Driving Style Assessment Based On the GPS Data and Fuzzy Inference Systems

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Abstract—Car insurance can be computed according to the client’s driving behaviour. This option is based on algorithms which use data from the black box. To carry out the monitoring function, the black box integrates an Inertial Navigation System (INS) sensors, a Global Positioning System (GPS), which are Micro Electromechanical Systems (MEMS) based and a flash memory.

Researchers were interested in driver behaviour modelling by means of Kalman Filtering (KF) and Hidden Markov Modelling (HMM) and most of them are based only on the driver’s acceleration profile during a period of time.

This research paper expands the number of parameters, by adding the jerk, to estimate the driver aggressiveness. It proposes two approaches for driving behaviour supervision based on the vehicle velocity signal which is acquired from the Global Positioning System (GPS). The first approach presents three driving behaviour indicators based on the vehicle acceleration and jerk. Simulation results show some weaknesses in terms of driver aggressiveness estimation. For this purpose, the second approach is based on a developed Fuzzy Inference System (FIS) model. The inputs of the FIS model are the vehicle acceleration and jerk and the output remains the aggressiveness score. Experimental results show that the driver aggressiveness is better estimated by the proposed FIS model since the two input parameters are taken into account simultaneously. Furthermore, it will be shown that the defuzzification techniques and the GPS signal noise have an impact on the driver behaviour estimation.

Keywords—Pay How You Drive, driver behaviour indicator, Global Positioning System (GPS), On Board Diagnostic (OBD), Fuzzy Inference Systems (FIS).

ACRONYMS

DK Driven Kilometers
FA Forced Acceleration
SD Sharp Deceleration
OV Over Speeding
TT Travel Time
VL Vehicle Location

I. INTRODUCTION

Insurance companies attract automotive clients according to the offered services. Most of them are based on the Pay As You Drive (PAYD) model (the number of kilometers traveled) and/or the number of accidents in each year to compute insurance discount.

Nowadays, telematic devices (black boxes) offer personalized insurance cost based on the Pay How You Drive (PHYD) model. As shown in the table I, the PHYD model can be based on the supervision of the Over Speeding (OS) and the acceleration profile (Forced Acceleration (FA) or Sharp Deceleration (SD)). To achieve these features, the black box integrates an Inertial Navigation System (INS), a Global Positioning System (GPS) and the developed integration algorithms.

The GPS and INS device prices have an important impact on the black box cost and performances. A high-precision GPS and/or INS are very expensive. On the one hand, the development of Micro Electro Mechanical Systems (MEMS) allows dealing with the price of these telematic devices. On the other hand, the expected data accuracy may not fit the insurance requirements. Certainly, the GPS noises have an impact on the driver aggressiveness score. Therefore, most of the existing research work is based on the data fusion methods with the INS data to reduce the GPS noises and to have the required accuracy. This paper presents a new model to estimate the driver behaviour using only the GPS which is MEMS based. From the vehicle velocity, the acceleration and the jerk parameters are computed. By combining these two parameters, which are given from the same source, two methods are presented in this paper to estimate the driver aggressiveness. This approach forms the main advantage of the presented work. The first method, which is the simplest one, proposes three indicators. The first and the second indicators are based on the vehicle acceleration and jerk separately, and the third one combines the two of them. Since the simulation results show some weaknesses in this method, a Fuzzy Inference System (FIS) approach is presented. The developed FIS model has the acceleration and the jerk as inputs and the aggressiveness score as output. With the proposed membership functions, the rules table and the suitable defuzzification technique, the 3D representation of the relationship between the acceleration, the jerk and the driver aggressiveness is developed.

The second section of this paper presents the first approach for driver aggressiveness estimation using the proposed three simple algorithms and the related simulation results. The third section presents the second
approach, which is based on our developed Fuzzy Inference System (FIS) model, and the related results given from experimental test. The fourth section concludes and gives outlooks.

<table>
<thead>
<tr>
<th>Country</th>
<th>Insurance company (Program)</th>
<th>Parameters</th>
</tr>
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<tbody>
<tr>
<td>USA</td>
<td>Metromile (Per Mile)</td>
<td>DK, VL, FA</td>
</tr>
<tr>
<td></td>
<td>Allstate (Drive Wise)</td>
<td>DK, OS, FA</td>
</tr>
<tr>
<td></td>
<td>Progressive (Snapshot)</td>
<td>DK, VL, VA</td>
</tr>
<tr>
<td>UK</td>
<td>Direct Line (Drive Plus)</td>
<td>DK, VL, OS, VT</td>
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<tr>
<td></td>
<td>Money SuperMarket</td>
<td>OS, FA, SD, TT</td>
</tr>
</tbody>
</table>

II. DETERMINISTIC INDICATORS FOR PAY HOW YOU DRIVE (PHYD) CONCEPT

A. Introduction

Table I presents the difference between the Pay How You Drive (PHYD) models adopted by some auto insurance companies. From this table, the PHYD model is mainly based on the driver’s acceleration profile. Where some other auto insurance companies add more options to the model such as over speeding (OS) or mobile phone usage while driving as Jie in [1].

This paper proposes another parameter to be taken account. This one is called the jerk which is the variation of the acceleration during a time period. These two parameters (acceleration and jerk) can be derived from the vehicle velocity which can be acquired from the GPS and/or the OBD (reference). The first PHYD model is given by deterministic indicators of acceleration and of jerk. These indicators are presented in the second paragraph. The third paragraph tests these indicators and presents the limitations. The fourth paragraph concludes this section.

B. Indicators

The first PHYD indicator is based solely on the acceleration profile. In fact, when the acceleration (or the deceleration) exceeds a predefined limit, the driver is considered aggressive. As it is more important than this limit, the driving style is more aggressive. As the acceleration approaches to zero, the driving style is good. According to these assumptions, the first PHYD indicator can be defined as

$$A_{AG} = \frac{a}{a_{max}}$$  \hspace{1cm} (1)

where a is the vehicle acceleration and a_{max} the vehicle’s comfort acceleration limit. According to Ge in [2], a_{max} = 4 \text{ m.s}^{-2} in case of acceleration and a_{max} = -3 \text{ m.s}^{-2} in case of deceleration.

The second PHYD indicator is related to the variation of the acceleration during a time period. This parameter is defined as the vehicle jerk. In [3], Molina suggests that a good driver is characterised by a comfort driving profile where the jerk is ranged in [-4 \text{ m.s}^{-3}, 3 \text{ m.s}^{-3}]. Then, the related PHYD indicator, which is given by

$$J_{AG} = \frac{\dot{a}}{a_{max}} = 100 \frac{J}{J_{max}}$$  \hspace{1cm} (2)

where J_{max} is the vehicle comfort jerk limit. It is equal to 3 \text{ m.s}^{-3} in case of acceleration and -4 \text{ m.s}^{-3} in case of deceleration. Here, as the jerk gets more important than the predefined comfort jerk limit, the driving behaviour shifts to an uncomfortable state and the driver is considered more aggressive.

For reasons which will be presented shortly, the third PHYD indicator is a trade-off between the first and the second indicators. It is given by the following expression:

$$J_{AAG} = 100 \left[ \alpha A_{AG} + \beta J_{AG} \right],$$  \hspace{1cm} (3)

where \((\alpha, \beta) \in \mathbb{R}^+ \times \mathbb{R}^+ \) and \(\alpha + \beta = 1\).

These three presented indicators will be tested under simulation to analyse the performances of this proposed PHYD model.

C. Simulation test and results

1) Description: The simulation test is done by means of the CARSIM\(^1\) vehicle simulator. This one includes a "complete" mathematical vehicle models which reproduce accurately the vehicle dynamic.

In this section, the C-Class vehicle Hatchback 2012 OSG model is chosen for driving aggressiveness analysis. Table II presents the simulation parameters used in this section. The target forward speed function in CARSIM is used to generate the estimated vehicle velocity during 400 s of simulation. It is given by the blue curve in figure 1(a). The vehicle response in terms of velocity is represented by the red curve in the figure 1(a) and measured for 400 s of simulation. As shown in this figure, the vehicle’s velocity response (red curve) is delayed relative to the velocity control laws (blue curve) due to the driver reaction time and the inertia of the vehicle.

Figures 1b and 1c present the response of the vehicle in terms of acceleration and jerk respectively. These two parameters are derived from the vehicle velocity. Based on these two figures, the driver aggressiveness is analysed during the simulation time using the above presented indicators given by equations (1), (2) and (3). Next subsection will present these indicators for the first 10 seconds of simulation to have a better zoom of the results and interpretation.

2) Results and discussions: Figure 2a presents a zoom of the acceleration profile during the first 10 seconds of simulation. Figure 2b presents the related aggressiveness indicator given by equation (1) during the first 10 seconds. According to this figure, when the acceleration is close to zero, the driving style becomes good since the

\(^1\)CARSIM is a vehicle simulator used to simulate the vehicle mechanical behaviours, involving the 3D dynamic vehicle response and the driver actions.
TABLE II: Simulation parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
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<tbody>
<tr>
<td>Brake torque at wheel</td>
<td>250 (Front), 150 (Rear)</td>
<td>M·m/MPa</td>
</tr>
<tr>
<td>Engine</td>
<td>125</td>
<td>kW</td>
</tr>
<tr>
<td>Speed transmission</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>Simulation step time</td>
<td>0.025</td>
<td>s</td>
</tr>
<tr>
<td>Simulation stop time</td>
<td>400</td>
<td>s</td>
</tr>
</tbody>
</table>

aggressiveness indicator is near zero. As the aggressiveness indicator $A_{AG}$ get near to one, the driver approaches the limit of the good driving style. In fact, the vehicle acceleration (respectively the deceleration) approximates the predefined limit 4 m.s$^{-3}$ (respectively, −3 m.s$^{-3}$). As the value of the aggressiveness indicator get greater than one; the driving is considered more aggressive.

Figures 2c and 2d present the vehicle jerk response and the aggressiveness indicator given by equation (2) respectively. From these two figures, as the sudden change in acceleration (jerk) gets more important (uncomfortable driving), the driver is considered more aggressive. In fact, when the jerk is close to zero, the driving style is considered comfortable (non aggressive driving). As the aggressiveness indicator $J_{AG}$ gets near to one, the driver approaches the limit of the comfortable driving style. In fact the jerk approximates the predefined limits (3 m.s$^{-3}$ or −4 m.s$^{-3}$). As the aggressiveness indicator gets greater than one, the driving is considered more aggressive.

On the one hand, according to figure 2b, the driving style is non-aggressive since $A_{AG} \leq 1$. On the other hand, figure 2d shows that at the start-up, the aggressiveness score is high and the driver has been considered aggressive since $J_{AG} \geq 1$. Then, the applied acceleration is small but the variation (jerk) is high. This phenomenon can be shown when the vehicle is in the Stop and Go scenario as in our case. Therefore, $A_{AG}$ and $J_{AG}$ cannot estimate separately the driver aggressiveness, in this case. In addition, the driver’s acceleration profile (forced acceleration and sharp deceleration) cannot accurately estimate the driving aggressiveness profile. For this reason the third indicator, defined by equation (3), has been developed.

Figure 3 presents the aggressiveness profile given from the indicator $J_{AG}$ for $\alpha = 0.5$ and $\beta = 0.5$ during the first 10 seconds of simulation. At the start-up, the aggressiveness score remains 0.64. This value is the trade-off between the two aggressiveness scores given by $A_{AG}$ and $J_{AG}$ indicators.

The choice of the values of $\alpha$ and $\beta$ can be made according to the scenario. For example, at the start-up, the value of $\beta$ can be equal or greater to $\alpha$. In fact, in the Stop and Go scenario the applied acceleration and its variation (jerk) have to be taken into account to estimate the driver aggressiveness. As the vehicle departure is fast as the traffic congestion decreases while maintaining a comfortable start.

Figures 4a and 4b present the aggressiveness indicator $J_{AG}$ during the simulation time and the related histogram respectively. The histogram is designed to have an overview of the most computed aggressiveness scores during a period of time.

Overall the simulation time, the driving style can be considered good. In fact, the most observed aggressiveness score is in the interval [0; 0.1] according to the figure 4b.

D. Conclusions

This section has proposed three aggressiveness indicators with the related simulation results. The first and the second indicators are related to the acceleration and the jerk parameters respectively. The third one combines them into one algorithm. The main advantage of this approach is the simplicity. Nevertheless, the major challenge is the determination of the optimal $\alpha$ and $\beta$ values to have the best aggressiveness estimation of the driving style.

To overcome this problem, the next section presents our
The drawback of this method consists in the limitation of the states number to estimate. For this purpose, the Multiple Dynamic Model (MDM) is proposed.

2) Multiple Dynamic Model (MDM): In the Multiple Dynamic Model (MDM), there is a Kalman filter model for each of driver behaviour state. The general Multiple Dynamic Model expression is given by

$$\hat{X}_k^{(i)} = X_k^{(i)} + K_k^{(i)} (Y_k - h^{(i)}(X_k^{(i)}, t)),$$

where $\hat{X}_k^{(i)}$ the optimal estimate of the state vector $X_k$, $Y_k$ the sensor measurement, $K_k^{(i)}$ the $i^{th}$ Kalman gain matrix and $h$ is the function of the sensor measurement. With this approach, there is a Kalman filter model for each predefined driving situation (aggressive driver, normal driver...). The driving style is determined by choosing the model that has the best fit to the observed behaviour. In the Multiple Dynamic Model, all the process has a fixed likelihood at each time step. Nevertheless, according to [4], this is uncharacteristic of most driving situations. In addition, this approach is time and memory consume since each model is attributed to each driving style. Therefore, a generic model for driver behaviour recognition has to be investigated. This one must take into account the constraints of time and memory.

3) Hidden Markov Models (HMMs): In the literature, Hidden Markov Models (HMMs) is widely used for speech recognition. Nevertheless, this approach was developed for driving behaviour recognition. In this paragraph, some of its application to driving style estimation is presented.

Vehicle theft protection becomes a wide research area during the last decades. In [5], by analysing the dynamic human behaviours, Meng uses the machine learning method and Hidden Markov Model (HMM) to detect the difference between the predefined driving style and the measured one. By this approach, Meng detects if the driver is the owner of the vehicle or not.

In [6], Wang proposes two methods for driving situation recognition using the features of gas pedal pressure, steering angle, engine speed and vehicle speed. The first stage is used to determine if the driver is in stopping situation or not. In the second stage, an optimal Human Markov Model (HMM) based method is designed to improve performances of the driving behaviour recognition.

In [7], Kuge proposes a driver’s behavior recognition method based on the Hidden Markov Models (HMMs) to characterise the driving manoeuvres and uses it in the framework of a cognitive human behaviour model.

4) Gaussian Mixture Model (GMM): In [8], Angkititrakul developed a stochastic driver behaviour model to characterise individual driver by using a Gaussian Mixture Model (GMM). Here, the mass data should be collected and processed in-time in order to establish individual driver models more accurately.

5) Other approaches: In [9], Trang proposes a foot gesture analysis based method to model and predict the driver behaviour. This work is done using optical flow based
foot tracking and a Hidden Markov Model (HMM) based technique to characterize the temporal foot behaviour.

In [10], Bernet chooses to evaluate the driver behaviour using the developed device for eye tracking. Based on the optical rules, Bernet analyses the driver distraction.

6) Conclusions: As presented in this subsection, the driver behaviour has been studied by different researchers with distinctive methods. The presented methods show some weaknesses in terms of time consume and memory allocation. In addition, these methods need more parameters than the available ones from the GPS. The next subsection presents our new FIS model for driver behaviour assessment using only the GPS data.

B. Fuzzy Inference Systems (FIS) based driver behaviour modelling

1) Introduction: To compute the output of an FIS, the following steps have to be analysed: the determination of a set fuzzy rules, the fuzzification of the parameter inputs using the input membership functions, the combinations of the fuzzified inputs using the fuzzy rules to synthesise the rule’s strength, the computation of the rule’s consequences and the defuzzification of the output distribution.

In this subsection, the second paragraph describes the FIS model. The third paragraph presents the related results and discusses the impact of the defuzzification techniques and signal errors on the driver behaviour estimation.

2) FIS model description: The fuzzification step of the inputs is done by the acceleration and the jerk membership functions which are given by figures 5 and 6 respectively. In figure 5, the acceleration is SD (Sharp Deceleration) when the driver applies a sharp deceleration with the vehicle’s maximum capability. The term ”Good” refers to an acceleration between -3 m.s^{-2} and 4 m.s^{-2} as suggested by Ge in [2]. An FA (Forced Acceleration) corresponds to an acceleration that exceeds 4 m.s^{-2}.

The choice of the ”Good” jerk range, which is [-4 m.s^{-3}, 3 m.s^{-3}], is based on the work done by Molina in [3]. In figure 6, the jerk is ”Dangerous” when it is equal or less than -4 m.s^{-3}. It is a risky jerk because it corresponds to an emergency braking scenario. When it is close to zero, it is considered ”Good”. The jerk is ”Bad” when it is equal or greater than 3 m.s^{-3} which corresponds to the positive variation in the acceleration. This situation happens in the Stop and Start scenario.

The fuzzy rules are given by table III. In this one, only the fuzzy AND operator is applied. When the acceleration is ”FA” AND the jerk is ”Bad”, the driver is ”aggressive”. The FIS output is the aggressiveness scores. These latter ranges from 0% (good driving style) to 100% (aggressive driving style). 50% is considered ”Normal” driving as shown in figure 7.

<table>
<thead>
<tr>
<th>Acceleration</th>
<th>Jerk</th>
<th>Dangerous</th>
<th>Good</th>
<th>Bad</th>
</tr>
</thead>
<tbody>
<tr>
<td>SD</td>
<td>-</td>
<td>Aggressive</td>
<td>Normal</td>
<td>-</td>
</tr>
<tr>
<td>Good</td>
<td>-</td>
<td>Aggressive</td>
<td>Good</td>
<td>Aggressive</td>
</tr>
<tr>
<td>FA</td>
<td>-</td>
<td>-</td>
<td>Normal</td>
<td>Aggressive</td>
</tr>
</tbody>
</table>

Fig. 5: Acceleration membership function

Fig. 6: Jerk membership function

Fig. 7: Aggressiveness membership function
The defuzzification step consists in the conversion of a composed membership function into a single crisp value. In this paper, it will be shown that the defuzzification techniques have an impact on driver behaviour estimation accuracy.

3) Experimental test description: The experimental test has been made by the vehicle Dodge 2012 of the LASSENA laboratory. The OBD Wiz and the OBD II link Sx from Scan tool are used for the data acquisition from the OBD. The test is done in the city of Montreal and the trajectory is represented by the green line in figure 8. It contains 36 stops and different road types (highway, urban,...).

The black box is designed in the LASSENA laboratory. It integrates the GPS and the INS, which are MEMS based. It includes also a flash memory that can save the different driving parameters such as the position and the velocity (GPS) of the vehicle during the test.

We note that the frequency of the OBD is 1 Hz and the GPS frequency is 3 Hz. But the OBD’s data are more accurate than those of the GPS (since it is MEMS based device). Then, the OBD’s data are considered as the reference.

In figure 8 the red colour in the trajectory indicates the places where the black box (GPS) lost the signal. To carry out this problem, a simple algorithm is developed. It consists in the interpolation between the points before and after the lost point.

Since the vehicle acceleration and jerk are not provided by the OBD and the GPS, the velocity signal, which is available, is derived.

Figures 9a, 9b and 9c present the raw measurement of the velocity, the acceleration and the jerk measurements during the 2450 s respectively. These parameters are computed from the OBD and the GPS simultaneously to analyse the driver aggressiveness using the developed FIS model.

4) Results and discussion:

a) Relationship between the aggressiveness score, the acceleration and the jerk: Figure 10a presents the driving aggressiveness score as functions of the jerk and the acceleration with the Middle Of Maximum (MOM) defuzzification method. Here, as the jerk and the acceleration are closed to zero, the driving behaviour is “Good”. In addition, as the jerk gets the maximum positive or negative values, as the driving style is considered “aggressive”. This conclusion follows the predefined fuzzy rules given by the first and the third columns of table III.

b) Impact of noise on the driver aggressiveness score: Figure 11 presents the aggressiveness score as a function of time according to the OBD and the GPS data, with the proposed FIS model, for the first 50 seconds of the test. Here, the computed aggressiveness score from the OBD data is considered as the reference since these data are more accurate than those acquired from the GPS.

In figure 11 presents the impact of noises, in the GPS
signal (velocity), on the aggressiveness score. For example, at time \( t = 40 \) s, the aggressiveness score is 3\% according to the OBD data. However, from the GPS data, the aggressiveness score remains 65\%. Then, the noised data have an impact on the driver behaviour evaluation.

**Fig. 11:** Aggressiveness score according to the OBD and the GPS data with the proposed FIS model

Figure 12 presents the percentage of time, relative to the travel time, as function of the five aggressiveness score intervals using the GPS and OBD data with the proposed FIS model. According to this figure, most of the driving time is spent with aggressiveness scores between 0\% and 20\% in case of OBD and GPS data. However, the percentage of time is different, 62\% in case of OBD and 92\% in case of GPS data. This is made because of the GPS data (velocity) is noised, and the signal is derived with its related noises.

**Fig. 12:** Aggressiveness summary according to the OBD and the GPS data with the proposed FIS model

Figure 13 compares two different FIS models. As in the literature, the first FIS has only the acceleration profile as input. The second FIS has the acceleration and the jerk as inputs. This figure shows that the driver aggressiveness score is more accurate when using the second FIS model when using the GPS data. Then, we can conclude that the choice of the jerk as the second input with the acceleration profile has an important impact on driver behaviour estimation, although the data are very noised. In fact, taking into account the variation of the acceleration (jerk) can reduce the error between the computed aggressiveness score from the GPS data and the one from the OBD data. This conclusion can be more pertinent when looking the figure 14. This figure presents the percentage of time spent with an aggressiveness score between 80\% and 100\% using different FIS approaches. At higher aggressiveness scores, the proposed FIS model with two inputs presents a good estimation of the driver behaviour. In fact, the error is equal to 0.25\% between the computed percentage of time from the GPS and the one from the OBD.

**c) Impact of defuzzification method on driver aggressiveness score:** On the one hand, the aggressiveness score in figure 10a is limited between 0\% and 100\%. Also, with the Largest Of Maximum (LOM), Smallest Of Maximum (SOM) and Middle Of Maximum (MOM) defuzzification methods, the aggressiveness score is in the same range. On the other hand, figure 15a presents the aggressiveness score given by the Centroid defuzzification method with the same FIS model. In this latter, the aggressiveness score is limited between 20\% and 80\%. This interval remains narrower than the one given by figure 10a. We note that this same result is obtained by the bisector defuzzification method.

Since, the aggressiveness score has to be in \([0\%, 100\%]\), the LOM, SOM and MOM defuzzification techniques are the most convenient to the driver behaviour recognition using the proposed FIS model.

Figures 10b and 15b present the driving behaviour histograms related to the MOM and Centroid defuzzification techniques respectively. On the one hand, figure 10b shows that the most observed aggressiveness score is equal to
5) **Conclusions:** This section presented an FIS model for driver aggressiveness assessment using a single OBD data (velocity) as reference. We concluded that the defuzzification techniques and the signal noise have an important impact on the driving behaviour recognition.

IV. **Conclusions and future works**

This paper has presented two approaches for driver behaviour analysis in real-time mode. The first approach presented deterministic indicators, and the second one presented the FIS model. This latter has shown better performances when using the profile of the acceleration and the jerk simultaneously. Compared to the literature approaches, which used only the acceleration profile, this proposed one estimated more accurately the driver aggressiveness when it is between 80% and 100%.

Future work can be concentrated on the development data fusion algorithms to reduce noises.

**REFERENCES**


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5%. On the other hand, figure 15b shows that the most observed aggressiveness score is 20%. This conclusion is a consequence of the choice of the defuzzification technique. Then, the choice of the defuzzification technique has to be more investigated while evaluating the driver aggressiveness. Nevertheless, the driving style can be considered good during the experimention with these two defuzzification methods. However, the insurance discount, based on our proposed PHYD model, will differ from one method to another.