvo cars, this is currently done through actual driving and measurements on certain tracks.

1.2 Aim

The aim of this thesis work is to quantify a metric with which the head toss can be determined and measured as well as creating a model of input signals for a four poster rig in order to objectively evaluate the metric for any chassis. This would give Volvo the ability to directly compare different chassis and chassis setups with regards to head toss, in an objective manner.

1.3 Limitations and Delimitations

This project is a Master's thesis which means that certain criteria are applied from the institution written for. The time frame for this project is set to 20 weeks in order to entail a total of 30 ECTs worth of work.

Concerning that this project is in first hand made for Volvo cars, a certain level of confidentiality regarding performance results and sensible information is dictated by the type of employment contract dictated by Volvo cars. Delimitations with respect to the project specification, decided by Volvo cars, will be to only examine the head toss of a front seat occupant.

The project is conducted during the spring of 2021 which is strongly influenced by the highly active restrictions and recommendations caused by the Covid-19 pandemic. This leads to limitations due to social distancing and preventive measures which affects the nature of resources for especially the subjective data gathering since a larger extent of people can not be involved.

A literature study is conducted and limited to the databases available and accessed by the Chalmers University of Technology institution as well as the data base of Volvo cars.

1.4 Problem Formulation

Is it possible to create a set of input signals, valid for all vehicles, for Volvo cars' four poster rig in such a way that the degree to which a certain chassis or chassis setup affects head toss can be measured in an objective manner? Subsequently allowing for objective ranking of vehicles with regards to head toss.

2

Theory

The following chapter contains the theory used and collected before and during the execution of the project.

2.1 Head Toss Definition

Head toss is defined as a jerking motion of the head that is out of sync with the torso. This involuntary motion usually occurs as a response to a sudden roll of the vehicle, a roll which is usually induced from an uneven road surface or a pothole. The level to which the subject is affected by the roll motion is partly determined by how prepared the subject is, and if they have the time to tense their muscles or not. Secondly, the frequency of the roll plays a large role. Experiments have shown that a roll of the chassis with a frequency below 2 Hz does not lead to a head toss motion, as the head and torso move in sync below that frequency. However, the same experiments have shown that frequencies between 2-8 Hz are the range in which the head and torso go out of sync, causing constructive interference between the head and torso, thus increasing the head movement. This causes the head to violently get thrown to the opposite side from the torso, this is defined as a head toss. At frequencies above 8 Hz, the phase lag of the head absorbs the input from the torso by destructive interference. (Gysen, Janssen, Paulides, & Lomonova, 2010)

2.2 Subjective Testing

It has for a long time been a difficult task to produce reliable results from subjective testing. Human errors imprint the quality of a study in bias-like ways. The measurements are the instruments to either confirm or deny the hypothesis. In the selection of which measurement to use, the factors deciding it is always the human mind dictating the hypothesis and selecting measures to test it. In data collection, the executioner of the experiment may induce errors by being an observer and influence the subject to desired outcomes. The experimenter may often unintentionally communicate the wanted outcome of the test to the subject in question. This results in an unwanted error generated from the subject as it responds to the expectations at the same time as performing the task to be tested. (Muckler & Seven, 1992)

For example, the experimenter explains to the subject to drive a car normally over the road bumps on a certain track and evaluate the discomfort created in the head movements from the bumps. The subject focuses not only on driving as it would normally do in other circumstances, but anticipates the feeling of doing so which can result in abnormal rigidity in the neck to either suppress the head movement or exaggerate it to affect the subjective feeling.

The analysis of data may be influenced subjectively in the visualization and nature of the analytical methods used. In statistical methods, subjective and arbitrary thresholds are usually set e.g. significance levels (0.05,0.01). The visualization of data is decided by the analyst to be as subjectively descriptive as possible to him or her. The descriptive view is thus accepted by a biased source.(Muckler & Seven, 1992)

Subjective measurements in vehicle ride and handling can be evaluated by a scale established by SAE Recommended Practice for specified vehicles, maneuvers, road and driving conditions, proving grounds, and public grounds. The scale proposes a possibility for an evaluator to numerically assign the ride and handling performance. The scale is divided into the event types: disturbance and control. These event types contain adjectives describing levels of desirability from nominal to maximum best. The numerical scale stretches from 1 to 10 with each number corresponding to an adjective in each event type e.g. a disturbance level of annoying and control of poor, would result in a rating score of 4. Equally, a disturbance of imperceptible and control of excellent, would result in a rating score of 10. This is visualized in table 2.1. (Vehicle Dynamics Standards Committee, 2016)

Additionally, the perception of comfort may not always be pointing to an improving direction. Subjective perception of comfort or risk does not necessarily have a strong relationship with actual risk (Nathanail, 2008). The actual safety of the vehicle and its perceived comfort is certainly something that should be a well thought out compromise.

Table 2.1: Subjective rating scale

Event		
	Disturbance	Control
10	Imperceptible	Excellent
9	Trace	
8	A little	Good
7	Some	
6	Moderate	Fair
5	Borderline	
4	Annoying	Poor
3	Strong	
2	Severe	Very poor
1	Not acceptable	

2.3 Objective Testing

The essence of using measurable data in a study is to objectively be able to analyze and draw conclusions. By measuring accelerations from accelerometers, series of data points can be mapped out during the desired time which can describe the experimenter's task in an objective way.

Several methods are often used in the evaluation of vehicle vibration comfort, which analyzes the frequency weighted root mean square (FWRMSA) and vibration dose value (VDV) of vibration accelerations to map to different comfort stages(Park & Subramaniyam, 2013). These methods have been evaluated and questioned and found inconsistent regarding their results. These inconsistencies lie in the nature of how different vibration spectra and vibration magnitudes lead to different discomfort levels (Kaneko, Hagiwara, & Maeda, 2005)(Zhou & Griffin, 2017). The objectification of mapping vibration signals to the subjective perception of comfort is therefore difficult and nonlinear which suggests use of deep learning as a tool for connecting the subjective and objective data(Du, Sun, Zheng, Feng, & Li, 2021).

To ensure objective testing, the need of the experiment to have good repeatability is important (Uberti, Gadola, Chindamo, Romano, & Galli, 2015). The transfer of testing a vehicle in the real world to a controlled indoor environment such as in a test rig may induce the desired repeatability. It is additionally mentioned to be desirable in cases of comfort testing to use a test rig (Jayasuriya & Sangpradit, 2014). A four-poster rig can induce wheel excitations to replicate the driving of a vehicle on a road. The time of exposure to vibration is critical for a human's perception of comfort (Griffin & Erdreich, 1991). This would mean that an experiment on a four-poster containing a subject evaluating the comfort by being exposed to vibration, would have to evaluate the time that the subject is exposed to vibrations.

2.4 Vehicle Dynamics

The international standard for defining axis and movements in a vehicle chassis followed during the completion of the project as well as throughout this report is the standard brought forward by the international standard organization. The definition of such states that the x-axis runs longitudinally along the length of the car, with the positive direction pointing toward the front of the car. The y-axis is normal to the x-axis running laterally from side to side, with the left being the positive side. Lastly, the z-axis runs vertically, with its positive direction defined as up. Furthermore, the rotating motion around each axis is defined as rotation around the x-axis is roll, rotation around the y-axis is pitch, and rotation around the z-axis is yaw. All of the above-mentioned definitions are illustrated in figure 2.1. (International Standards Organization [ISO], 2013)

The motion of the vehicle that induces the head toss is lateral roll, meaning roll around the x-axis or that the cars sway from side to side (Gysen et al., 2010). Head toss could also be induced by causing lateral forces on the human body between 2-8 Hz e.g. from violently turning side to side, however, such scenarios rarely exist in real-world driving scenarios. The roll of a chassis is a byproduct of the wanted road handling characteristics of modern vehicles. As roll is an unwanted characteristic when driving in corners at higher velocities, automotive manufactures add anti-roll bars, illustrated in figure 2.2, as well as stiffer suspension. The stiffer suspension simply makes the suspension compress less under a load at which a softer suspension would compress more, causing the vehicle to stay more level. The anti-roll bars work by connecting the left and right suspension to each other and is used to limit the amount of roll that occurs. It does this by transferring the torque from one side to the other so that if the left suspension compresses, a moment travels through the anti-roll bar and compresses the right suspension as well. This keeps that vehicle level in roll, it can however still pitch, as the front and rear suspension are independent. (Bharane, Tanpure, Patil, & Kerkal, 2014)

Head toss does however most often occur at lower speeds. The measures put into the vehicle to keep it from rolling when cornering are the same ones limiting its ability to absorb bumps and uneven road surfaces at lower speeds (Zulkarnain, Imaduddin, Zamzuri, & Mazlan, 2012). For example, when a vehicle with soft suspension and

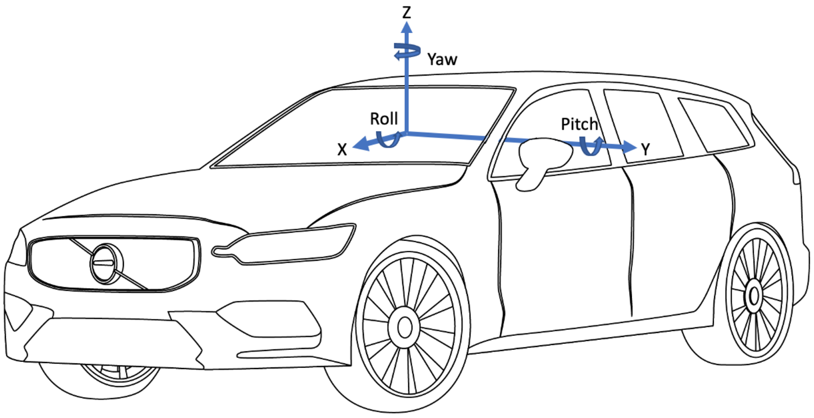

Figure 2.1: Vehicle coordinate system definition.

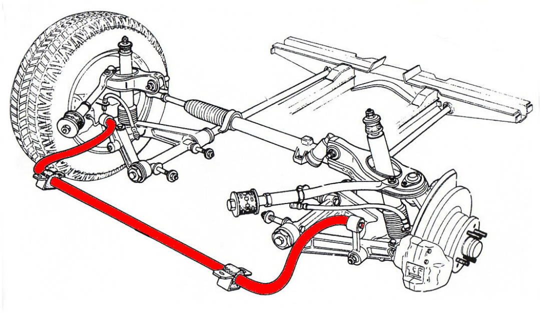

Figure 2.2: Simple anti-roll bar, the bar connects the two sides, causing the wheels to move more in sync. (Mason, 2016)

no anti-roll bars drives over a speed bump at 10 *kph* with its left side, the soft suspension absorbs the travel with minimal translation to the chassis. However, if a vehicle with a stiffer suspension passes over the same bump, the stiffer suspension will compress less, meaning that a portion of the impulse will travel through the chassis, at the same time the anti-roll bar will compress the right side. As the left suspension could not absorb the entire bump, that side of the chassis has been lifted while the right side has dipped due to the effects of the anti-roll bar. The effect of this is that the roll induced is even bigger than what it would have been without an anti-roll bar.

2.5 Test Rig

The four-poster rig, commonly referred to as a shake rig, used throughout the project is located a Volvo's Hällered proving ground. The rig consists of four hydraulic actuators located one under each wheel that are able to subject a car to any road condition in a controllable and repeatable manner. However, the rig is not able to replicate any lateral forces nor is it able to make changes to the front wheel angle as the actuators are only able to move vertically.

2.6 System Identification

System identification allows for the estimation of the output of a dynamic system. Using collected input and output data, estimations can be made for the differential equation that describes the system. This can be done by using a variety of different methods, such as differential equations, transfer function modelling, or more recently, neural networks. By using collected input and output data, a model for the output can be made using the input data. The model can then be used to predict the output in a scenario where the output data is unknown. (Ljung, 1999)

For the duration of the project, the method identified to provide the most useful output was the transfer function modelling, as it is a good model for identifying frequencies. System identification using transfer function models are based of the transfer function model representation, which is defined as: (Keesman, 2011)

$$Y(s) = U(s)G(s) \tag{2.1}$$

Which describes the relationship between the Laplace transformed input $Y(s)$ and the transformed output $U(s)$ by using the transfer function $G(s)$ (Keesman, 2011). If the dynamic relationship between input and output is unknown, an estimate transfer function can be obtained by Laplace transformation of an estimation input response system. The estimation for the input response can in turn be obtained if collected input and output data are used as reference. (Keesman, 2011)

2.7 Neural Networks

In signal processing, neural networks have been used frequently due to their wide application form to solve many different varieties of problems (Hu & Hwang, 2002). The techniques available by neural networks thrive in pattern recognition, data analysis and control. The characteristics of this tool is the high processing speed and the ability to learn from itself with a given set of examples. Neural networks are created from programmed instructions originally from Turing, von Neuman and Babbage. These instructions are inspired by the human brain in its constellation of biological structure. The structure of such consists of a starting point and an ending point with numbers of paths or decisions (neurons) that a signal (or data) moves through. A conversion of start to end is thus made that converts a set of input variables into a set of output variables. The transformation from input into output is governed by the parameters on the way from the start to the end. The parameters are determined by the training of the network and functions similarly to the mapping of polynomial functions. The network that transforms a set of inputs into a set of outputs in a non-linear way is regarded as a feedforward neural network. (Bishop, 1994)

2.7.1 The Neuron

The neuron of an artificial neural network can by the McCulloh-Pitts model be seen as a mathematical process that sums the weighted input and transforms it with a non-linear activation function to generate an output. This is illustrated by Bishop (1994) in figure 2.3.

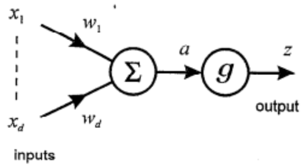

Figure 2.3: A McCulloh-Pitts model of a neuron in an artificial neural network (Bishop, 1994)

2.7.2 Levenberg-Marquardt Backpropagation

In computer science, backpropagation is an algorithm that is using parallel training to enhance the efficiency of the network. Backpropagation is considered a supervised learning technique and minimizes the error of the network by gradient descent (Alsmadi, Omar, & Noah, 2009). There has been much research to optimize the backpropagation method since it first arrived. This research can be divided into two categories. The first category involves rescaling variables, learning rate, and using momentum. The second category focuses on the standard numerical optimization techniques (Hagan & Menhaj, 1994).

The Levenberg-Marquardt (LM) algorithm can be used to train feedforward neural networks using nonlinear least-squares incorporated to the backpropagation algorithm (Hagan & Menhaj, 1994). The LM algorithm is designed to minimize the error function and can be expressed by equation 2.2.

$$E = 1/2 \sum k(e_k)^2 = 1/2||e||^2 \tag{2.2}$$

Where e_k is the error in pattern number k, and e is the vector with the errors (Alsmadi et al., 2009). The combination of backpropagation and LM algorithm is described by Hagan Menhaj (1994) and can be summarized by 5 steps as they make an LM modification to a backpropagation algorithm seen in the following list:

- Feed input to a network and calculate the sum of square errors of all inputs.
- Compute the Jacobian matrix.
- Solve the LM modified equation to obtain $\Delta \underline{x}$.
- Recompute and modify parameters to result in a new sum of squares of errors.
- Conversion of the algorithm if the gradient norm or sum of square is less than a predetermined threshold.

The conclusion of the algorithm was that it shows great efficiency in the training of networks up to a few hundred weights.

2.8 Classification Trees

Classification trees are a type of decision tree that classifies data into specific labels. Depending on statements that the tree has (branches), the data continues to the next statement by either being true (left) to the statement or false (right) until it reaches a point where there are no longer has any options to move (leaf). The essence of this technique can easily map out an algorithm's way of functioning by viewing the branches. It is the algorithm that creates the statements that the data goes through, and aims to minimize the weighted sum of the class impurities of each branch. (Buntine, 1992)

To visualize a simple classification tree, imagine having data for different countries involving numerical and categorical data. The data are continent, average humidity, and area. In figure 2.4 a modelled classification tree tests sets of the data to predict which country the sets belong to.

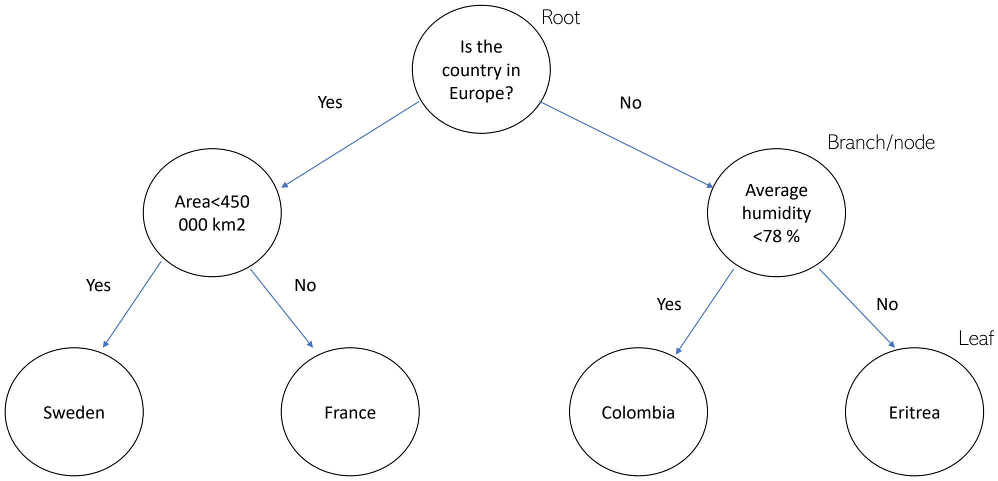

Figure 2.4: Classification tree of labelling countries

2.9 Ensemble Learners

The ensemble method in machine learning can be viewed as the usage and combination of different algorithms and models to produce a collaborated model. The different models are treated as different actors in a committee that acts as decision-makers. The conclusion that the committee makes will be the predicted outcome of the ensemble learner. The committee functions by having each committee member (model) give appropriately combined predictions which would result in a better average result than any committee member on their own. The decisions of each committee member can be combined by methods using averaging, probabilistic methods, and voting. The essence of using different models is that they may perform better and worse on different inputs. Therefore, the ensemble can use certain models for certain data that have a nature in which the models performed well on previously and thereby distributing sectioned data to the different models to achieve an overall higher performance. (Brown, 2010)

In statistical machine learning, algorithms such as decision trees find solutions to a learning problem by stating a hypothesis (statement or branch) that converts the input data to the desired output. Instead of using a single hypothesis, ensemble learning algorithms construct a set of hypotheses and choose a set of weights to create a classifier $H(x)$ (equation 2.3) that utilizes the numerous hypothesis to predict labels of new data points.

$$H(x) = w_1 h_1(x) + ... + w_k h_k(x) \tag{2.3}$$

Where w is the set of weights that corresponds to the set of hypothesis h. (Dietterich et al., 2002)

2.10 Boosting

In the training of a model, boosting is regarded as a repeating training process that feeds the model selected data to enhance its performance. The boosting algorithm inputs different sets of data or weighting of data to detect the model's "weak point" where it performs badly. The boosting algorithm combine the weak points into a rule that is more accurate than the model. The selection of what data to feed into the model is made by putting weight into data that the model earlier misclassified which results in the model having to train on its most difficult training examples. (Schapire, 2003)

3

Method

The methods of this thesis consists of combining subjective and objective testing in order to analyze the natures and reasons of a head toss.

3.1 Physical Driving

Within the scope of the task that this project represents, a large amount of physical driving of cars was necessary. The driving was conducted at Volvo's Hällered proving ground in Sweden. Hällered is a state of the art test track, containing 15 different tracks. All designed to test various aspects of a car (Volvo Cars, 2021). For the duration of this project, various different tracks were used. For confidentiality reasons they will not be named but described by their characteristics and usability. Furthermore, the data collected on the tracks were collected at 100 Hz as it was considered high enough in order to identify the relevant frequencies that causes head toss, as defined in section 2.1.

3.1.1 Initial Tests

In order to get an idea of what scenarios induce a head toss in a vehicle, a day was spent driving at Hällered proving ground on different sections of tracks, at different velocities, and in different vehicles. This was done in collaboration with and under the tutoring of Bo Krüger and Tobias Ersson. With their extensive knowledge in vehicle dynamics and subjective car comfort, they helped to establish how a head toss feels and how to differentiate it from other uncomfortable movements. During these tests, identification of tracks which were suitable for head toss testing regarding number of occurrences and harshness, was also conducted.

The identified sections contained various different elements considered likely to cause head toss in real-world driving. For example, patched asphalt, common in city streets and urban areas have a tendency to cause head toss as they often excite all four wheels of the car at different amplitudes and frequencies, and cause the car to roll and sway along the frequencies identified in section 2.1. Furthermore, a section of bumps was driven over with only the left side of the vehicle, as well as a dip or crevice in a section of rural road that only affected the right wheel. All identified track sections and the velocities that caused some degree of head toss on each section can be seen in table 3.1.

3.1.2 Head Toss Track Data Collection

In order to define an objective metric to relate to head toss, it was decided to collect chassis data from track driving. By collecting data and subsequently analysing it, a better idea of what causes the head tossing motion would be developed, and therefore a more robust method of data collection could be developed. The data collection was done using a car that will henceforth be called "car A" which is an SUV type of vehicle. The car had accelerometers placed on both B-pillars, measuring accelerations on the y-axis, since two accelerometers in the y-direction along with the distance between them can be used to determine roll. These sensors can be seen in figure 3.1a. A triaxial accelerometer was placed on the driver seat's headrest (figure 3.1b), as well as a single y-axis accelerometer that was placed on the drivers head.

(a) Y-axis accelerometer fitted vertically on both B-pillars, pictured on the left B-pillar.

(b) Triaxial accelerometers measuring accelerations on driver seat headrest.

Figure 3.1: Accelerometers attached for the initial data collection.

Table 3.1: The types of track identified to cause head toss, along with the speeds identified to capture the frequencies required.

	Track	Velocity
1	Bump	12 kph
2	Bump	15 kph
3	Bump	20 kph
4	Patched	12 kph
5	Patched	20 kph
6	Patched	30 kph
7	Dip	70 kph
8	Dip	80 kph

Moreover, an Inertial measuring unit (IMU) pictured in figure 3.2, was placed in the centre of the car to measure a considerable amount of attributes such as body roll, acceleration and rotation in all axis, velocity etc. A software was used for the data collection of the IMU as well as the CAN-bus of the car which measures data such as steering angle, steering wheel torque etc.

Once all sensors were placed in the car and the data collection software had been set up, the car was driven along the earlier identified sections of track at different velocities. Each track section and each velocity were driven three times, in order to make sure that the data was properly collected. Every time a head toss occurred, the passenger pressed a button in the software to mark the exact time and location in the data that a head toss had occurred. In addition, every time a head toss occurred, it was given a value between 1-9 based on the scale presented in section 2.2. This was done with the intention of being able to later determine which sensor or movement of the chassis had the greatest influence in the harshness of the identified head toss. The collected data was later analysed with the intention of finding a correlation between chassis movement and head toss occurrence.

Figure 3.2: Inertial measuring unit (IMU), placed over the transmission tunnel in the car, the measuring unit itself can be seen in red between the front seats.

3.1.3 Track Surface Data Collection

To enable the testing on the four-poster rig, input signals to the rig had to be defined. To create the input signals, data was collected from accelerometers on the wheel hubs. The accelerometers collected acceleration data along the z-axis from the centre of each wheel hub. This would allow for the rig to be tuned to mimic the exact accelerations each wheel experienced on the track. The accelerometers were attached to the wheel hubs using freely rotating, and rotationally symmetric bearings specifically built for attaching sensors to the wheel hubs. To keep the bearings from rotating with the wheel, they were fixed in rotation using a simple damper attached to the car body with suction cups. The set-up for attaching the accelerometers to the wheels is pictured in figure 3.3.

With the sensors attached to the car, it was driven on different sections of tracks, which can be seen in table 3.2. A recording of the sensors was made for each selected track and velocity that were supposed to be represented by the four-poster rig. The specific sections of track and the respective velocities were chosen based on the results from section 3.1.2. The resulting data was later used for tuning the rig to match the track surface, in section 3.2.1.

Figure 3.3: Single axis accelerometer attached to the left front wheel using a freely rotating set-up.

Table 3.2: The track sections recorded using accelerometers fitted to the wheel hubs.

	Track	Velocity
1	Bump	12 kph
2	Bump	15 kph
3	Bump	20 kph
4	Patched	12 kph
5	Patched	20 kph
6	Patched	30 kph

3.2 Rig Test

In order to develop an experiment that evaluates the subjective perception of a head toss, the physical driving testing was converted to an indoor controlled environment for enhanced repeatability using a four-poster rig. In the following sections, unless otherwise mentioned, the test vehicle was car A.

3.2.1 Rig Program Creation

From the measured accelerations of the sensors attached to the wheel hubs driven on the physical track, the data was transformed in Matlab to ASCII format consisting of five features. The five features were the following listed metrics:

- **Time**
  Measured in seconds from the GPS of the IMU.
- **Front left wheel acceleration**
  Measured in mm/s^2 from the accelerometer on the front left wheel hub.
- **Front right wheel acceleration**
  Measured in mm/s^2 from the accelerometer on the front right wheel hub.
- **Rear left wheel acceleration**
  Measured in mm/s^2 from the accelerometer on the rear left wheel hub.
- **Rear right wheel acceleration**
  Measured in mm/s^2 from the accelerometer on the rear right wheel hub.

The data from the wheel hubs were cleaned and cut to be able to compile into a file corresponding to the different selected tracks in table 3.2. The compiled file thereby contained a continuous replication of the different roads pasted together into a single run with different velocities automatically changing for each section. The length of the program was additionally made to not surpass an exaggerated amount of vibrations to ensure a good experiment (section 2.3).

The compiled file of transformed data was fed into the rig program that therefrom tuned the excitations of the pillars to reciprocate the accelerations of each wheel. This was done by attaching sensors to the wheels (that were now stationary), seen in figure 3.4, to feed data to the rig program. The program executed a spectrum sweep of amplitudes and frequencies to learn the input-output relation. With input being the pillar displacement and output the sensor accelerations, a mapping of these was made.

[redacted]

Figure 3.4: Tuning the rig to replicate physical driving by feeding sensor data from the wheels.

3.2.2 Experiment Creation

With a completed test program of the rig, the set up for subjects to evaluate the perception of a head toss feeling began. The sensors for the experiment were chosen to be placed similarly to the physical driving set-up of the car. The placement of sensors was the following:

- **Right B-pillar**
  Triaxial accelerometer
- **Left B-pillar**
  Triaxial accelerometer
- **Driver's seat rail**
  One directional accelerometer measuring z-acceleration
- **Driver's head by attaching a sensor to a cap**
  Triaxial accelerometer

The experiment set-up made it possible to record the data during an execution. The experiment consisted of a subject in the driver's seat wearing the sensor-attached cap, a person supporting the driver's tasks in the passenger seat, and a person running the rig program from the control room. The subject in the driver's seat was solicited to be seated normally, looking forward, and signal the passenger when a head toss occurred by calling out the rating (table 2.1) of its consequence. The person in the passenger seat noted the rating and the time of the occurrence. In this particular set-up, there was no possibility for a trigger function to work as a time marker for a head toss. Therefore, the person in the passenger marked the occurrence in time with a stopwatch. During the experiment, data were recorded by the rig program from all the sensors at 512 Hz.

3.2.3 Validation Data Collection

To ensure a good data analysis validation, more data from different cars would make sure that a comparison and model over-fitting validation. It was therefore clear that more vehicles needed to be tested by the same experiment as car A. Two cars, significantly different from car A and each other, were also tested. The first vehicle, car B, is a high powered performance wagon with a specially tuned and stiff chassis. Meaning that the suspension is stiff, has less travel, and the anti-roll bar being stiffer than in a normal family vehicle. The second car, car C, is a normal family wagon with a suspension set-up similar to car A but with a lower car body, which in theory should limit the roll. This vehicle also has anti-roll bars but with a lower torsional stiffness than car B.

Both of the above-mentioned vehicles were tested in the same way as car A, described in section 3.2.2. The head toss and head acceleration was collected, along with the data from the same positional placed sensors on the chassis as car A. The resulting data would be used for validation testing of the data analysis but not for any model development or training.

3.3 Data Analysis

With data collected, the process of mapping the data could begin. It was the sensors attached to the car that functioned as input signals to the general mapping. As the relationship between head toss and chassis movement would show to be more complex than anticipated, a need for models that could predict head toss arose. These models would have to be able to predict head toss despite the non-linearity and complexity of the relationship. Three different models for prediction were identified, neural networks, classification tree, and ensemble learning. Due to the different nature of each section of the rig program, the models were trained with data that had similar attributes which lead to four different models of sections per algorithm used. The data was partitioned into:

- **Bumps section**
  The data was very stable until two big amplitude spikes that correspond to the car running over a bump. Repeated three times for different velocities.
- **Patched section 12 kph**
  The data was fairly stable with minor amplitudes and low frequencies.
- **Patched section 20 kph**
  The data was fairly noisy with large amplitudes and moderate frequencies.
- **Patched section 30 kph**
  The data was very noisy with moderate amplitudes and large frequencies.

The problem formulation of what the models were supposed to solve was decided to be a form of prediction of what the subjects of the tests had experienced when accelerations from the sensors was generated from the car's chassis movement. The usage of the collected data can therefore be described as in figure 3.5.

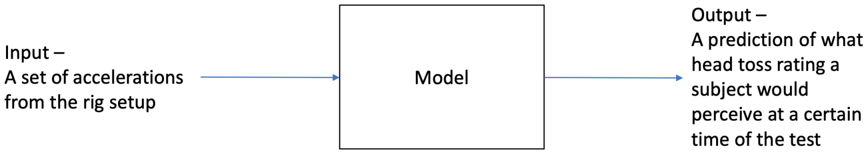

Figure 3.5: Description of method for data analysis

In the pre-processing of data, the subjective rating measured from the experiment was transformed into vectors that matched the length of the sensor data. The vectors consisted of the number ten when there had been no signal projected from the subject and the integer communicated from the subject at a position in the vector corresponding to the time the stopwatch had marked the occasion. The data from the stopwatch was transformed into time steps of $1/512th$ of a second to match the recording of the data at 512 Hz. The indices of head toss occurrences could therefore be set in the created vector. The vector was additionally modified to set the 512 precedent values of the head toss index to the rating score. This was done in order to represent the head toss more accurate as it is the swing of the head that can be estimated to last one second. This vector would come to be the target vector of labels to train the models. The vector can be described by equation 3.1.

$$\begin{aligned} &V = (x_1, ..., x_k), \\ &(x_{i_1} - 512, ..., x_{i_1}, ..., x_{i_j} - 512, ..., x_{i_j}) = R, \\ &I = (i_1, ..., i_j), \\ &R = (r_1, .., r_j) \end{aligned} \tag{3.1}$$

Where V (e.g. seen in figure 3.6) is the target vector containing the rating values x, I the index vector containing the indices of a test's head toss occurrence i, and R the vector of rating scores containing the corresponding ratings r to the occurrences i.

Moreover, in the data analysis it was considered unsustainable to involve the future head movement as inputs to models. The potential of the models is to test a large number of cars in an easy manner which necessitate minimal set-up and people involvement. Additionally, the subjection of vibrations to the human body was in section 2.3 considered harmful during longer exposure. These two reasons constitute the decision of developing models without using head movement as input.

3.3.1 System Identification Toolbox

It was considered preferential to develop a dynamic model of the relation between chassis accelerations and head accelerations as the mathematical relationship between the two is unknown. Since the head acceleration was found to be connected to the head toss but would be unsustainable to test in large numbers of tests, the modelling of it from this project's experiment would be of use. It was therefore decided to use the System identification toolbox in Matlab. The toolbox allows for a model of a dynamic system to be estimated using a variety of different techniques. This is done by supplying the toolbox with both the input and output data with which the toolbox will develop a model based on the technique chosen. The model will thereafter, as explained in section 2.6, be able to predict an output based on data in the same format as the original input data.

The toolbox was utilized to find a mathematical relationship between accelerations of the chassis and the drivers head. As stated in section 2.1, frequency is important when identifying head toss. As such, transfer function modelling was the chosen method due to its ability to match frequencies, as stated in section 2.6.

Due to head toss being a lateral head motion, it was decided to not use the collected x-axis acceleration data with the benefit of keeping the mathematical model simpler and save on computational time. In turn, the head accelerations were predicted along the z-axis and y-axis. The sensors used for input and output can be seen in table 3.3

Table 3.3: Input and output used in the system identification between chassis and head acceleration.

Input	Output
Driver seat rail z	Predicted head z
Left B-pillar z	Predicted head y
Left B-pillar y	
Right B-pillar z	
Right B-pillar y	

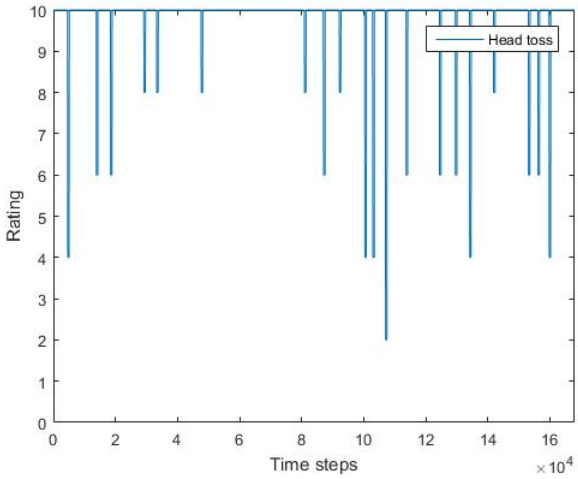

Figure 3.6: Plot of vector V showing the occurrence and rating of each head toss recorded on a time step axis.

3.3.2 Neural Network

To find a correlation between the movement of the head and the head toss occurrence, a neural network was trained to predict the occurrence and rating of head tosses based on the predicted head acceleration from the system identification, as seen in table 3.4. This was done using Matlab function *train*, which allows for a shallow neural network to be trained. The network can be optimized based on which algorithm chosen as well as how many neurons the network uses. In order to find the optimal network, a process of iteration was used where the number of neurons as well as the algorithm and training data, was modified. This was done until a network with a satisfactory output was found. It was established that a Levenberg-Marquaudt algorithm with 10 neurons should be used for the neural network. Once a final neural network was trained, the Matlab function *sim* could be used in conjunction with new input data in order to predict the head toss of untrained data.

Table 3.4: Input and output used in the training of the neural network

Input	Output
Predicted head z	Head toss
Predicted head y	

3.3.3 Classification Tree

A classification tree method was used in the Matlab's machine learning toolbox. The function used was *fitctree* which uses an input of features and labels to create a multi-class binary classification decision tree. The function has attributes that can be manipulated in order to grow the tree. The input to the tree was 4 data channels consisting of the z-accelerations and y-accelerations of the left and right B-pillar. The target labels were the earlier created rating vectors V. The manipulation of minimum leaf size was decided by measuring the K-fold loss of different leaf sizes. When the model was created, the *predict* command on Matlab could perform tests for new data sets. The classification tree was trained on data from one of the first runs.

3.3.4 Ensemble Learning

An ensemble learning method was used to train sensor data to the labelled rating vector. Contrary to the classification tree method, the ensemble method *fitensemble* was used to form a regression model by boosting regression trees. The input was the z-accelerations and y-accelerations from the left and right B-pillar and the output was V. The *fitensemble* function takes "Method" as an input variable, which was specified to "LSBoost" and 100 cycles, which is a least-squares gradient boosting strategy that grows shallow decision trees. The model was trained with the same data as the classification tree.

3.3.5 Validation

With the different models designed, they were tested with the data collected for validation (section 3.2.3) in order to ensure their validity. The use of *predict* and *sim* generated predicted rating vectors and was compared to the test data's appurtenant labels V. The comparison consisted of counting the number of predicted head tosses and their average rating for each section by calculating the error in comparison to the vector V. This was done with three randomly selected experiment recordings from car A, B, and C.

In the post-process of the predicted output from the models, a section of which can be seen in figure 3.7, the data were processed through a model re-maker to resemble V. This was done in order to keep the same form of visualization throughout the project. This inverted *skyline* appearance, illustrated in figure 3.8, was made by programming the prediction vector by partition in lengths of 1000 data points which corresponds to 2 seconds. All values in each section were set to the minimum value found inside the interval. If the minimum value was not below a certain threshold, the whole section is set to the base value of 10. The threshold for each section was tuned to fit the specific model used for that section.

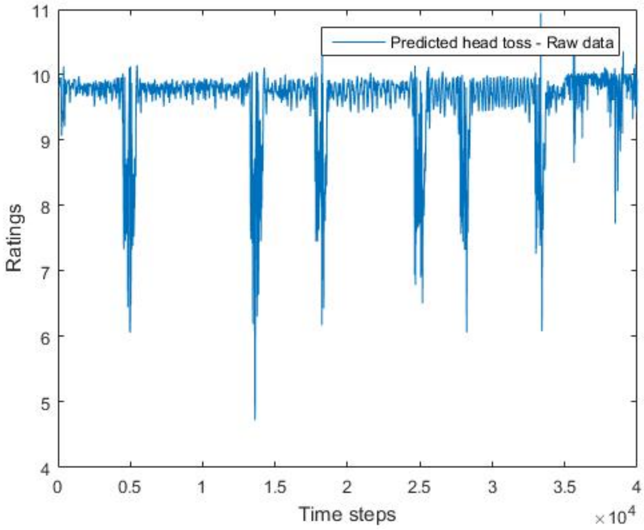

Figure 3.7: Plot showing raw data output from a model.

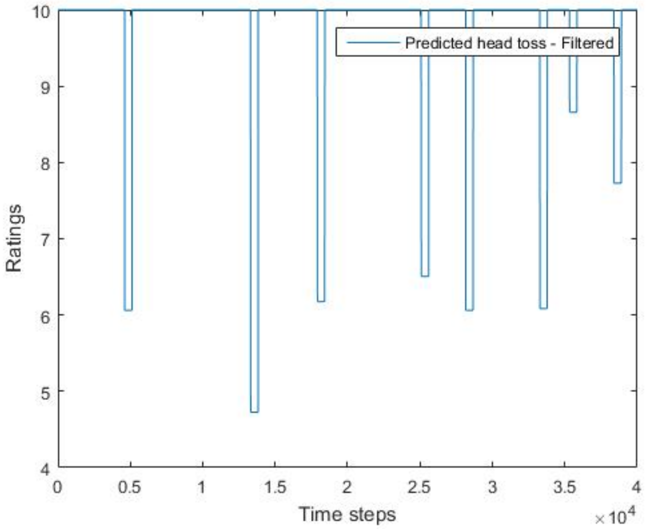

Figure 3.8: *Skyline* plot created by filtering the raw data in sections of 1000 values.

3.4 Head Toss Program Design

In order to utilize the developed models in a straightforward way, a Matlab program was designed. The intention of the program was that any car could be placed on the four-poster rig with the same types and placement of sensors as the experiment to be run through the program, explained in section 3.2.1. The ASCII file that the rig outputs could then be loaded into the Matlab program, after which the program outputs the predicted number of, and estimated rating of head toss. The program logic and functions were designed using the results from section 3.3.5.

4

Results

The results of the project consist of the outcome of the methods used to measure the subjective feeling of a head toss in an objective way. What was found using the methods described in the previous chapter and are presented in the following chapter.

4.1 Physical driving

The first data-collection of head toss yielded a large quantity of data. It was seen that there is a connection between head toss and head acceleration. It was however not always a relation that a large head acceleration would result in a head toss, as can be seen in the figure 4.1. In this figure, the occurrence of head toss is visualized with a *skyline* plot (section 3.3.5).
In figure 4.2, it is clear that the head acceleration at $t = 65000$ has caused a head toss, but the seemingly similar head accelerations at $t = 73000$ $t = 80000$ did not cause a head toss. Taking a closer look at the chassis data, in this case the left B-pillar, also reveals that the chassis movement was similar in the above case, as can be seen in figure 4.3. There seems to be a complex distinction in the data between a head toss and no head toss.

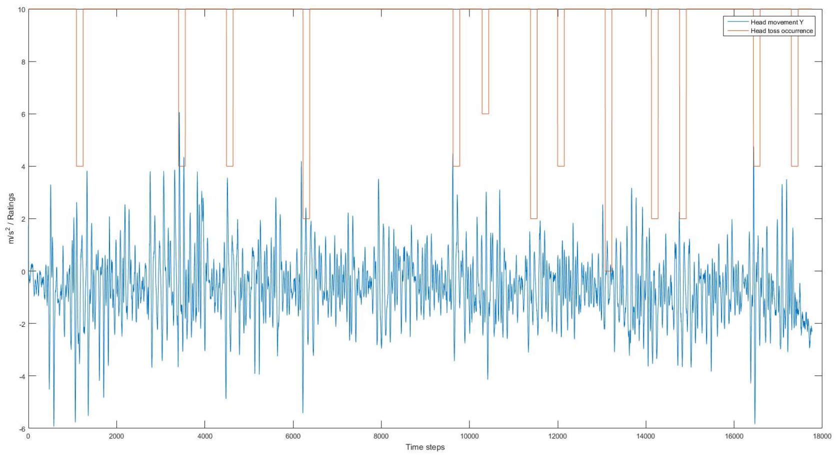

Figure 4.1: *Skyline* plot of data collected during the first tests, here showing head acceleration vs. head toss occurrence.

As a consequence of the head toss data collection, it was decided that more data was needed, specifically the head and the B-pillars' z-acceleration. This lead to the decision to collect further data on the rig instead of on the track, as the rig allows for more triaxial accelerometers to be used.

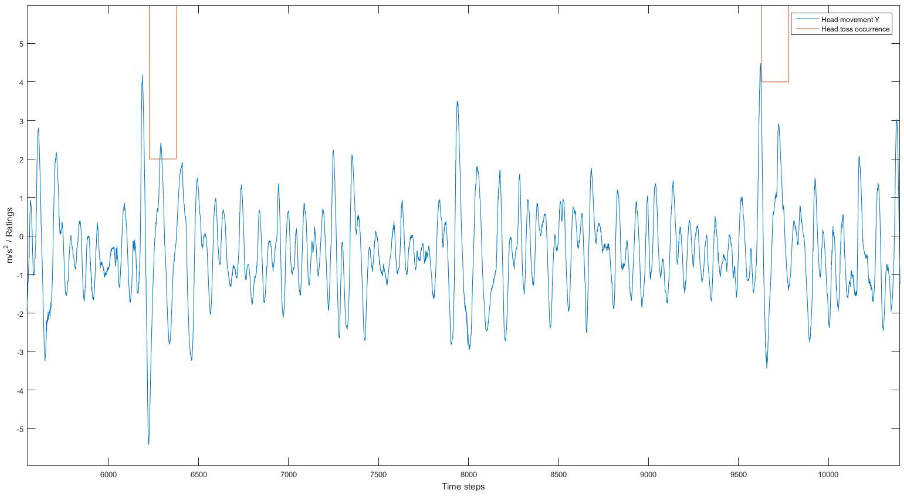

Figure 4.2: *Skyline* plot of data collected during the first tests of head acceleration along the y-axis vs. head toss occurrence.

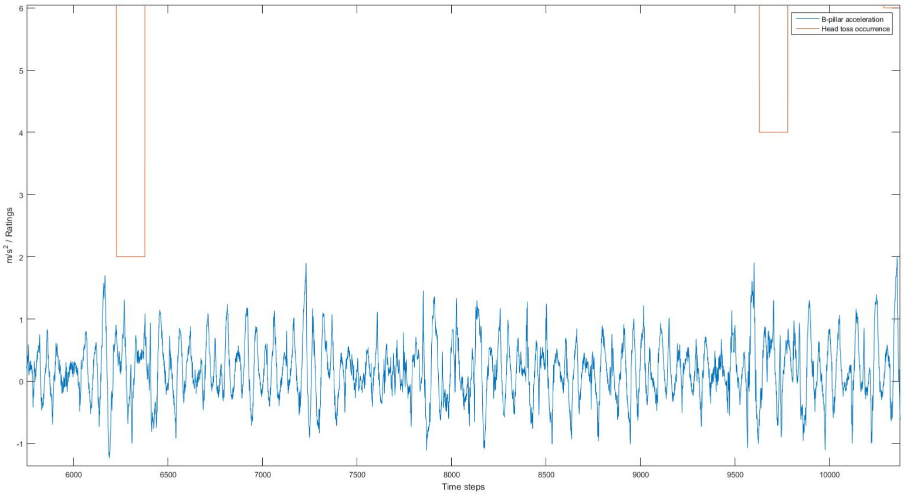

Figure 4.3: *Skyline* plot of data collected during the first tests, showing head acceleration vs. head toss occurrence.

4.2 Rig tests

The rig program was a run of 328 seconds that mimicked the feeling on driving on the corresponding track sections. This became a proficient tool for the objective and subjective testing of a head toss because of its controlled environment and repeatability (section 2.3). The experiment created on the rig was found to be flexible and highly manageable. The set-up of sensors was a fast process that could begin as fast as the car had been mounted to the rig. The car was easily exchangeable for another model since the pillars were adjustable from the control room, making it able for vehicles with different wheelbases to be involved in the experiment. The results of the rig tests was ASCII files containing 167936 data points from each sensor used in the set-up for experiments.

4.3 Data analysis

The analysis of the data produced from the rig tests was found to be useful in the mapping of the objective measures to the subjective perception. The results were insightful to how the accelerations from the chassis would indicate a certain rating. A realization from the model results was that the scale can be seen as continuous rather than binary categorical, which means that a prediction from a model can be between two numbers e.g. 4.5.

4.3.1 System Identification & Neural Network

The neural network was not able to accurately predict head toss occurrence based on chassis data. Therefore, as explained in section 3.3.1, the system identification toolbox in Matlab was used to predict head acceleration based on the chassis accelerations. The system identification tool that showed to have the best fit with regards to both amplitude and frequency was transfer function modeling. A section of the fitted prediction can be seen in contrast to the real head acceleration in figure 4.4. The result from the system identification was a predicted acceleration matrix for a theoretical driver's head y-accelerations and z-accelerations which was used as the input for the neural network. The *skyline* plot of the neural network model predicting head toss can be seen in figure 4.5.

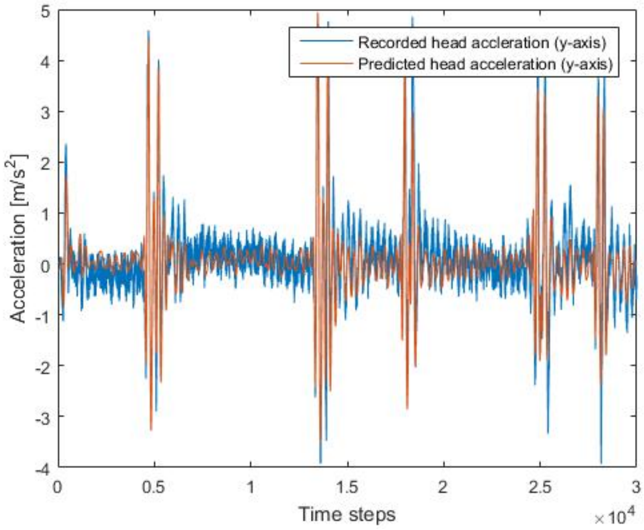

Figure 4.4: Recorded head accelerations vs. head acceleration predicted by a transfer function model.

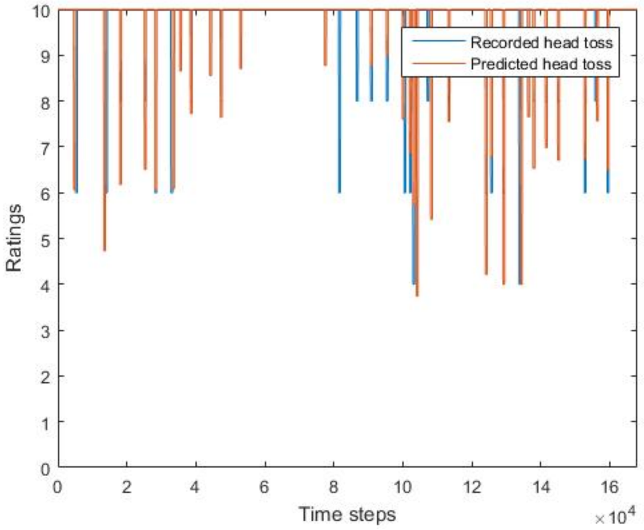

Figure 4.5: Recorded head toss occurrence vs. head toss occurrence predicted by transfer function input to a neural network.

4.3.2 Classification Tree

The classification tree model was a model that differentiated from the other methods in particular because of its binary classification in opposition to the other regression models. The computation of the minimum leaf size can be explained in figure 4.6 where the K-fold loss error of the bump section has been plotted as a function of minimum leaf size. The lowest error at 46 leaf size was chosen for this section.

The grown tree can be viewed in a graph mode in appendix A.1, where the branches state the variables: x1 the y-acceleration in the left B-Pillar, x2 the z-acceleration in the left B-pillar, x3 the y-acceleration in the right B-pillar, and x4 the z-acceleration in the right B-pillar. The results from testing the model on another set of data from another car were the predicted rating of the data set. The prediction can be seen in figure 4.7 where the predicted head toss occurrences and their rating are visualized in blue, and the real interpreted rating perceived by the subjects (V), in red. The data that the model used for prediction is visualized in its normalized form around the x-axis in the plot.

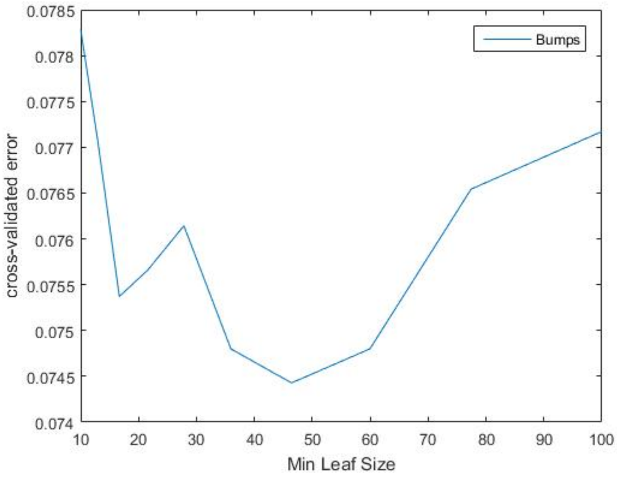

Figure 4.6: K-fold loss of minimum leaf size selection in a classification tree for the bump section

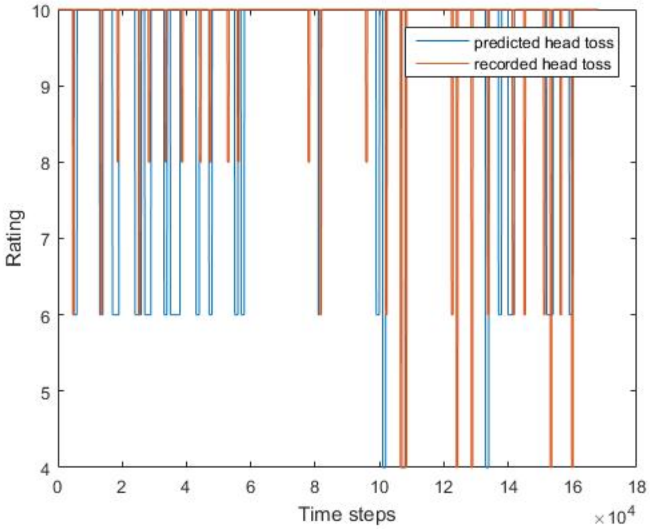

Figure 4.7: Prediction of head toss using a classification tree

4.3.3 Ensemble Learning

The ensemble tree model design resulted in a robust model that performs well on most sections of the program except the last part which is the patched section in the highest velocity. The ensemble, which is a regression model, predicts continuous values and can by the same appearance as the classification tree prediction be studied in figure 4.8.

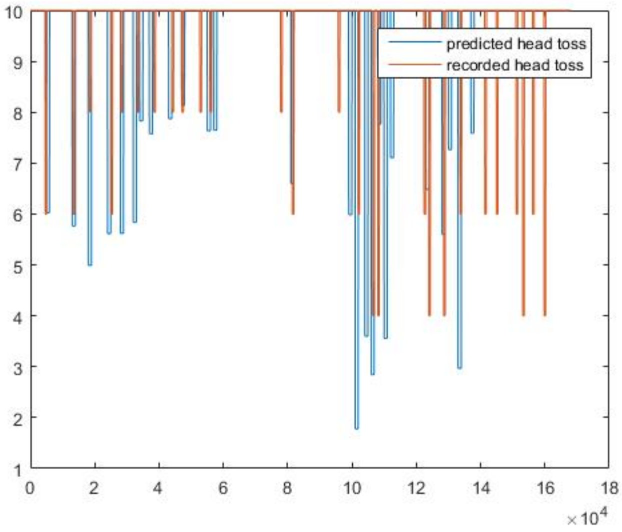

Figure 4.8: Prediction of head toss using an ensemble learner

4.3.4 Validation

The tables with the resulting data from the performance comparison can be seen in table 4.1 as well as in appendix A.2. The tables contain the real numbers at the top, which is the numbers corresponding to the average rating and occurrence of head tosses recorded during that section of the rig data collection. Furthermore, each model's predicted number of occurrences and the average rating predicted for that section is calculated. Every model's average rating error is displayed along with how many head toss occurrences the model mispredicted.

Tables 4.1, A.1, and A.2 were compiled into table 4.2 containing every model's average performance over each track section. The table contains the total average number of errors for every model over each section, along with the corresponding average error in rating. The table visualize the models' relative performance and aid the decision of which to use for each section.

The models were evaluated based on the product of their rating and occurrence errors, choosing the model with the lowest product as the best performing model. The chosen model for each section is highlighted in green, with the second-placed model in yellow, and last in red. The final choice of models ended up as follows:

- Bumps - Ensemble
- Patched 12 *kph* - Ensemble
- Patched 20 *kph* - Neural Network
- Patched 30 *kph* - Neural Network

Table 4.1: The performance of all prediction models for each section and their relative error to the real data for head toss in car B.

Car B						
		Bumps	Patched 12	Patched 20	Patched 30	Total
Real	#	6	8	7	6	27
	Rating	7	7.75	4.8	5.4	24.95
NN	#	6	10	9	9	34
	Rating	5.2	7.8	5.2	6.2	24.4
	# error	0	2	2	3	7
	Rating error	1.8	0.05	0.4	0.8	3.05
C Tree	#	9	9	5	4	27
	Rating	6	6	4.8	6	22.8
	# error	3	1	2	2	8
	Rating error	1	1.75	0	0.6	3.35
Ensemble	#	6	14	16	0	36
	Rating	5.6	7.8	5.6	10	29
	# error	0	6	9	6	21
	Rating error	1.4	0.05	0.8	4.6	6.85

Table 4.2: The average performance for every model over each section, color coded based on relative performance.

Track		NN	C Tree	Ensemble
Bumps	Avg # errors	0.000	2.333	0.000
	Avg rating error	1.267	1.067	1.067
Patched 12	Avg # errors	1.333	1.667	2.667
	Avg rating error	0.416	1.650	0.150
Patched 20	Avg # errors	3.000	4.000	6.667
	Avg rating error	0.733	0.733	0.733
Patched 30	Avg # errors	2.000	2.333	6.000
	Avg rating error	0.533	0.667	3.733

4.4 Head Toss Program

A general final model consisting of an ensemble learning model for the first two sections and a neural network model for the last two sections could be retrieved from the validation of the data analysis. These model choices derive from their performance, as explained in section 4.3.4. To make the developed models more user friendly, they were compiled in to a Matlab script, as explained in section 3.4.

During the execution of the Matlab script, a dialogue box appears asking the user to select an input file. This file has to be of the same format as the previously used ASCII files from the rig, i.e. a file generated from the same experiment as the project's (section 3.2.2). The program starts off by cleaning the file, turning it into a matrix and clearing away all the header rows before starting its calculations. The data is then divided in four different sections: bumps, patched 12 kph, patched 20 kph, and patched 30 kph. Each section is thereafter put through their respective model depending on the results from section 4.3.4. Once the head toss occurrence for each section is predicted, the results from each model are compiled into one complete vector. The vector is then modified to a *skyline* plot using the same process as explained in section 3.3.5. With the calculations for each section done by their respective models, and the output formed to the *skyline* format, the program outputs the result in three different plots. The first output, presented in figure 4.9, is an overview of the predicted occurrence and each head toss predicted rating over the entire run, with markings of where each section starts, as well as a small explanatory figure of the rating scale along the y-axis. This gives the user a quick overview of how the car or chassis setup performed in each section.

For further analysis, the user is also presented with two graphs. The first one shows the average rating for the head tosses predicted in each section in figure 4.10. If the user wishes to see the rating of each head toss in a certain section this is available in figure 4.9. The second graph, see figure 4.11, uses the same format as in figure 4.10, but shows the user the number of head tosses predicted in each section as opposed to their rating.

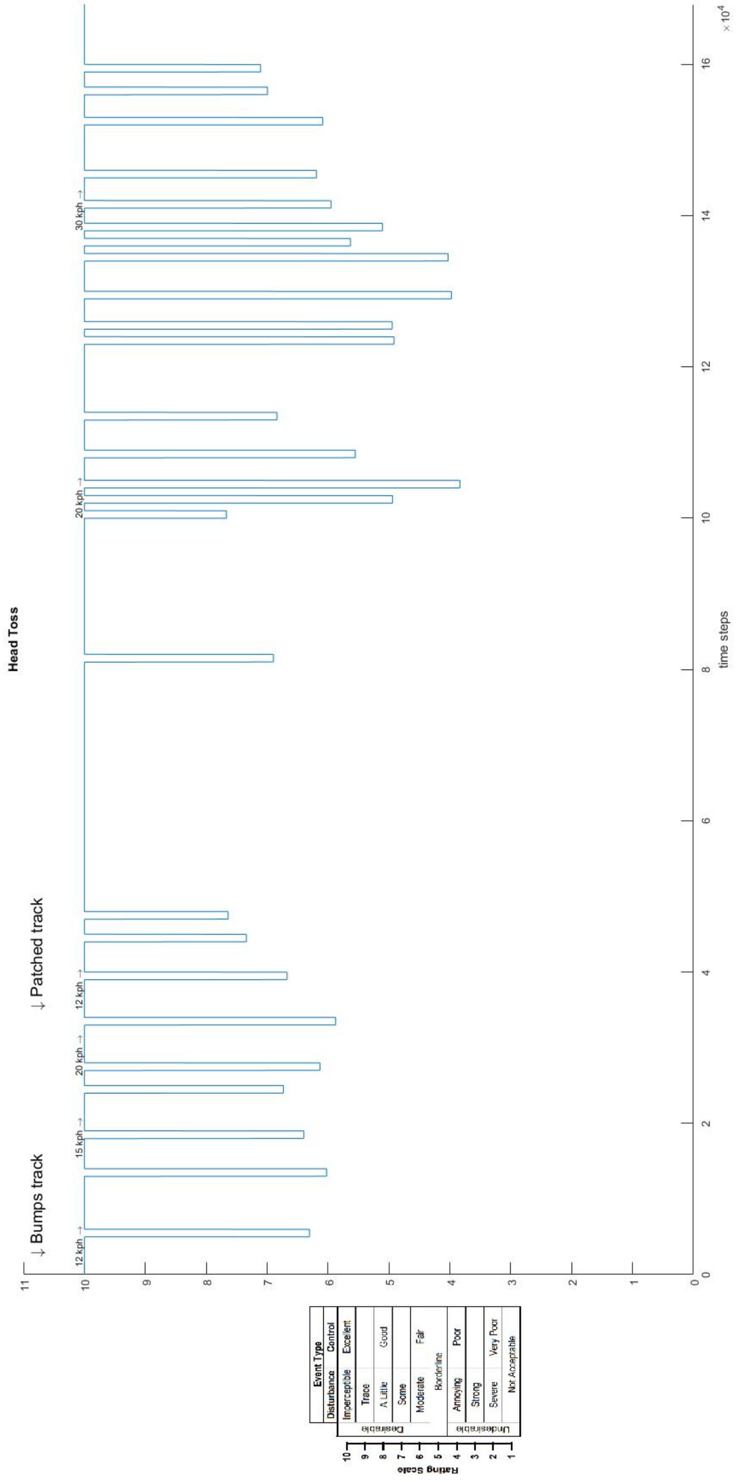

Figure 4.9: Example *Skyline* plot of head toss for a car run in the rig program predicted by a model

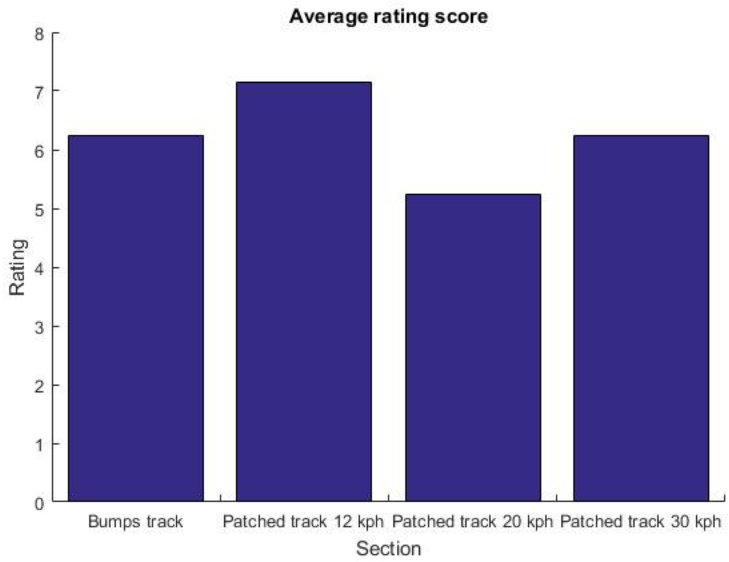

Figure 4.10: Example of average rating of head toss for a car run in the rig program predicted by a model.

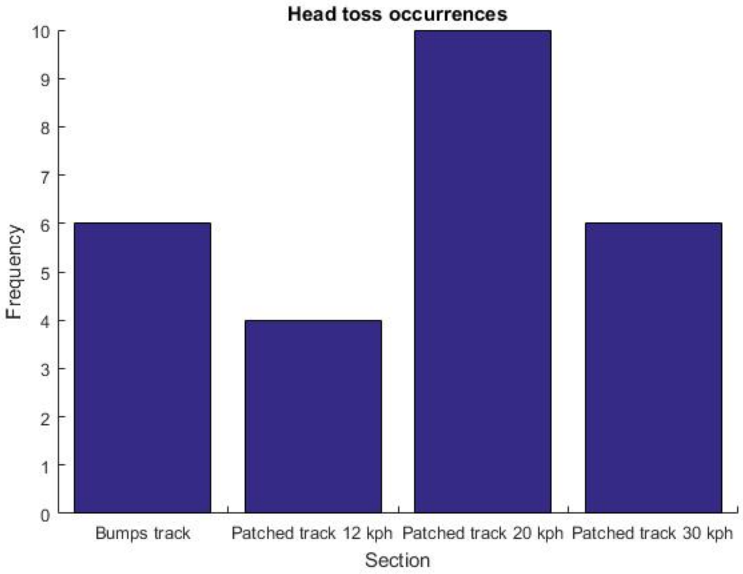

Figure 4.11: Example of number of occurrences for a car run in the rig program predicted by a model.

5

Discussion

This chapter will discuss the outline of the project, along with recommendations for further work on the subject.

5.1 Result & method discussion

The experiments shows a relationship between the subjective perception of a head toss and the objectives measures that can be gathered from a test on a four-poster rig. It is however a non-linearity in the mapping of the objective metrics to the subjective rating scale which shows in the relatively low accuracy of the predictions. The imperfection of the models can origin from the complexity and non-linearity of the input-output relation, but also the inconsistency of the target vector V. The inconsistency of V derives from the experiment's evaluation task for the subject to communicate at an exact point where the perception of head toss corresponded to a rating. This task demands high precision and makes the scenario complex in the steps that the experiment demands the subjects to evaluate the perception of head toss. The driver's seat subject is signalling to the passenger what rating was perceived, then the passenger seat subject is marking the rating from the signalling at that instant. The substantial process of creating the markings of observed head tosses is not only complex of nature, but has increased intricacy as the interval between occurring head tosses decreases. The reason is that the process of marking a head toss takes considerable time for the passenger seat subject to note the rating and marking the point of time which in occasions where two occurrences follow each other rapidly, would demand the passenger to mark and note quickly which may cause a lag of time marking or general inaccuracy. Moreover, a high frequency of head tosses during a long time may cause a discrepancy in the perception of the head toss as mentioned in section 2.3. A dispatched phase shift error of head toss occurrence is therefore a reasonable prediction.

Moreover, the error in terms of rating magnitude of the prediction compared to the perceived rating can be acknowledged as an enhanced value that resembles the reality more than the rating communication of the subject. The rating scale used to quantify the subjective feeling of a head toss is a categorically numeric scale that differentiates ratings in terms of head toss harshness. In reality, head toss is a spectrum of comfort that begins at minimum comfort and goes up to maximum comfort. In between the two borders, the comfort is a perpetual degree of comfort that is more accurately described as continuous than categorical. A prediction of a head toss rating of 2.11 can therefore be more descriptive and accurate than the categorization of a 2 on the scale.

In the model design phase, it became apparent that the partition of the data into the four different sections was critical to the performance of the models. This can be understood as the bump section had very notable occurrences of head toss since the data consisted of stable accelerations and large amplitudes spikes. This trained the models in a very generic way as it simply categorized the stable data as no head toss and the spikes as a rating based on the amplitude. The classification tree in appendix A.1 modelled an algorithm in an explanatory way for the bump section. The difficulty of the modelling appeared when the data had attributes of high frequency and equivalent amplitudes. These attributes were to a large part found in the patched section's higher velocities (20 kph and 30 kph). In those data sections, non-linear conditions between the input and output govern the performance of a prediction model. The head toss prediction seems thus to be dependant on a more complex hypothesis than what the classification tree and ensemble learned regression trees is able to produce. The neural network is therefore a more appropriate tool for these section as it enables mapping of complex and non-linear relations between input and output. The resulting performance of the different data analysis tools is supporting the assertion as the neural network models indeed perform better on the patched section 12 kph and 20 kph.

5.2 Potential of methodology in production domain

The project realizes a conversion from physical outdoor testing in real-world scenarios into a controlled indoor environment in a set-up that enables high repeatability. The evaluation of ergonomics and comfort experience an enhancement of flexibility in the conversion of environment. The possibility of large scale tests in a rapid manner enables the development of robust models that can evaluate and compare modifications to the equipment or product that is being tested. The data-driven development of ergonomics and comfort can thus be applied to operators' conditions in a production domain. For example, the project's testing of a car as a product can directly be transformed into a forklift evaluation. The methodology remains in the form of transforming the real-world situations in which comfort is imperilled into a compiled rig program that contains the different elements which disrupt safety or comfort aspects. In the same manner as the project measures and quantify an objective metric, the forklift can be compared to modifications or surrogate models which subsequently leads to the ability to choose the best solution.

The value of this project therefore stretches further than the head toss evaluation of a car. The methodology accounts for the objective evaluation of a subjective feeling in a unique manner. In the potential of the production domain, the enhanced comfort, safety, and ergonomics of operators is valued as a prospect to a factory. Therefore, there exists an interest in the production domain to adapt this project's creation.

5.3 Recommendation for further work

The project was conducted on the proving grounds of Volvo. The number of scenarios of head toss occurrence was thereby limited to the tracks available at the proving grounds. In order to have a larger variety of scenarios, the rig program would need to have additional data to replicate those scenarios. Therefore, recordings made in the same manner as the project's method to convert the proving ground surfaces to the four poster rig, would provide the extension of the rig program. The recordings of new data can therefore be scenarios on public roads that show head toss behaviours of a different nature than what can be found on the proving grounds. By recording these selected road sections and transfer the data to rig signals, the program can be extended resulting in a more robust experiment.

Furthermore, the machine learning tools of the project can be trained with more examples in order to enhance their performance. This can be done using more sensor data that derive from different cars.

6

Conclusion

This project entails the realization of the objective testing of the subjective feeling of head toss. A data recording of road surfaces generating head toss was converted into a four-poster rig to enhance objective performance of repeatability and control. In the controlled environment, chassis data consisting of sensors attached to the B-pillars and driver's seat rail was considered the metric related to head toss. The usage of machine learning to analyze the data, resulted in a prediction model constructed from the best performing models. The metric was quantified using the prediction model to generate objective values which consists of the rating and occurrences of head toss. Due to the results of this project, it is possible for Volvo to use the rig program and set up as well as the head toss program to compare different cars' head toss performance in an objective manner. The aim of this project is therefore reached and the problem formulation is resolved.

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A

Appendix A

A.1 Classification tree layout

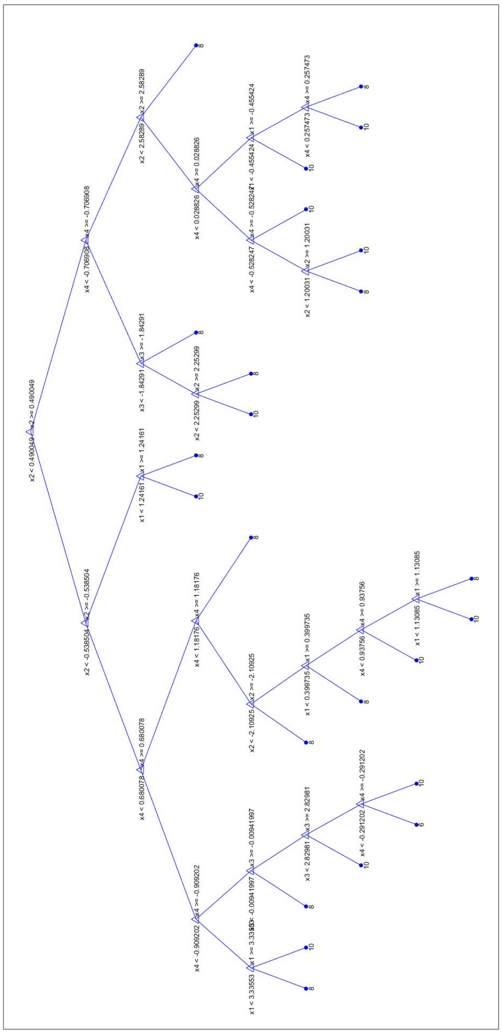

Figure A.1: Classification tree of the bump section

A.2 Model performance table

Table A.1: The performance of all prediction models for each section and their error relative the real data, here predicting the head toss in car A.

Car A						
		Bumps	Patched 12	Patched 20	Patched 30	Total
Real	#	6	6	9	6	27
	Rating	6.6	7.6	6	7.4	24.95
NN	#	6	8	11	6	31
	Rating	6	8.4	5.8	6.8	27
	# error	0	2	2	0	7
	Rating error	0.6	0.8	0.2	0.6	2.2
C Tree	#	8	8	6	4	26
	Rating	6	6	4	6	22
	# error	2	2	3	2	9
	Rating error	0.6	1.6	2	1.4	5.6
Ensamble	#	6	7	15	0	28
	Rating	6.4	7.7	6	10	30
	# error	0	1	6	6	13
	Rating error	0.2	0	0	2.6	2.8

Table A.2: The performance of all prediction models for each section and their error relative the real data, here predicting the head toss in car C.

Car C						
		Bumps	Patched 12	Patched 20	Patched 30	Total
Real	#	6	11	10	6	33
	Rating	7.6	7.6	4.8	6	26
NN	#	6	11	15	9	41
	Rating	6.2	8	6.4	6.2	26.8
	# error	0	0	5	3	8
	Rating error	1.4	0.4	1.6	0.2	3.6
C Tree	#	8	9	3	3	23
	Rating	6	6	4.6	6	22.6
	# error	2	2	7	3	14
	Rating error	1.6	1.6	0.2	0	3.4
Ensamble	#	6	10	15	0	31
	Rating	6	7.2	6.2	10	29.4
	# error	0	1	5	6	12
	Rating error	1.6	0.4	1.4	4	7.4

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