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# Driver Behavior Analysis Using Multiple Sensor Data Fusion and Pattern Recognition

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**ABSTRACT**

Driver behavior analysis deals with modeling the behavior of a vehicle driver through his operation of driving controls such as shifting gears, steering wheel movement, acceleration and braking patterns. To analyze the behavior, multiple sensor data fusion techniques have been used which provides a platform to fuse the data available from the various sensors and also provide "new data" containing more information and reliable. We have captured the data associated with the aforementioned parameters and attempt to gather the various characterizations or behavioral patterns of the driver.

**KEY WORDS**: Driver behavior analysis, Data Fusion, Statistical inference, Pattern Recognition, automotive embedded systems

## 1. INTRODUCTION

A modern mid-range automotive consist more than 35 sensors which continuously monitor various parameters critical and vital to improve the performance of automotive systems. Surprisingly, the data from the sensors possess other vital information that can be extracted through various techniques. A driving task can be categorically classified into several parts, as mentioned Eason (2003), where Strategic, Tactical and Operational levels which have been discussed extensively. The strategic level involves those aspects of driving that involve prior decisions such as the route to take, time for the trip and alternate route analysis. The next level is tactical which discusses about various characteristics of tactical decisions undertaken by the driver. These may include certain attributes such as over-taking, road rash, collision avoidance driving. The last level is Operational which gives the actual driving tasks being employed by the driver. These tasks may include throttling, braking and shifting the gears. Based on these levels, we identify certain characteristics and attributes of the overall driving task that help us analyze how a driver is driving the vehicle. We basically try to assess the driver's performance based on safety, comfort, convenience and fuel consumption.

Generally the events performed by drivers are given as Jerky braking, Rash driving (bumpy), Cornering, Collision driving (tailgating), Gear shifting and Number of starts/stops. There is a need for a platform to integrate data coming from different/multiple sensors in the system which requires architectures that ensemble various levels of abstractions related to the system. The JDL model (Joint Directors of Laboratories) is a model shown in figure 1, formulated to include the data coming from various sensors in a target application and fuse them as new and intelligent information.

Typically models can vary according to the degree of fusion and application required. One of these models that fit the required application in driver behavior analysis is the Waterfall Model. It is a very simple and generic adaptation of the JDL Model to include all the required sensors. The Waterfall model is shown in the figure 2.

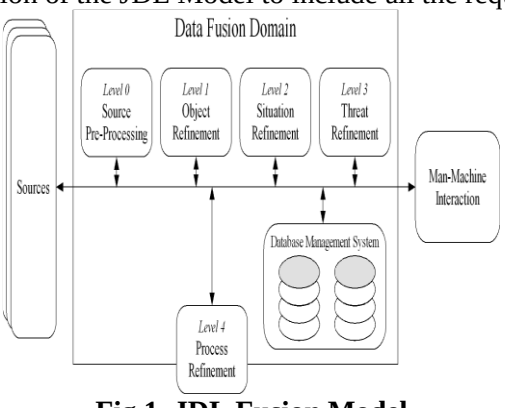


**Fig.1. JDL Fusion Model**

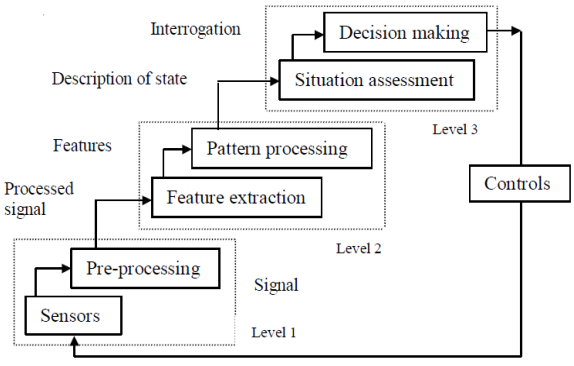


**Fig.2. Waterfall Architecture**

Sensor planning and the choice of architecture play a major role in determining the data acquisition part. Statistical inference is used to fuse data coming in from different sensors and update our beliefs about the occurrence of driving events. After these events are quantified, a classifier is used to classify the data into appropriate class labels.

There are various techniques to analyze the information available. According to Hugh Durrant-Whyte and Thomas Henderson (2008); and Rajive Joshi and Arthur Sanderson (1999), we can broadly classify the inference techniques as Probabilistic Methods (those that involve Evidence theory, Statistics, Recursive Operation and

Bayesian Analysis), Least Square Based Estimation Methods (those such as Optimal Theory, Kalman Filtering, Uncertainty, and Regularization) and Intelligent Aggregation (such as Fuzzy Logics and Neural Networks).

To update our beliefs about a hypothesis, we use evidence (data) coming from the sensors. This is accomplished through the use of Bayesian Inference. The formal representation of which is shown below:

$$P(H \mid E) = [P(E \mid H) / P(E)] \times P(H) \quad (1)$$

Where we have, P (H | E) gives the updated belief after occurrence of evidence E from P (H), P (E | H) gives the occurrence of E given hypothesis H, P (H) gives the priori probability before occurrence of evidence E, P (E) gives the overall occurrence of E, not necessarily related to H alone, P (E | H) / P (E) gives the maximum likelihood.

Posteriori Probability = Maximum Likelihood x Priori Probability (2)

Beyond this, we need a classifier that assigns the particular degrees of beliefs after updating to class variables that represent the occurrences of events. Using this as the inference engine in our system, we proceed to model the various parameters and assess them accordingly. This project takes one such, important subjective characteristic of the automotive and tries to make the best use of information that is abundantly available in the automotive. Through this we attempt to analyze the actions being undertaken by the driver and in real time display the count of events recognized by the system. For example, display the total number of times a bad maneuver has happened, indicate gear shifting for the most optimal RPM and in turn get better fuel economy and also display all of the parameters being monitored in real time to the driver

## 2. MODELLING

According to the requirements we have identified in the Literature Survey section, we need to model these events into quantifiable parameters that our processing device has to easily recognize and read repetitively. We proceed with modeling the events accordingly. Normally, a driver when interacting with the vehicle has access to: Accelerator Pedal, Brake Pedal, Steering Wheel, and Transmission Gear.

These are the interactions at the most immediate disposal of the driver. We cannot model all of the events completely without the use of sensors to measure the quantities that vary according to driving. Some of these sensors are: Inertial Measurement Unit (Accelerometer), Range Sensing Unit (mm Wave Radar or Ultrasonic Range Sensing Module).

With these sensors and the measurement equipment, we can classify them into Direct and Indirect, based on how the driver interacts with the vehicle.

**Table.1.**

| Sensor | Measured |
|---|---|
| **Direct** (Based on cause)**:** | |
| Acceleration | Throttle |
| Braking / Deceleration | Amount of Brake |
| Steering | Steering Position |
| Gear transmission | Position of Gear Lever |
| **Indirect** (Based on Effect)**:** | |
| Accelerometer | Acceleration in X, Y and Z (with respect to vehicle frame) |
| Ultrasonic Range Sensor | Distance between vehicle to object (another vehicle, separator) |

Now, we are in a position to model the events associated to driving, as told in the beginning of this section and in the literature survey. We need to choose three parameters to model the Bayesian Inference Engine, these are, the Conditional Probability P (E | H), the Priori Probability P (H) and the Maximum Likelihood Estimator (MLE) which is a ratio of the Conditional Probability and the Model Evidence P (E).The Bayesian Inference Engine will give the Posteriori Probability which is also a Conditional Probability, which is updated by the evidence. Thus the Posteriori will support our Hypothesis that a given event has occurred.

**Jerky Braking:** Involves a rapid increase in the amount of brake applied (as the cause), results in a massive change in acceleration in the axis along the movement of the vehicle and a consequently decreasing RPM. We can choose our Prior as the probability that the driver will apply rapid brakes which may or may not result in a rapid change in acceleration, which can be initially biased or unbiased.

$$P(\text{Jerky\_Braking} \mid \text{Change } A_x) = \left(\frac{P(\text{Change\_}A_x \mid \text{Jerky\_Braking})}{P(\text{Change\_}A_x)}\right) \times P(\text{Jerky\_Braking}) \quad (3)$$

**Rash Driving:** This particular event can be broadly defined in many ways, but with respect to safety and comfort, we define it to be the event when the driver applies abnormal Throttle which results in a bumpy axis which is perpendicular to the vehicle's body.

$$P(\text{Rash Drive} \mid \text{Change } A_z) = \left(\frac{P(\text{Change\_}A_z \mid \text{Rash Drive})}{P(\text{Change\_}A_z)}\right) \times P(\text{Rash Drive}) \quad (4)$$

**Cornering:** This event involves a rapid Steering Wheel maneuver (towards the Left or Right) following which, because of the tangential centrifugal force, there is an increase in acceleration in the axis perpendicular to the side of the vehicle body (lateral axis).

$$P\left(\text{Corner} \mid \text{Change } A_y\right) = \left(\frac{P\left(\text{Change\_}A_y \mid \text{Corner}\right)}{P(\text{Change\_}A_y)}\right) \times P\left(\text{Corner}\right) \qquad (5)$$

**Tailgating:** This event involves a Steering Wheel maneuver (a little to the Left or Right) which leads to the vehicle running too close to another vehicle in the front or towards either of the sides, whose distance is detected by the Ultrasonic Range Sensing Module.

$$P\left(\text{Collision} \mid \text{Distance}\right) = \left(\frac{P\left(\text{Collision} \mid \text{Distance}\right)}{P(\text{Collision})}\right) \times P\left(\text{Distance}\right) \qquad (6)$$

These are some of the modeling techniques to estimate and update our belief that a particular event has occurred and to keep count of the event(s) in order to keep record, display the data in real time and consequently assess the performance the driver for the entire trip. The other parameters that are taken into account to fill in the necessary blanks have been discussed in the next section, where the testbench setup, components used, data preprocessing are alighted.

**Testbench setup:** To obtain the data, we need to appropriately choose the hardware components.

- LPC2148 32-bit Microcontroller by NXP (Philips) with ARM7TDMI-S Architecture
- Linear Potentiometer x 3 (Steering, Acceleration, Braking)
- HC-SR04 Ultrasound Range Sensors x 3 (Front, Left and Right)
- Reed Switches (Transmission Gear)
- ADXL335 Analog 3-Axis Accelerometer (X, Y and Z axes)
- JHD162A 16x2 LCD Module
- UART with PC
- LEDs

The direct interactions can easily be measured using a Linear Potentiometer, whose position changes can effectively be quantified into Voltage changes and therefore, after passing it through an Analog to Digital Converter, we can get the appropriate, corresponding values. The indirect measurements are more parameter and variable oriented, therefore we consider cost and complexity as a factor in deciding the Ultrasound Range Sensor (<4m) and the Accelerometer (IMU).

The Transmission Gear (with shifts 1, 2, 3, 4) is modeled with the help of Reed Switches (that act as magnetic relays) and permanent magnets. These are used as external interrupts to drive the flow of program which Illustrated as SPST switch in the schematic. While choosing the appropriate processing unit, we make note of the requirements such as, number of ADC channels, External Interrupt Pins, General Purpose IO Pins, responsiveness and finally data handling capabilities. Based on the requirements, we choose the ARM (RISC based, 32-bit high performance embedded Microcontroller) architecture, more specifically, the LPC2148. (As an additional advantage, it also has an inbuilt CAN Controller Unit). For displaying and indication purposes, we make use of the PC UART, LEDs and LCD. The Software Development Tool used is Keil uVision v4.0 with Embedded C as the programming language. The Hardware Schematic is shown below in figure 3.

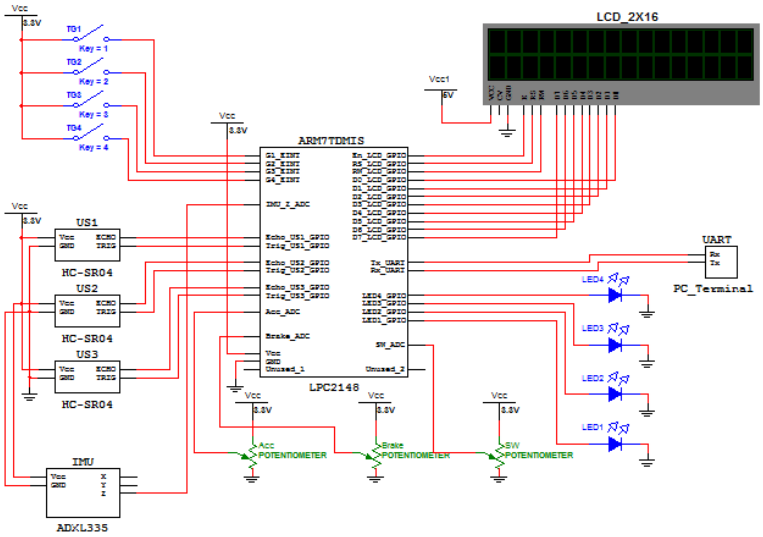


**Fig.3. Hardware Schematic Diagram**

**Table.2. Specifications of Sensors need to be preprocessed**

| Sensor | Steering wheel | Acceleration Pedal | Brake Pedal |
|---|---|---|---|
| Description | Modelled using a Rotary Potentiometer | Modelled using a Linear Potentiometer | Modelled using a Linear Potentiometer |
| Vref | 3.3 V | 3.3 V | 3.3 V |
| Resolution | 10 bits ( 1024 levels ) | 10 bits ( 1024 levels ) | 10 bits ( 1024 levels ) |
| Position | Center – '0'<br>Left - '100'<br>Right - '+100' | Min Throttle – '0'<br>Max Throttle – '100' | Min – '0'<br>Max - '100' |

**Table.3. Specifications of Sensors need to be preprocessed**

| Sensor | Transmission Gear (G1, G2, G3, G4 ) | Accelerometer (X, Y and Z axes ) | Ultrasonic Range Sensing Module |
|---|---|---|---|
| Description | Modelled using Array of Reed Switches | ADXL335 | HCSR04 |
| Vref | 3.3 V | 3.3 V | 5 V |
| Resolution | 10 bits (1024 levels) | 10 bits ( 1024 levels ) | |
| Position | 'ON' State for > 3.3 V<br>'OFF' State for < 2.2V | | |
| Range | | -4g to +4g | Object Distance < 4m |

After the Microcontroller has been programmed to read the sensors, pre-process it as required; now it can be fed into the Software Model and the Bayesian Inference Engine to generate the results appropriately. For this, we need to program our software model to accept certain parameters that are specific to one vehicle. In this case, we choose the Chevrolette Corvette [7], with the following specifications: Gear Ratio [1st Gear (2.97:1), 2nd Gear (2.07:1), 3rd Gear (1.43:1), 4th Gear (1:1)], Axle Ratio (3.42), Wheel Diameter (17"), Average Fuel Consumption (11.48 kmpl), Weight (1754 kg), Crank Radius (65 mm), Horse Brake Power (405 bhp), Speed per 1000 RPM [ 1st Gear (12.4 kmph), 2nd Gear (17.7 kmph), 3rd Gear (15.9 kmph), 4th Gear (22.7 kmph).

With these specifications, we establish a reasonable relationship of the input parameters from the sensors to estimate the Vehicle Velocity in kmph, Vehicle Fuel Economy in kmpl and Engine RPM.

$$v = \frac{RPM \times \pi \times D}{G_r \times A_r} \qquad (7)$$

Where, $v$: Vehicle Velocity, $RPM$: Revolution per Minute of Engine, $D$: Diameter of wheel, $G_r$: Gear Ratio, $A_r$: Axle Ratio.

$$T = \frac{HP \times 33{,}000}{2\pi \times N} \qquad (8)$$

Where, $T$: Torque, $HP$: Horse Brake Power, $N$: RPM

$$T = F \times r \qquad (9)$$

Where, $F$: Force, $r$: Radius of Crankshaft

$$F = m \times a \qquad (10)$$

Where, $m$: Mass of car, $a$: Acceleration

$$a = \frac{\Delta v}{t} \qquad (11)$$

Where, $\Delta v$: Change in Velocity, $t$: Reaction Time

## 3. RESULTS

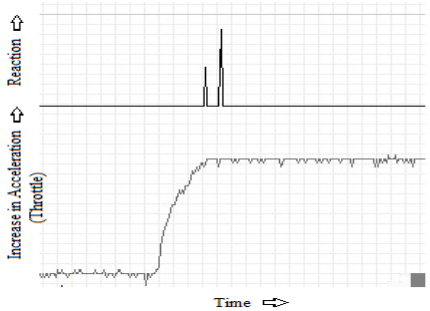


**Fig.4. Sample rash driving event that shows increasing acceleration (action) with a bumpy Z axis (reaction)**


**Fig.5. LCD Output Sample**

G – Gear Position, B – Number of Jerky Braking Events, R – Number of Rash Driving Events, O – Number of Objects gone close to by Driver, C – Number of Cornerings done

## 4. CONCLUSION

- This system, eventually leads to better driving, more safety and convenience as bad driving behavior can be recognized and categorically avoided over a period of time.
- Achieves better fuel economy by identifying driving events and behavior that alter and affect fuel consumption.
- It has a direct application for usage in self-driving cars and driverless systems through the design of intelligent transport systems.
- The vehicle, through the system, can understand the usage of resources, features and different characteristics that vary from driver to driver. Through this, the usage of features can be optimized.
- Dynamic setting of the various features in the vehicle, based on usage is another application. This can be a very helpful tool in assessing a post-crash reconciliation scene along with the help of event data recorders.

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