A Method to Identify Aggressive Driver Behaviour Based on Enriched GPS Data Analysis

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***Abstract*—The main cause of road casualties is related to the driver behavior. The identification of unsafe driving is an important step in order to take actions to change this situation. A novel approach to address driver behavior is called naturalistic driving. This approach tries to understand drivers' behavior during everyday trips by analyzing their moving recorded data through non intrusive GPS gathering devices. Based on that premise, this paper presents a method aimed at identifying aggressive behavior in order to reduce the risk of accidents. As a consequence, it is expected to improve drivers awareness about theirs drive behaviors as well as to notify transportation and insurance companies about the driver's way of driving. The proposed method is composed of four steps, which includes data gathering, pre-processing, semantic enrichment and Trajectory Aggressivity Indicator (TAI) calculation. This indicator varies from 0 to 100 where 0 means no aggressive behavior and 100 means very aggressive behavior. The main contribution is to provide an adaptive approach that considers environmental conditions as weather and traffic to better estimate the TAI. Preliminary results pointed out that the method can identify aggressive behavior almost in a real-time manner, which might be used to notify dangerous behavior before an accident happen.**

***Keywords*–Naturalistic driving; Driver profile; Aggressive driving; GPS; Speed; Acceleration.**

I. INTRODUCTION

The number of fatal casualties on road crashes reached 1.25 million people in 2015 and it is the main cause of death among people aged 15 – 29 years old [1]. More than 95% of such accidents are caused or contributed by driver behavior factors [2]. However, even with several governmental actions devoted to reducing traffic accidents, until now there is no signal of traffic deaths declination worldwide [1].

As driver's behavior is the main cause of road casualties, the identification of unsafe driving attitudes is an important step towards taking actions to reduce them. Several methods have been studied in order to obtain a better understanding of driver behavior. However, as pointed out by Ellison et al. [3], research methods using demographic profiles, self-reported behavior and personal risk perceptions tend to assume homogeneity of behavior within groups. Moreover, self-reports and questionnaires are sensitive to user perspective, which might give a false sense of secure/insecure manners.

A novel approach to address driver behavior is called Naturalistic Driving Study (NDS). The NDS can be defined as "A study undertaken to provide insight into driver behaviour during everyday trips by recording details of the driver, the vehicle and the surroundings through nonintrusive data gathering equipment and without experimental control" [4]. This approach uses equipment like GPS device, video camera and audio recorder to obtain daily data. However, it is important to enforce the unobtrusive requirement in order to gather natural behavior for long periods of time.

The most common approaches to naturalistic behavior analysis are based on Global Positioning System (GPS) data and video recording. This work analyses naturalistic driving over data from GPS devices embedded into a smartphone. This approach has been chosen because smartphones are largely used by drivers and have all the required features to collect and transfer positioning information. In this work, these data concern the so-called trajectories.

Although GPS data already bring meaningful trajectory information, when combined with other extra information it is possible to leverage the positioning contextualization. Some of the information that can contribute to bringing context of driving movement are weather condition and road speed limits. Such information is crucial to better calculate the driver's behavior indicator. So, in this work it is assumed that the identification of drivers' behavior can be better defined when GPS trajectory data are enriched with weather and speed limit contextualization.

Based on the aforementioned assumptions, the objective of this work is to identify drivers' aggressive behavior based on the analysis of their trajectories enriched with weather and speed limit data, using a naturalistic approach. As a consequence, it is expected to contribute to improve drivers awareness about theirs driving behaviors as well as to notify transportation and insurance companies about the driver's way of driving.

This paper is structured as follows. Section II presents the related works. Section III details the proposed method and its conceptual characteristics. Section IV presents the results assessment. Finally, Section V contains conclusions and further works.

II. RELATED WORK

Driving behavior is a subject of extensive research in psychology, as stated in works like [5] and [6]. In contrast, naturalistic driving research is relatively new, but are gaining

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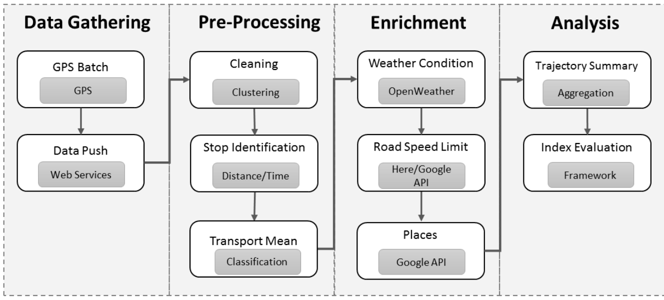

Figure 1. Proposed method to evaluate driver's trajectories

special attention due to the emerging of new technologies to data gathering. In this section, the most significant works on natural driving will be discussed.

Carboni [7] proposes a method that identifies drivers' behaviours considering three anomalies over accelerations and directions: a) abrupt movements (acceleration and deceleration); b) lane changes; c) Excessive speed. As result, the algorithm is capable of classifying drivers in the following categories: careful, distracted, dangerous and very dangerous. It was evaluated using a low number of trajectories collected from buses and cars in a very restricted area. Its main contribution is the identification of anomalous behavior, drivers classification and dangerous places.

Ellison et al. [8] propose the Driver Behavior Profile (DBP) evaluated through the Temporal and Spatial Identifiers (TSI) indicator. The temporal factors considered are purpose, date and time, the day of week and number of passengers. Behavioral factors considered are speed, acceleration and deceleration. Results indicate that different road environments elicit different behavioral responses. The authors also suggest that DBP might be used to test the effectiveness of changes to infrastructure, education campaigns or legislation proposals.

Siqueira [9] evaluates chase behavior comparing the trajectory of two objects. The proposed method considers a target and a pursuer trajectory and compares both against space and time using algorithms to identify pursuit (TRA-CHASE) and another to classify pursuit type (CLASS-CHASE). Its main contribution is the definition of the following chase patterns: a) Detective; b) Meeting; c) Capture; d) Assault; e) Hunting.

Based on the literature review, it can be seen that the assessment of drivers' behaviours using their trajectory data is a fresh and open research field. Moreover, as far as it was possible to search, it was not found any work that addresses the identification of aggressivity profiles based on weather and local speed constraints on a near real time manner as it is proposed in this work.

III. PROPOSED METHOD

As showed in Figure 1, the proposed method is composed of four phases: i) Data gathering; ii) Pre-processing; iii) Segment enrichment and iv) Aggressiveness evaluation. The following subsection describes in details each one of this phases.

The method enriches and evaluate a trajectory trough a set of a segment of 1 km long. Thus, a trajectory with 25 km will be composed of 25 segments. Every segment is enriched individually with its own speed limit, weather details and important places.

The aggressive behavior is evaluated considering speed and acceleration maneuvers. To obtain an aggressiveness index, a speed and acceleration stratification is proposed. The speed is based on the traffic violations of the Brazilian Transit Code (BTC). An incremental fine is issued to the driver accordingly the percentage of excessive speed based on the local speed limit. Table I presents the current penalties of BTC with respective fine and penalties.

TABLE I. SPEED VIOLATION AND FINES FROM BRAZILIAN TRAFFIC CODE

Violation	Severity	Fine
Up to 20%	Medium	USD 25.37 / 4 points
From 20% up to 50%	Severe	USD 37.91 / 5 points
Over 50%	Very Severe	USD 171.34 / 7 points / Suspension

Several researchers addressed acceleration limits associated with causalities and high risk of being involved in an accident. According to [10] a risk of collision starts from $-4m/s^2$. Similar conclusions were obtained by [11] with a risk of accident involvement around $-5m/s^2$. Considering mentioned works, we propose a stratification of acceleration according to Table II. A total of eight groups is considered to evaluate driver speeding up and breaking.

TABLE II. ACCELERATION DISTRIBUTION BY SEVERITY

Severity	Acceleration m/s^2
Dangerous	[-9.0 a -14.0]
Aggressive	[-5.5 a -9.0)
Normal	[-3.0 a -5.5)
Safe	[0 a -3.0)
Safe	[0 a 1.5)
Normal	[1.5 a 3.5)
Aggressive	[3.5 a 7.0)
Dangerous	[7.0 a 12.0]

A. Data Gathering

The data gathering is enabled by an Android application that periodically collects the driver's current geo-positioning and time. The application was developed to collect data as a background service using one second time interval to request the GPS sensor as well as the clock. This strategy enforces the approach to register the driving behavior as more naturalistic as possible because the driver does not need to open the application on every journey since it is always tracking the smartphone position. The collected data is sent as a stream over Internet, or mobile communication like 3G or 4G, to the server periodically within intervals of 60 seconds.

B. Pre-processing

The pre-processing phase includes trajectory cleaning, segmentation and transportation mean identification. The trajectory cleaning is performed by the DBScan clustering algorithm. It is a density based algorithm proposed by Ester et al. [12], which classifies every point as CORE, BORDER or NOISE. Such classification is based on the input parameters $minPts$ and ϵ. Every point which has at least $minPts$ in a ϵ radius will be classified as CORE. A BORDER is a point which does not satisfy the CORE criteria but it is connected to a CORE. Every point which is neither a CORE nor a BORDER is classified as NOISE.

Regarding the trajectory segmentation, the proposed method considers two ways of segmenting a trajectory. The first one is a result of the absence of GPS signal, which might occur due to several situations like the impossibility of GPS device to contact enough satellites, localization service disabled or smartphone turned off. As consequence of the inability to collect GPS coordinates, the data will have a time interval without any position. Based on empirical evaluation, it was defined a number of points threshold (NPT=10) and a time frame (TF=30s) to identify time stops and thus split a trajectory into sub-trajectories. A stop is considered if the number of coordinates collected during latest TF is less or equal to NPT.

The second way of segmentation is used to find situations where the driver remains stopped in a certain place for a predefined time interval. This segmentation tries to identify whether the driver is moving or not (i.e. fueling at gas a station). Based on empirical evaluation over data previously collected, it has been defined 300 meters as distance threshold within 5 minutes of time threshold. Those values are able to identify a fast food stop and still avoid to split the trajectory in every semaphore.

The last step of the pre-processing is the identification and distinction of transportation mean between Motorized Transport (MT) and Non-Motorised Transport (NMT). This is necessary since the data gathering is performed by smartphone and thus several means of transportation are presented in the trajectories. The proposed method applies a classifier in order to identify the transport mean splitting trajectory accordingly. The classifier was trained with 55% of the Geolife dataset[13] using the J48 algorithm from Weka [14]. The output from J48 is a decision tree which indicates that motorized movements usually will present speed over 15 km/h. However, during a heavy traffic, semaphores and crossings it is possible that an MT coordinates might be confused as an NMT. To ensure that trajectory will not be split on every crossing, a threshold for MT and NMT was defined based on data gathered during real experiments. A minimum of 5 coordinates over 15 km/h is enough to identify a MT while a minimum of 15 is necessary to detect an NMT.

C. Semantic Enrichment

The semantic enrichment intends to attach additional information in the trajectory in order to help the calculation of more accurate driver's aggressive behaviour. There are several external factors that affect traffic safety and that can not be extracted by GPS device itself. Some of the currently supported ones are road speed limit, weather conditions and important places surrounding. These factors impact in the aggressiveness analysis over speed and acceleration limits.

There are three types of trajectory semantic enrichment currently supported: weather, road speed limit and important place. Every semantic element impacts the aggressiveness analysis over speed and acceleration.

During a trajectory, the driver may travel through different roads with different speed limits. To gather this information the method makes requests to external APIs of services like Google Maps. However, as the speed limit of certain roads would not be available through an API service, several strategies are applied in order to define to speed limit:

- Speed limit API – Consists of requesting to a specialized web service the speed limit of a specific road;
- Inverse geocoding and database query – The road name is obtained through inverse geocoding. Thus, a query is performed against an internal database of registered roads and its respective speed limit is retrieved.
- Inverse geocoding and road type definition – Roads which are not registered in the internal database have the speed limit defined accordingly to its prefixes. In Brazil, there are five type of roads formerly defined by national authorities as shown in Table III.
- Average speed evaluation – This approach guess the maximum speed based on previous segment speed average. The speed will be limited according to Table III, which means that a segment with an average speed of 33 km/h will be classified as max speed of 40 km/h.

TABLE III. SPEED LIMIT BASED ON BRAZILIAN TRAFFIC CODE

Road Type	Speed Limit
Highway	110 km/h
Roadway	80 km/h
Arterial roadway	60 km/h
Municipal streets	40 km/h
Local streets	30 km/h

Although there is not formal law defining the impact of weather conditions on the road, the public authorities are allowed to issue a fine in case of driver conducts the vehicle in a dangerous manner. The BTC stands that "a fine is applicable if the driver is driving with incompatible speed considering the road conditions". Weather is one of the aspects that affects the road conditions and hence the driving safety. In order to consider the weather in driver's behaviour, every segment is enriched with weather conditions through calls to Weather API. Depending on the weather condition, a reduction over speed limit and acceleration is applied according to Table IV and Table V.

TABLE IV. WEATHER IMPACT OVER ROAD SPEED LIMIT

Weather	Speed Reduction factor
Drizzle	10%
Light rain	15%
Moderate rain	20%
Heavy intensity rain	25%
Very heavy rain	30%

The speed reduction is based on the principle that traveling at 95 km/h on a sunny day is secure considering a highway with speed limit of 110 km/h. However, such speed might be dangerous under heavy rain. Since it has not been found specific reduction values in the literature, Table IV has been defined based on automotive specialists recommendations [15].

The wet road also has an important impact on the car friction to gain speed and mainly to reduce speed. Hence, the same acceleration intensity for the dry road will be more dangerous if applied to the wet road. To obtain the reduction factors presented on Table V a model based on Newtonian classical physics was designed. This model considered a well

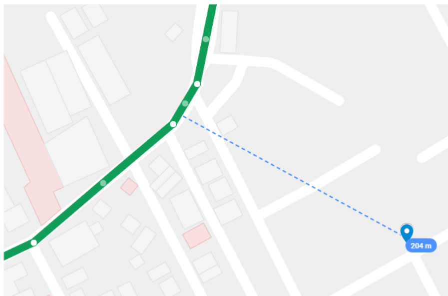

Figure 2. Important place mismatch by street name

balanced car and a simple friction model between the road and the car tires. As result, the relationship of acceleration and road friction was obtained according to (1), where a is the acceleration, μ is the road friction and g is the gravity of earth. Applying a road friction coefficient for each weather condition (1) it was possible to obtain the acceleration reduction factor for each one of them, respectively.

TABLE V. WEATHER IMPACT OVER DRIVER ACCELERATION

Weather	Friction	Reduction factor
Dry weather	0.85	-
Drizzle	0.80	6%
Light rain	0.7	18%
Moderate rain	0.6	29%
Heavy intensity rain	0.5	41%
Very heavy rain	0.4	53%

$$a = g\mu/2 \tag{1}$$

Finally, as last semantic enrichment, a search for important places is performed in order to identify buildings which require speed reduction. An external service from Google [16] is used to retrieve important places near to a specific coordinate. These important places include schools, universities, hospitals, and health care institutions. Once an important place is found within a circular area of 1 km radius distance from driver's current position, the maximum speed is reduced to 30 km/h ever.

To indeed consider a found important place as a speed limit reducer, the important place must be on the same road where the driver is traveling. One example of such situation is presented in Figure 2. This is ensured by matching the driver's current street name and the name of the street where each one of the found important places is located.

D. Aggressiveness Evaluation

The evaluation phase calculates the aggressiveness indicator using speed and acceleration values combined with the semantic enrichment done previously. The indicator varies from 0 to 100 where 0 means no aggressivety and 100 high aggressivety. Currently, the method considers BTC definitions to obtain the indicator, but it can be configured to any other country and laws. In the same way, BTC increases the fine according to the level of the transit violation, the method applies stronger weights to highlight the driver aggressiveness. Those weights were defined considering BTC rules and adjusted using hit and try over real trajectories. Table VI presents weights for speed violations and Table VII presents weights to acceleration categories.

TABLE VI. WEIGHT ACCORDING TO SPEED BEHAVIOR

	Speed behavior	Weight
1	Under speed limit	0
2	Up to 20% over the limit	1.5
3	From 20% to 50% over the limit	3.0
4	Over 50% over the limit	5.0

TABLE VII. WEIGHT ACCORDING TO ACCELERATION BEHAVIOR

	Acceleration Type	Weight
1	Safe	0
2	Normal	1.5
3	Aggressive	3.0
4	Dangerous	5.0

During a full trajectory, the aggressive behavior might appear occasionally. However, those specific moments are the most common situations of accidents. So, a segment indicator is obtained by the composition of two sub-indexes: exclusive aggressive index and mean index. A segment is evaluated considering speed and acceleration by calculating Segment Aggressiveness Indicator (SAI) accordingly to (2).

$$SAI = \frac{((ASEI * p_{as}) + (MSI * p_{ms}))}{2} + \frac{((AAEI * p_{aa}) + (MAI * p_{ma}))}{2} \tag{2}$$

$ASEI =$ Aggressive speed exclusive index
$MSI =$ Mean speed index
$AAEI =$ Aggressive acceleration exclusive index
$MAI =$ Mean acceleration index
$p_{as} =$ Aggressive speed percentage
$p_{ms} =$ Non aggressive speed percentage
$p_{aa} =$ Aggressive acceleration percentage
$p_{ma} =$ Non aggressive acceleration percentage

Every coordinate of a segment is evaluated individually to be classified according to speed and acceleration using classification presented in Table I and Table II.

The ASEI and MSI indexes are obtained accordingly to (3) and (4). Equation 3 discard safe values, so pa_k is the percentage k class considering only aggressive behavior, w_k is the weight of class k and avg_k the average speed of k class aggressive coordinates. On the order hand, Equation 4 considers all coordinates, so pm_k is the percentage k class and avg_k the average speed of k class coordinates.

$$ASEI = \sum_{k=2}^{4} w_k * pa_k * avg_k \tag{3}$$

$$MSI = \sum_{k=1}^{4} w_k * pm_k * avg_k \tag{4}$$

The acceleration indexes are obtained in the same way as speed. The Exclusively Acceleration Index (AAEI) is obtained by (5). The equation is composed of the sum of aggressive acceleration evaluation and the sum of aggressive deceleration. The w_k is the weight, pa_k is the percentage and avg_k is the acceleration average for class k. Similarly, (6) gives the mean acceleration evaluation.

$$AAEI = \sum_{k=1}^{3}(w_k * pa_k * avg_k) + \sum_{k=6}^{8}(w_k * pa_k * avg_k) \quad (5)$$

$$MAI = \sum_{k=1}^{8} w_k * p_k * avg_k \quad (6)$$

The Trajectory Aggressiveness Indicator (TAI), presented in (7), is composed of all segment indicators and it reflects the general behavior of a driver in a specific trajectory.

$$TAI = \frac{\sum_{i=1}^{n} SAI_i}{n} \quad (7)$$

IV. Assessment

In order to assess the proposed method, it has been collected a set of trajectories surrounding the city of Blumenau, in the so-called Itajai River Valley Area, Brazil, from February to October 2016, summing up 7.911 kilometers. Currently, the data set contains more than 2.000 hours of 10 drivers performing daily activities, such as going to work, to the gym, to restaurants and to home. However, there are also several trips in highways like BR-101 and BR-470.

Results indicate aggressiveness tendency once drivers join the roadways (max speed of 80km/h) and highways (max speed of 110km/h) with an average TAI of 36.87. Urban trajectories resulted in a lower TAI average of 17.98. This can be explained by the fact that urban roads usually prevent drivers of speeding with semaphores, heavy traffic, pedestrians and radar speeds.

The method is able to correctly identify driver aggressiveness considering external conditions like weather conditions and important places closeness. This result could be analyzed in the scenario of a trip from Governador Celso Ramos/SC/Brazil to Blumenau/SC/Brazil during a rainy day between 08:21:15 PM - 9:57:36 PM comprising $106.26km$.

The trip starts at a highway limited by 110 km/h in a light rain night. Since light rain was identified, the method applies a speed reduction factor of 18% resulting in 90.2 km/h max speed. Later, the driver join the SC-412 roadway, which is limited to 80 km/h, and thus the speed limit was reduced to 65,6 km/h. Finally, an urban area is reached and so the speed limit was reduced from 50 km/h to 41 km/h. In the same way, the acceleration limits were also reduced accordingly to Table VIII for all segments.

The aggressiveness evaluation results to a TAI of $29,91$, which can be described as a moderate aggressive driving. However, such indicator was only obtained due to the weather conditions. Otherwise, in a sunny day, the TAI would be $18,96$. So, without the weather condition enrichment, the driver would be considered a safe conductor one during this trajectory.

Table IX and Table X show in details the speed distribution and acceleration distribution, respectively. Table IX shows that without semantic enrichment 86.34% of speed coordinates would be considered safe, however considering the weather condition the safe speed coordinates reduce to 46.50%. A similar effect can be seen over acceleration, Table X presents that intermediate accelerations increased 0.62%, as well as aggressive accelerations appeared in wet road.

TABLE VIII. ACCELERATION LIMITS CHANGED BY REDUCTION FACTOR (18%)

Classification	Standard Limit	Reduced Limit (18%)
Dangerous	[-9,0 a -14,0]	[-7,38 a -11,48]
Aggressive	[-5,5 a -9,0)	[-4,51 a -7,38)
Intermediate	[-3,0 a -5,5)	[-2,46 a -4,51)
Safe	[0 a -3,0)	[0 a -2,46)
Safe	[0 a 1,5)	[0 a 1,14)
Normal	[1,5 a 3,5)	[1,23 a 2,87)
Intermediate	[3,5 a 7,0)	[2,87 a 5,74)
Dangerous	[7,0 a 12,0]	[5,74 a 9,84]

TABLE IX. SPEED DISTRIBUTION CONSIDERING WET AND DRY ROAD

Classification	% Wet road	% Dry Road
Under limit	46,50%	86,34%
Up to 10%	27,13%	8,25%
From 10% to 20%	14,78%	1,67%
From 20% to 50%	8,28%	1,31%
Over 50%	3,32%	2,43%

TABLE X. ACCELERATION DISTRIBUTION CONSIDERING WET AND DRY ROAD

Classification	% Wet Road	% Dry Road
Safe	97,65%	98,40%
Intermediate	2,22%	1,60%
Aggressive	0,13%	0%
Dangerous	0%	0%

The aggressiveness evaluation indicates that the driver rarely applies abrupt movements. However, the majority of the trajectory is performed using a considerable dangerous speed. During the trip, a maximum speed of $120.71\ km/h$ was registered while the speed average was $75.37\ km/h$. Also, few accelerations associated with risk of accidents were registered mainly on deceleration with the max of $-5.03\ m/s^2$.

Several scenarios were evaluated in details in order to assess the method accuracy in a qualitative approach. Due to space limitation, it was not possible to present all of them, but the method obtained satisfactory results considering urban trajectories, roadway trajectories and also hybrid ones.

During the assessment, it was identified some improvements and limitations that need to be addressed in further works. For instance, the road speed limit is susceptible to errors due to the lack of GPS accuracy. The impact of such errors is considerable when the algorithm has to define the speed limit by inverse geocoding. Figure 3 presents a speed limit changed from 80 km/h to 50 km/h due to an incorrect inverse geocoding query. As consequence, the segment 53 evaluated the driver behavior as very aggressive (limited at 50 km/h), although he/she was not driving aggressively in the correct street (limited at 80 km/h).

Some scenarios indicate that the segment size of 1 km should be reduced in order to obtain more accurate results. Otherwise, the verification of the important place street does not match with the driver's current street due to road changes.

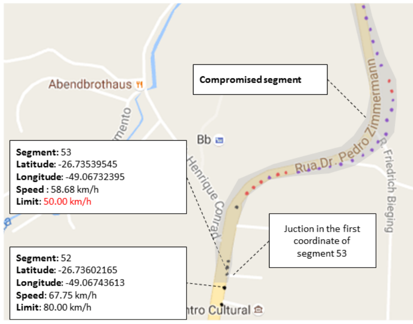

Figure 3. Junction compromising speed limit of a segment

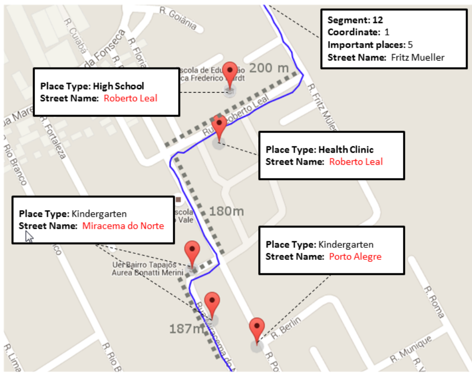

Figure 4. Five important places missed by 1 km segment using first coordinate street name

Figure 4 present this situation where the segment street name is defined by its first coordinate. However, the driver changes streets passing in front of an important place, which is placed in a different street name. The situation is ignored by the method since the segment street name and important place street name do not match.

Finally, the pre-processing phase seems to be effective but has several improvements that may be done. The DBScan cleaner is able to remove noises distant 30 meters from the core, but this is not sufficient to clean noises under such limit. To solve this situation another approach must be used since the noise under 30 meters are common on GPS devices.

V. Conclusion

This paper has presented a naturalistic driver method to identify driver's aggressive behavior. The method is composed of four steps that are capable of gather, clean, enrich and analysis the drivers' trajectories in order to identify aggressive behaviours in a near real time response. The main advantage of such method is its adaptive approach that considers environmental conditions as weather and road speed limits to better estimate the driver aggressivity indicator. This indicator varies between 0 and 100 where 0 means no aggressivity while 100 means the highest aggressivity possible. Moreover, the method can bring fast feedback to the drivers about their aggressive behaviours on specific situations and can help them to change habits in order to avoid accidents.

Another contribution is that the aggressivity indicator might be adapted according to every demand. This approach might be useful to transportation companies willing to improve the safety of their drivers. Moreover, identifying aggressive drivers allow insurance companies to offer discounts accordingly to every driver profile.

Although the proposed method is already under experimental usage, several improvements are possible. For instance, abrupt movements like passing or crossing lanes are no considered yet and can be added in future works. Another improvement might be explored information available for other sensors from the smartphone such as accelerometer. Finally, it is also important to conduct a massive evaluation to improve weather reduction values based on real data.

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