Alignment and Tire Error State detection using Chassis States, Modes, and Measurements

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I. Introduction

As part of autonomous vehicle research at Ford Motor Company, a 2017 model year Ford Fusion was instrumented for collection of some chassis CAN signals buses and internal control module signals. The data was collected with dSPACE Autobox real-time system. Over the course of year the test vehicle was modified with different tire and alignment conditions resulting degraded handling. Test drives were performed on public roads throughout Southeast Michigan in both degraded and nominal vehicle condition. The resultant data comprises roughly 85 GB of data sampled at 100 Hz stored several hundred labeled data files. The task of the work is to differentiate between different degraded conditions and nominal vehicle conditions using pattern recognition techniques. This work supports the development of chassis prognostics for future Ford products.

II. Data Labeling

Each data file (.mat) has been hand labeled with some degree of consistency. A summary of the initial examination of data labels is shown in Table I. While the first few entries are self explanatory for any motor vehicle operator, the last few may not be so diagrams and explanations have been provided in Figures 1 to 4 and the following subsections.

Unchecked degraded or improper alignment or tire(s) can cause other chassis components to wear at an accelerated rate, leading to costly repairs. Beyond repair costs, driver assistance technologies rely on modeling of vehicle systems behavior to carry out guidance of the vehicle. When the systems acting to control to a path no longer behave within expectations due to the error states like the ones listed in the table, negative consequences could result. These range anywhere from scaring an unwitting occupant to failing to remain along a specified path.

A. *Tire Condition*

The labels for tire condition are ”Conicity - Left”, ”Conicity - Right”, ”Good”, and ”Bad”. To better understand these terms, it is helpful to examine Figure 1 showing the cutaway view of a radial tire.

TABLE I: Initial examination of data file label categories

Label Category	**Description**
Experiment Name	Identifier given to experiment version
Experiment Number	Three digit counter, unique to experiment name
Drive Location	Short description of where the test was performed
Left Tire Pressure	Left tire pressure test condition (psi)
Right Tire Pressure	Right tire pressure test condition (psi)
Tire Condition	Tire test condition, one of the following: `Conicity Left` `Conicity Right` `Good` `Bad`
Alignments Bias	Alignment test condition, one of the following: `Left` `Right` `Misaligned - Unspecifed` `None`
Vehicle Loading	Vehicle weight test condition, one of the following: `GVWR Left` `GVWR Right` `GVWR Centered` `1UP`

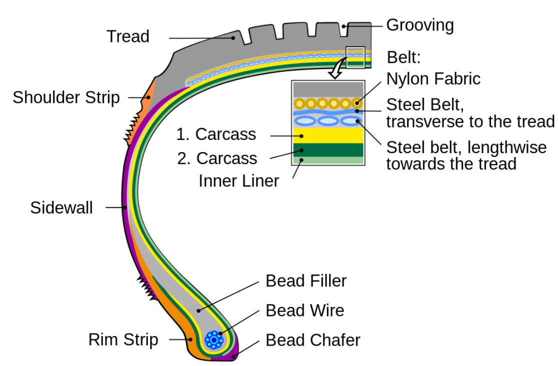

Fig. 1: Radial tire structure, courtesy of Creative Commons

”Bad” tires might denote any number of conditions, but likely refers to uneven tread, sidewall, or shoulder wear. Common causes of these kinds of wear are over or under inflation, worn suspension components, or incorrect suspension and steering alignment. ”Conicity” or ply-bias refers to a defect of the tire belts in manufacturing. This defect leads to the tire profile becoming conic and increase lateral pull in on direction or another.

B. Alignment

Alignment refers to setting the wheels relative to each other and to the car body to the design condition. The most important parameters of which are the caster, camber, and toe of the right and left wheels and the total developed by their combination. Figure 2 - 4 have been provided for reference on these parameters.

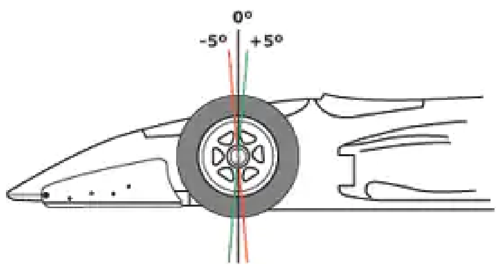

Fig. 2: Camber is the angle describing the inward or outward tilt of wheel from the vertical. Inward camber can help maintain heading under loss of traction, but an excess may decrease stability. Outward camber can reduce acceleration performance in a straight line. Ultimately camber is set to balance cornering performance and tire wear.

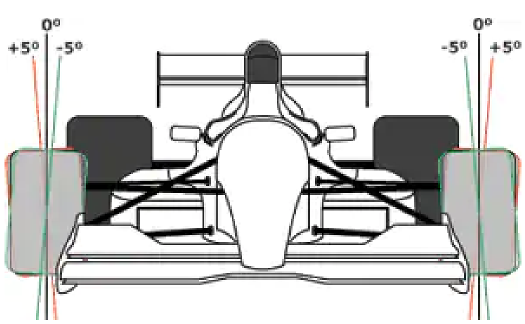

Fig. 3: Caster is the angle made with the vertical axis and the line between the steering’s upper and lower pivot points. The choice of caster balances steering efforts, straight line tracking, and the ability to corner. Incorrect caster may effect any of these vehicle dynamics attributes.

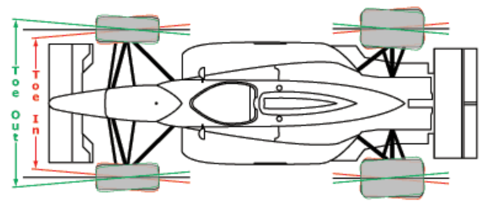

Fig. 4: Toe is the angle that either tire makes with the longitudinal direction. Toe has a great affect on under steer or over steer. Improper toe may negatively affect drivability and handling. Toe is the most critical factor for tire wear.

C. Vehicle Loading

Vehicle loading refers the distribution of weight in the vehicle. The labels we have for the different tests are Gross Vehicle Weight Rating (GVWR) is the maximum loaded weight the vehicle has been designed to sustain. The position of the load right, left, and center has been added as a label and was tested as a noise factor.

III. Features

The raw dataset are signals from the chassis CAN and different electronic modules in the vehicle. Some signals are measurements of physical signals of the vehicle and others are states or modes. There are roughly 85 recorded channels of physical measurements, states or modes, and more processed versions of either of the latter two.

Expected vehicle directional control properties and responses can be predicted using dynamical models and vehicle properties. Some of the properties and responses that we can predict have been recorded. Given that, it may prove useful to examine the modeled behavior and actual behavior as features. However, that topic is premature in this document.

A. Data Format

```
/Data
  expNumN-1
  expNumN
    Info
      RevisionMajor
      RevisionMinor
      MeasurementID
    X
      Name
      Type
      Data
      Unit
      Raster
    Y
      Recorded Signals
    Description
      General
      Recording
      Measurement
        XAxisOffset
        Length
        StartTimestamp
        StopTimestamp
      MDF
```

The data structure is given in the form of a tree. The most important point is that the data consists of X values representing time samples, and Y values representing the aforementioned signals, some of which will be useful for detecting degraded vehicle conditions. These signals are time series data sampled at 100 Hz. The other information in the data structure is largely meta-data.

B. Relevant Recorded Signals

Because there are so many recorded signals, some must be omitted. Following list contains the signals of interest in Y from the data structure. From this abbreviated list must be further refined before its clear what signals might be consider features. Of the signals, I believe some information to be helpful contextually to understand the the vehicle state and the state of the control modules - but not useful as a feature.

1) Antilock Brake Active
2) Actual Brake Torque
3) Propulsion Wheel Torque
4) Vehicle Roll Angle Estimate
5) Stability Control Activation Status
6) Estimated instantaneous battery current drawn by the PSCM
7) Compensated Steering Pinion Angle
8) Relative Steering Pinion Angle
9) Steering Column Torque
10) Traction Control Active
11) Vehicle Lateral Acceleration Rate Raw
12) Vehicle Lateral Acceleration Rate
13) Vehicle Longitudinal Acceleration Rate Raw
14) Vehicle Longitudinal Acceleration Rate
15) Vehicle Roll Angle Raw
16) Vehicle Vertical Acceleration Rate Raw
17) Vehicle Vertical Acceleration Rate
18) Vehicle Yaw Rate
19) Vehicle Yaw Rate Raw
20) Vehicle Velocity
21) Front Left Wheel Angular Rate
22) Front Right Wheel Angular Rate
23) Rear Left Wheel Angular Rate
24) Rear Right Wheel Angular Rate
25) Stability of Yaw
26) Steering Torque Disturbance Rejection State
27) Steering Torque Disturbance Rejection Feature Torque Request
28) Pull Drift Compensation Assist Torque
29) Torsion Bar Torque(?)
30) Filtered Torsion Bar Torque(?)
31) Steering Motor Torque Command
32) Steering Pinion Velocity Estimate

C. Potential Features

Many of the signals are highly correlated to each other. For instance, Vehicle Vertical Acceleration Rate and Vehicle Vertical Acceleration Rate Raw differ only because of signal conditioning and perhaps some filtering. This fact inflates the total number of signals that might be considered features. Reducing similar signals into a single and removing signals unrelated to this task leads to feature candidate signals.

- /Potential Features
  - Vehicle Control Algorithm Info
    - Traction Control Active
    - Stability Control Activation Status
  - Vehicle Body Motion Information
    - Vehicle Velocity
    - Front Left Wheel Angular Rate
    - Front Right Wheel Angular Rate
    - Rear Left Wheel Angular Rate
    - Rear Right Wheel Angular Rate
    - Roll Angle
    - Yaw Rate
    - Lateral Acceleration Rate
    - Longitudinal Acceleration Rate
    - Vertical Acceleration Rate
  - Anti-lock brake information
    - Anti-lock Brake Active
    - Actual Brake Torque
  - Steering Algorithm Torques Information
    - Pull Drift Compensation Assist Torque
    - Steering Torque Disturbance Rejection State
    - Steering Torque Disturbance Rejection Feature Torque Request
  - Steering Dynamics
    - Steering Pinion Torque
    - Steering Pinion Velocity
    - Steering Pinion Angle
  - Steering Power Assist
    - Steering Motor Torque Command
    - Estimated instantaneous battery current drawn by the Electric Power Steering - related to torque demand

Having narrowed down the original data-set, it is easier to describe the primary features of the raw data as the second level categories in the tree. Under each category a list of reduced signal names has been presented.

D. Feature explanation

The most important features of the dataset fall in the categories of Steering Dynamics, Steering Algorithm Torques Information, and Vehicle Body Motion Information. To to ground the reader in what these Steering Dynamics and Algorithms features represent physically Figure 5 has been included. Likewise, Figure 6 has been included to help explain Vehicle Body Motion Information.

Context Diagram.png

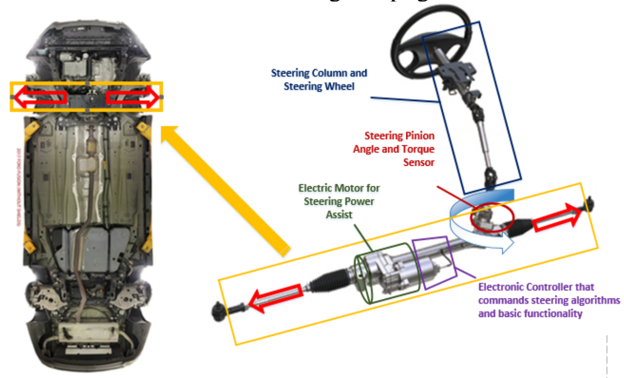

Fig. 5: A rack electric power steering system and its placement in the under body of a vehicle. The basic function of steering assist is to add gain to the drivers input torque and apply it to the wheels as a lateral force. This is accomplished by an electric motor that can be precisely controlled, a steering torque and angle sensor, and electronic control module to interpret signals, perform algorithms, and control the motor. Steering Torque Disturbance Rejection and Pull Drift Compensation are both examples of steering algorithms that improve driver experience. STDR is for dynamic disturbance rejection like going over a pothole, while PDC adjusts the motor torque no driver torque in situation like driving on a road with crown or slant.

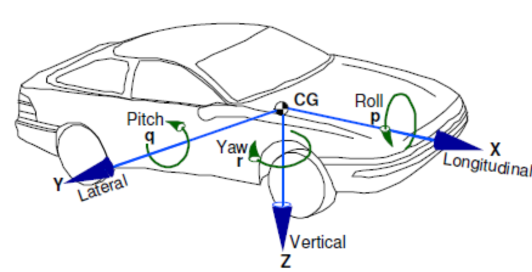

Fig. 6: SAE Vehicle Fixed Coordinate System with labels helping to explain the meaning of the Vehicle Body Motion Information signals

IV. Pattern Recognition Problem

The task of the work is to identify and differentiate between nominal and different degraded alignment and tire condition an listed in Table I using pattern recognition. This differentiation must work under many noise factors, such as vehicle loading, tire pressures, and location. Of the potential features, the steering dynamics and algorithm information offer the most related measurement of the symptoms resulting from Alignment Bias and Tire conditions.

A. Problem Manifested in Features

Pull Drift Compensation Torque normally is learning and compensating for quasi-static road disturbances. But in the condition where the vehicle is degraded resulting in pull to one side (biased misalignment or biased conicity tires) the distribution of these Pull Drift Compensation Torque would be altered. It would be the job of a machine learning technique to recognize this change and then decide whether or not it was due to tire pressure or a more serious issue. One could follow a similar train of thought with Steering Pinion Torque, Steering Pinion Angle, or Steering Motor Torque Command where the distribution of these signals would change slightly relative to those a nominal vehicle. Or at least that is the assumption.

Vehicle Body Movement Information is generally useful in trying to recognize issues with the patterns of the vehicle's dynamics. These signals are the resultant effects of vehicle forces. Forces which are effected by degraded conditions such as tires or alignment. Understanding vehicle body movement information and and steering dynamics together as a state may also be helpful. As would including models of some of these vehicle signals such as a bicycle or cornering compliance model.

B. Application of Pattern Recognition

The problem described is one of supervised learning, the data is labeled. The features are continuous and there are many more negative examples than positive ones. Here a positive example would be signals labeled with ”Conicity - Left”, ”Conicity - Right”, ”Bad” tire condition, ”Left” or ”Right” alignment bias, ”misaligned - unspecified”. And a negative one would be signals labeled with no such degraded conditions. So this a generative problem. Other conditions such as vehicle loading or tire pressure are noise factors, and ideally we would not like to make decisions independent of them.

The decision that the pattern recognition makes will be at its simplest a confidence or probability that a particular set of vehicle signals has a degraded condition. It could expand to a more granular diagnosis and classification of what condition seems to be there.