

# **A NEW METHODOLOGY TO MODEL DRIVER BEHAVIOUR ACCOUNTING FOR THE VARIATION IN DRIVING MANNER USING NATURALISTIC DRIVING DATA**

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## **ABSTRACT**

Our aim is to develop Advanced Driving Assistance Systems (ADAS) which are suitable for all customers in all driving conditions. To achieve this goal, a new methodology was developed to characterize driving manner in each scenario by a mathematical model based on Naturalistic Driving Study (NDS) data. To represent the variety of driving manners, a new parameter named “aggressiveness” is introduced. By adjusting “aggressiveness”, the ADAS’ behaviour can be modified, matching natural driving behaviour in a wide range of operating conditions. This methodology is applied to model when drivers start to brake when approaching another vehicle that’s driving in the same lane. This model can be used to detect when a driver is not assessing a threat correctly by comparing his instantaneous driving behaviour with his normal driving behaviour.

## **INTRODUCTION**

### **Background**

Driver behaviour models can be grouped in 2 types of models: “continuous” and “psychophysical” models. Continuous models [1, 2, 3] are effective in representing a realistic general motion of a vehicle. This makes them suitable for microscopic simulations of traffic. Unfortunately these models cannot represent a different driving style other than the one used to fit them. Psychophysical models [1, 4, 5] are based on the biological sensory perception of humans. They assume humans will react when the sensory input is above their perceptual threshold. These thresholds vary strongly among drivers and among driving conditions. None of the existing psychophysical models takes into account the influence of the driving conditions and the variation in driving behaviour between drivers. The Risk Perception (RP) [10] model is an example of a psychophysical model. It is a model for the relative distance when drivers start to brake when approaching a vehicle. The RP model estimates the influence of the driving conditions. However it doesn’t take into consideration the variation of driving manners.

### **Target & concept**

The target of this study is to develop a methodology to create driver behaviour models taking into consideration the influence of the driving conditions (e.g. driving speed) on the driving behaviour (e.g. relative distance at brake start) and the variation in driving manner. The driving manner is assumed to be the variation in driving behaviour that is not caused by the driving conditions. First the parameters representing the driving conditions and the driving behaviour are extracted from NDS data. Next the correlations between the driving conditions and the driving behaviour are identified. Finally the influence of the driving manner on the correlations between the driving conditions and the driving behaviour is modelled.

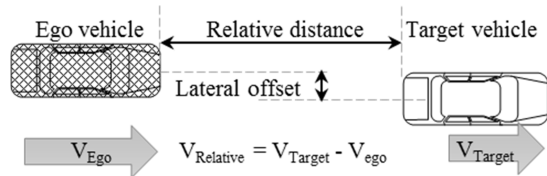
## **METHODOLOGY AND MODEL DESCRIPTION**

The below described methodology can be applied to all driving scenes. In this paper we explain how this method was applied to model when drivers start to brake when they approach a slower driving vehicle.

### **Driving scene extraction from naturalistic driving study data**

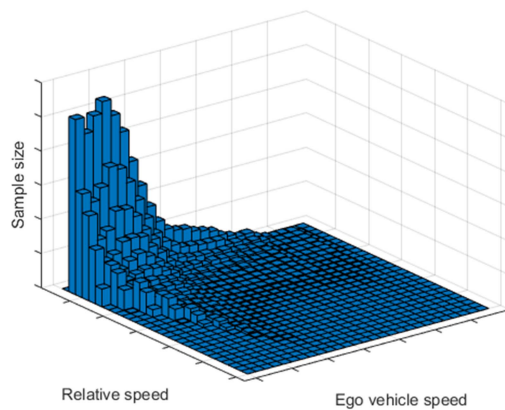
The data collected in France within EUROFOT FP7 EU project [6] was used to create this driving behaviour model. EUROFOT was a Naturalistic Driving Study (NDS): ordinary drivers’ own vehicles were instrumented,

and their behaviour continuously recorded during their usual trips. The French dataset was recorded between April 2010 and May 2012. It consists of 581 000 km / 13 400 hours of data. 35 private vehicles (14 Renault Clio III and 21 Renault Laguna III) were instrumented with a CAN / GPS data logger (CTAG data logger 2) and a millimeter wave long range radar (TRW AC20). Their owners lived in the West-Paris area. 5 additional vehicles (2 Renault Clio III and 3 Renault Laguna III) were instrumented with a 4-channel video logger, a Mobileye smart camera, and a Smarteye driver monitoring system. Each participant drove one of those vehicles during 3 two-weeks periods, which amounts to 15% of the dataset collected with this higher instrumentation level. The ego vehicle speed and brake activation were collected on the vehicles' CAN network, while the radar allowed measuring the relative speed, the longitudinal distance and lateral overlap to a target vehicle (Figure 1).



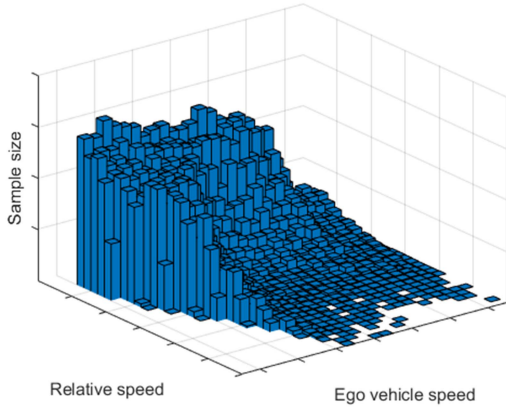
**Figure 1. Recorded parameters.**

To limit the events only to approaching another vehicle scenario, events with a lateral offset and a relative speed not exceeding a certain criteria, a positive target vehicle speed and a relative distance below 80m at the start of braking were selected. Lateral offset was calculated by compensating road curvature (estimated from yaw rate measurement). With these criteria more than 1 brake event per 3 kilometers of collected data was detected with a distribution as shown in Figure 2. Due to limitations of the allowed data to be extracted from the database, not all detected braking scenes could be extracted.



**Figure 2. Distribution of the detected braking scenes in EuroFOT database.**

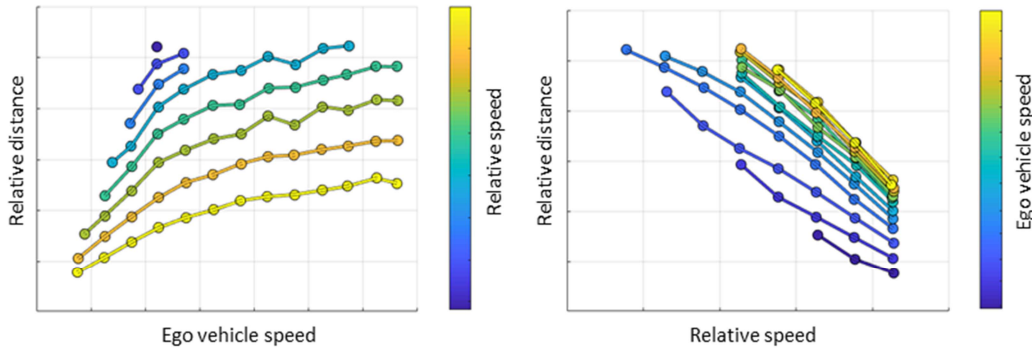
For the conditions where a very high amount of brake events are detected, a limited amount of samples was randomly selected for extraction. For conditions with a limited amount of detected brake events, all detected samples were selected for extraction. This resulted in a total of more than 80 000 selected brake events with a distribution as shown in Figure 3.



**Figure 3. Distribution of the selected braking scenes.**

### Correlations between driving conditions, driving behaviour and driving manners.

First the correlations between the driving conditions and the driving behaviour are identified. The relative speed and the ego vehicle speed at the start of braking are selected as driving condition parameters because they showed the highest correlation. The relative distance at brake start is selected as the primary parameter representing the driver behaviour. The driving manner is the variation in relative distance when drivers start to brake for constant driving conditions. To visualise the correlations between the driving conditions and the driving behaviour, all brake applications are grouped in bins with a similar driving condition (relative speed and ego vehicle speed). For each bin the distribution of the percentiles of the relative distance at brake start is calculated. The results of the 50<sup>th</sup> percentile can be seen in Figure 4.



**Figure 4. Relative distance at brake start in function of the relative speed and ego vehicle speed at brake start.**

For each percentile there is a linear influence of the relative speed and a quadratic influence of the ego vehicle speed on the relative distance. The model for the relative distance when drivers start to brake can therefore be written in as a bi-variable polynomial of second order in function of the relative speed and ego vehicle speed as described in Equation 1.

$$D_{rel} = p_{00} + p_{01} \times V_{rel} + p_{10} \times V_{ego} + p_{11} \times V_{ego} \times V_{rel} + p_{20} \times V_{ego}^2 \quad (\text{Equation 1})$$

$p_{00}$ ,  $p_{01}$ ,  $p_{10}$ ,  $p_{11}$  and  $p_{20}$  are fitting parameters that vary in function of the driving manner. Equation 1 can be written as the product of 2 matrices with all fitting parameters combined in one matrix (Equation 2).

$$D_{rel} = [p_{00} \ p_{01} \ p_{10} \ p_{11} \ p_{20}] \times [1 \ V_{rel} \ V_{Ego} \ V_{Rel} \times V_{Ego} \ V_{ego}^2]' = P \times V' \quad (\text{Equation 2})$$

In Figure 5 the surface is the relative distance calculated according to Equation 2 with the parameter matrix  $P$  optimised to fit the 50<sup>th</sup> percentile of the relative distance at brake start extracted from EuroFOT. The points are the 50<sup>th</sup> percentile of the relative distance at brake start extracted from EuroFOT.

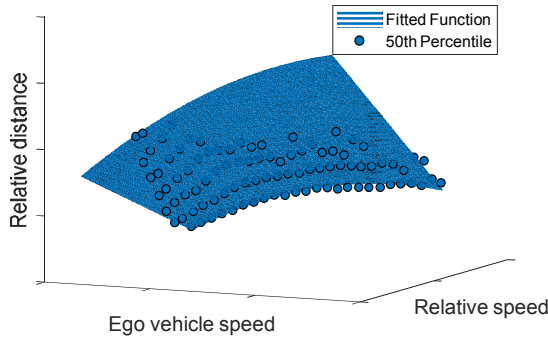


Figure 5. Comparison of 50<sup>th</sup> percentile relative distance at brake start from equation 2 and from NDS data.

To include the influence of the driving manner, the fitting parameters are calculated for every percentile of relative distance from the 5<sup>th</sup> until the 80<sup>th</sup> percentile. This range of percentiles was selected because the fitting accuracy reduces significantly when going outside of this range. To simplify the driver behaviour model it was assumed that the fitting parameters can be estimated in function of the distance percentile by 1<sup>st</sup> order linear regression (Figure 6).

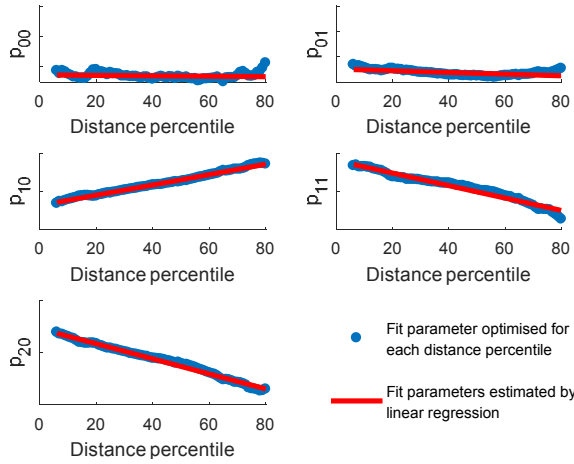


Figure 6. Fitting parameters for the range of 5<sup>th</sup> to 80<sup>th</sup> percentile of the relative distance.

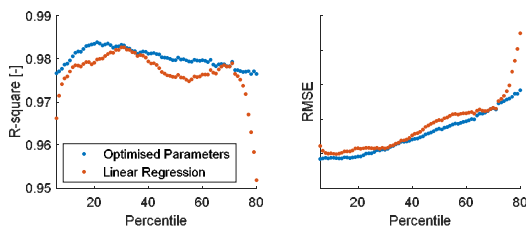


Figure 7. Fitting accuracy for the range of 5<sup>th</sup> to 80<sup>th</sup> percentile of the relative distance.

The fitting accuracy of the parameters estimated by linear regression is comparable to the accuracy of the optimised parameters for each percentile (Figure 7), therefore the assumption may be judged as reasonable. The model for the relative distance can be updated (Equation 3).

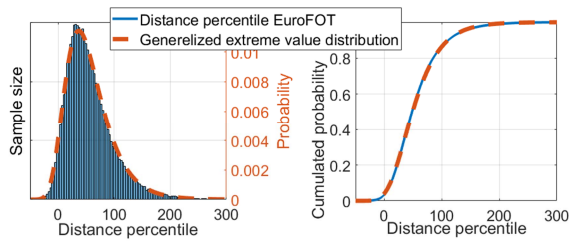
$$D_{rel} = (P_a \times \text{Distance Percentile} + P_b) \times V' \quad (\text{Equation 3})$$

The distance percentile can be calculated by Equation 4.

$$\text{Distance Percentile} = \frac{D_{rel} - P_b \times V'}{P_a \times V'} \quad (\text{Equation 4})$$

## Quantifying driving manner

The distance percentile is calculated for all brake events extracted from the EuroFOT database with Equation 4. The probability density distribution and the cumulative probability distribution of the distance percentiles are shown in Figure 8. The calculated distance percentiles have values outside the range of zero to one hundred. Two reasons can be identified for this: the first one is that the fitting by Equation 2 is not 100% accurate (Figure 7). The second reason is the error caused by estimating the fitting parameters by linear regression in function of the distance percentile.



**Figure 8. Distribution and cumulated probability of the distance percentile of all brake events.**

A new parameter named “Aggressiveness” is introduced to quantify driver manner. Aggressiveness is defined as one minus the cumulated probability of the distance percentile when drivers start to brake. E.g. a brake application with aggressiveness 60%, is a brake application that starts at a relative distance that is the 40<sup>th</sup> percentile of the relative distance of all brake applications with similar driving conditions.

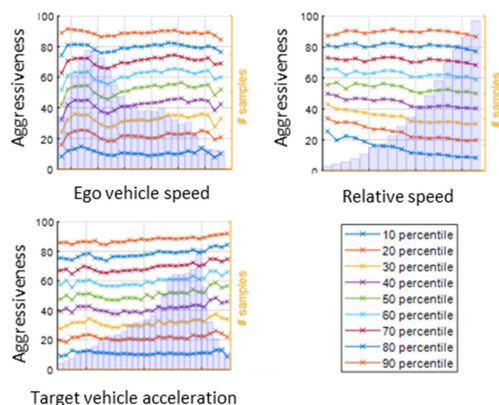
The distribution of the calculated distance percentiles is a generalized extreme value distribution (Figure 8). The aggressiveness can be calculated using the formula for the cumulated probability of the generalized extreme value distribution (Equation 5). The parameters  $k$ ,  $\mu$  and  $\sigma$  are calculated for the aggressiveness values calculated from EuroFOT data.

$$\text{Aggressiveness} = 1 - e^{-\left[1 + k \times \frac{\text{Distance Percentile} - \mu}{\sigma}\right]^{-1/k}} \quad (\text{Equation 5})$$

## VALIDATION OF THE DRIVER BEHAVIOUR MODEL

### Validation by EuroFOT data

The purpose of the driver behaviour model is to estimate the driver aggressiveness in function of the driving conditions and driving manner. If the influence of the driving conditions is correctly estimated, the distribution of the aggressiveness will be constant in function of the driving conditions. The distribution of the aggressiveness in function of the driving conditions for the brake scenes extracted from the EuroFOT database is shown in Figure 9. It can be noticed that the distribution of the aggressiveness is constant in function of the deceleration of the target vehicle although the deceleration of the target vehicle is not used as an input parameter to calculate the aggressiveness; we can therefore conclude that the target vehicle acceleration doesn't influence the relative distance at which drivers start to brake.



**Figure 9. Distribution of aggressiveness in function of the driving conditions for all brake events extracted**

from EuroFOT database.

### Validation by UDRIVE data

The driver behaviour model for brake start timing was also validated using the UDRIVE [9] passenger cars database. This database was constituted during the UDRIVE FP7 EU project which also followed the Naturalistic Driving methodology. Passenger cars data was collected in France, Netherlands, Germany, Poland and UK. This dataset consists of 1 994 000 km / 43300 hours of data collected by 122 vehicles (Renault Clio III, IV and Renault Megane III) / 196 drivers. One significant difference between UDRIVE and EuroFOT is the sensor used to measure relative speed and distance to the target vehicle (Mobile Eye Q2 camera for UDRIVE; TRW AC20 radar for EuroFOT). The same method used for the EuroFOT dataset was implemented to extract 691,053 brake events from UDRIVE database. The aggressiveness of each brake application is calculated using Equation 4 and 5, with all parameters optimised for EuroFOT data. For UDRIVE the distribution of the aggressiveness in function of the driving conditions is slightly less constant as for EuroFOT (Figure 10). There is a small influence of the relative speed and the target vehicle acceleration on the aggressiveness. Despite of this we can conclude that the driver behaviour model created by EuroFOT data is valid for UDRIVE.

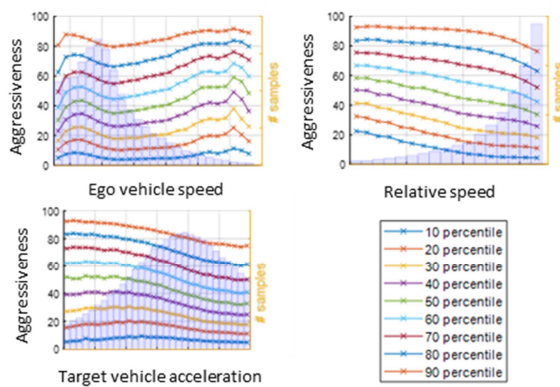


Figure 10. Distribution of aggressiveness in function of the driving conditions for all brake events extracted from UDRIVE database.

## RESULTS

### Comparison with other models for brake start timing

The same method was used to validate the accuracy of three main models for brake start timing; Time to Collision (TTC), Time Head-Way (THW) and RP (Figure 11). For each percentile of THW and TTC there is a significant influence of the ego speed and relative speed. The RP model can best estimate the influence of the driving conditions around its 50<sup>th</sup> percentile, however for other percentiles the RP model is less constant in function of the driving conditions. This demonstrates that among these models the aggressiveness model most accurately estimates the influence of the driving conditions on the driving behaviour for the complete range of driving manners.

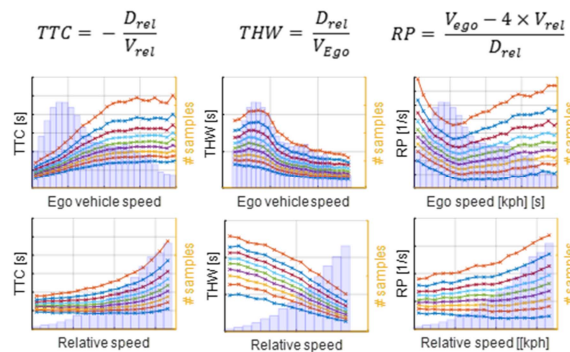
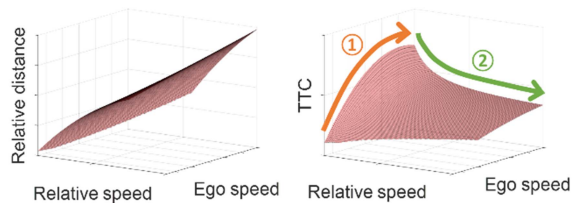


Figure 11. 10 to 90<sup>th</sup> percentile distribution of TTC, THW and RP in function of the driving conditions.

## Understanding the brake start timing model

The relative distance and the TTC at brake start are plotted for an aggressiveness value of 50 in Figure 12 which shows two trends. The first one is that TTC at brake start increases when the ego vehicle speed increases. This indicates that drivers prefer to take less risk when the driving speed increases. Similar behaviour has been reported by Kusano et al. in 2014 [10]. The second trend is that the TTC at brake start reduces when the relative speed to the target vehicle increases. This is confirming that the drivers are perceiving relative speed by visual looming cues [5, 8].



**Figure 12.** 50<sup>th</sup> percentile of relative distance and TTC at brake start.

## CONCLUSION AND APPLICATIONS

### Conclusion

A new methodology is proposed to create driver behaviour models from NDS taking into consideration the influence of the driving conditions on the driving behaviour for all variations of driving manners. A new parameter named “aggressiveness” is introduced to quantify driving manner.

### Applications

The brake start timing model can be implemented in a driver monitoring system. It can be used to detect when a driver is not recognizing a threat correctly by comparing his instantaneous driving behaviour with his average behaviour. When the driver’s instantaneous aggressiveness is significantly higher than his average aggressiveness and he didn’t react to reduce the criticality, it is likely the driver didn’t correctly assess the criticality of the scenario. When used to adapt the activation timing of a forward collision warning (FCW) system, two benefits are expected compared to an FCW with constant activation timing. The first benefit is that for more aggressive drivers the frequency of unnecessary FCW activation will reduce and thereby increase customers’ trust and acceptance of the FCW. This is assumed to result in a more efficient reaction of the drivers to the forward collision warning and therefore increase the accident reduction performance. A second benefit is that for less aggressive drivers the FCW can activate earlier compared to the standard timing without increasing the unnecessary activation rate. This will allow the driver more time to react to the warning and thus result in an increase of the accident reduction performance.

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