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Driver feedback mobile app

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Abstract

This paper faces the human factor in driving and its consequences for road safety. It presents the concepts behind the development of a smartphone app capable of evaluating drivers' performance. The app provides feedback to the driver in terms of a grade (between 0 and 10) depending on the aggressiveness and risks taken while driving. These are computed from the cumulative probability distribution function of the jerks (i.e. the time derivative of acceleration), which are measured using the smartphones' accelerometer. Different driving contexts (e.g. urban, freeway, congestion, etc.) are identified applying cluster analysis to the measurements, and treated independently. Using regression analysis, the aggressiveness indicator is related to the drivers' safety records and to the probability of having an accident, through the standard DBQ - Driving Behavior Questionnaire. Results from a very limited pilot test show a strong correlation between the 99th percentile of the jerk measurements and the DBQ results. A linear model is fitted. This allows quantifying the safe driving behavior only from smartphone measurements. Finally, this indicator is translated into a normalized grade and feedback to the driver. This feedback will challenge the driver to train and to improve his performance. The phone will be blocked while driving and will incorporate mechanisms to prevent bad practices, like competition in aggressive driving. The app is intended to contribute to the improvement of road safety, one of the major public health problems, by tackling the human factor which is the trigger of the vast majority of traffic accidents. Making explicit and quantifying risky behaviors is the first step towards a safer driving.

Keywords: Road safety; driving aggressiveness; driver feedback; smartphone app; driving performance.

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1. Introduction and objectives

Although declining in the recent past, the number of deaths as a result of road accidents is still one of the major public health problems in developed countries. Besides, accident rates for motorcycles are not following the general trends of road safety progress (see CARE, 2011), with the aggravating factor that motorcycle fleet is experiencing a huge increase (+22% over the period 2002-2007 as reported by the Association of European Motorcycle Manufacturers - ACEM). This situation urges to an increased effort for improving road safety with special consideration of motorcyclists.

Research efforts on road safety have been concentrated on infrastructures and vehicles. In spite of this, in over 90% of the cases the human behavior is the trigger of traffic accidents, as reported by SCT (2014). Scientific literature aimed to understand drivers' behavior is scarce, as pointed out by Chesham et al. (1993) or 2BESAFE (2011), and even more if one focuses on motorbike riders. The reason for this gap in the literature lies in the difficulties encountered in the scientific analysis of driver behavior. Challenges are technical, but also economical, due to the required instrumentation of a large number of vehicles in order to enable data collection on-road.

Understanding drivers' behavior is essential for the improvement of road safety. The design of relevant countermeasures for safety improvement, or the definition of the training curriculum in order to obtain the driving permit, must be based upon scientific evidences on driver behavior. Also external and objective feedback is needed by the driver in order to improve his driving skills. In fact, the lack of feedback to the driver is one of the main problems regarding the driving performance. For instance, Walton and Barthurst (1998) show that the vast majority of drivers consider their own driving skills better than average, regardless of their driving records. This is what psychologists call "optimistic bias". Even the circumstances when the driver is about to have an accident are perceived as proves of the ability at the steering wheel. This driving narcissism encourages an aggressive behavior as reported in Vanderbilt (2009).

This does not mean that drivers are unaware of the risks of driving. However, an overestimation of the social risks and an underestimation of individual risks occur. This means, for example, that while every individual driver is in favor of banning the use of mobile phones while driving, everyone uses them (see NHTSA (2007) for an interesting analysis of this phenomenon in relation to safety seat belts). It is common the idea that "it is the behavior of others that should be controlled, not mine". A similar phenomenon occurs in relation to the use of public transport.

Many drivers have driving habits with high accident probability without being aware of it, at all. One could be a bad driver for years without ever knowing it. Furthermore, a bad driver will not be in the best position to assess their own risk while driving. External feedback is needed. Currently, the feedback available to drivers is limited to the traffic tickets, the withdrawal of points in the driving license, and to the accidents suffered. Very often, drivers do not consider this feedback as objective. For instance, the driver may attribute traffic tickets to the bad character of the police officer "that needs to fine in order to meet his quota" and accidents to "external conditions" or "pure bad luck." Since most trips end without tickets or accidents, the idea that every day we are better drivers is reinforced.

Manuele (2003) postulates that this occurs because the feedback is limited to elements close to the apex of Heinrich's pyramid, composed of serious but rare events. Heinrich's pyramid is nothing more than a classification based on accident frequency and severity (see Figure 1). Heinrich proved that the key element to avoid the serious and less frequent events in the upper zone lies in the reducing the vast number of small events in the pyramid's base. This view is diametrically opposed to the concept of "accident" which implicitly covers all the negligent behaviors. The reality is that road accidents (i.e. the apex of the pyramid) do not happen by unpredictable laws, but by the fact that drivers routinely drive in a way (i.e. base of the pyramid) so that accidents become inevitable.

One of the first and only initiatives to increase the driver feedback was led by commercial vehicle fleets with slogans such as "Tell me how I drive" painted in the vehicle along with a phone number. However, in these examples the feedback comes late, it is of dubious quality, and it is biased towards the negative elements. Both, tools to provide feedback to the driver and scientific literature on the topic, are extremely limited.

In light of this background, the approach proposed in this paper consists on the development of a tool capable of monitoring the driver performance and to provide him with feedback. The conceptual framework behind this approach lies in the external "recording" of the driving activity in order to show to the driver things he is not aware of. Similarly as it is done in the learning of multiple sports, like swimming, tennis, golf... The obtained "driving grade" will also create a reputation system (indicator in relation to the mean) that human nature tends to maximize. Moreover, by

simply participating in an "experiment" the driver modifies his behavior trying to beat the system. This is called the Hawthorne effect in EMS Insider (2004). Knowing it or not, drivers will drive safer.
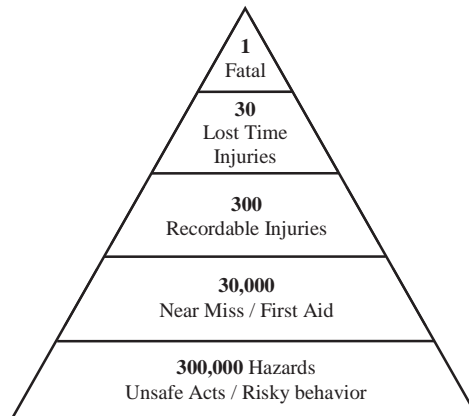

Fig. 1. An illustration of Heinrich's theory: The safety pyramid.

The tool will describe the driver performance, in terms of safe driving, with a quantitative indicator (i.e. a grade) and represent him in relation to the average driver (e.g. achieved percentile of the distribution of grades). A relationship between the obtained grade and the historical records of the driver (i.e. accidents or near accidents, traffic tickets, etc.) will be established in order to empirically relate the safety indicator with the risks faced and with the probability of an accident. The results of the measurements and model are translated into an easily understandable grade between 0 and 10, so that the final output will be a clear and objective feedback from which the driver can improve his safety on the road.

The tool (i.e. the instrumentation of the vehicle) should be minimal, economical, and adaptable to both, cars and motorbikes. Previous research on naturalistic driving studies have been undertaken with ad-hoc fully instrumented vehicles (see SHRP2 (2011) for a literature review), which implied very limited data samples. Here, the monitoring of drivers' performance will use their own smartphones. These fulfill all the technical requirements, and are ready available, waiting in the vast majority of travelling vehicles. The monitoring tool (i.e. the smartphone app) is designed so that it can be used by motorcyclists, a particularly vulnerable group experiencing worsening accident trends.

The rest of the paper is organized as follows. In Section 2 the methodology used to compute the grade is presented. This includes the identification of the driving context, the computation of the aggressiveness indicator from jerk measurements, and its relation to safe driving through the DBQ - Driving Behavior Questionnaire. Next, in Section 3 a very limited pilot test, with only 7 drivers, is presented. This is only intended to illustrate the application of the methodology. A more extensive test would be needed in order to derive robust results. Finally, in Section 4 some conclusions and directions for further research are outlined.

2. Methodology

Currently, most smartphones can register position and speed (with GPS accuracy). Also, the three component acceleration vector (from the internal accelerometer), rotation angles (pitch, roll and yaw) and rotational speed (from the internal gyroscope) can be measured. It is also possible to select the time averaging interval, reaching a maximum discretization of 0.02s (50Hz). These will be the input data.

The methodology used in order to compute the safe driving indicator from these raw measurements, is divided into three steps. First, the driving context is established. The dynamics of motion (i.e. speeds, acceleration and jerks) and their impacts on traffic safety are different depending on the driving context (e.g. urban vs freeway driving). Second, the indicator needs to be computed from the smartphone raw measurements. And third, this indicator needs to be related with the safe driving behavior. This third step is accomplished by relating the quantitative value of the indicator

with the qualitative drivers' behavior and their historical records in terms of safe driving. The Driver Behavior Questionnaire (DBQ) widely used in the study of drivers' psychology as proposed in Parker et al. (1995) or Zapf and Reason (1994) is used to this end.

2.1. Establishing the driving context

The proposed methodology establishes the driving context (e.g. urban, freeway, congested, rural road driving, etc.) using only the smartphone measurements, without any additional parameter or source of information. This avoids the complexity of using external infrastructures' cartography and other sources of real time traffic information.

Two variables are used in order to establish the driving context: the average moving speed, "$\bar{V}$", (i.e. only considering speeds above a minimum speed threshold, "V_{min}", below which the vehicle is considered to be stopped), and the portion of time stopped "P_s". Both variables are computed from raw GPS measurements with a frequency "τ", and averaged over a time interval "Δt". In the pilot test presented in Section 3 these parameters take the values of "$\tau = 0.1s\ (10Hz)$", "$\Delta t = 5\ min$", and "$V_{min} = 2\ km/h$".

Finally, the "$(\bar{V}, P_s)$" data points are grouped into homogeneous patterns using cluster analysis. Cluster analysis is a technique used to classify objects in homogeneous groups, called clusters (see Anderberg (1973) for a complete description of the cluster analysis method). Agglomerative hierarchical clustering is used here.

2.2. Monitoring driving behavior: The tool and definition of the indicator

Smartphones are equipped with an internal accelerometer. This provides measurements of the acceleration vector, in relation to the phone coordinate axis. From acceleration data, the jerk (i.e. the derivative of acceleration with respect to time, also called "surge") can be estimated. The jerk is a physics measurement considered to describe the aggressiveness in movement. Using the central differences method to compute the time derivative from discrete data points, the three components of the jerk vector (i.e. longitudinal, transversal and vertical jerks) with respect to the smartphone orientation, are obtained. However, the longitudinal and lateral jerks with respect to the direction of movement are the ones needed. Therefore, the smartphone coordinate axis need to be reoriented with respect to the movement. One option could be to pre-orientate the smartphone in the vehicle, so that the coordinate axis of the smartphone and the vehicle coincide. This solution would invalidate the use of the app in motorcycles where the orientation of the vehicle is variable with the movement. In order to solve this, auto-calibration of the smartphone's coordinate axis is needed.

The experimental jerk data (presented in Section 3) reveal a useful property to achieve the auto-calibration. Jerk vectors are characterized by a primal variance direction. In other words, the hull of all jerk vectors is an ellipsoid of revolution (see Figure 2). A Principal Component Analysis (PCA) applied to the (x, y, z) jerk vectors, determines that the direction of maximum variance always correspond to the direction perpendicular to the ground. This has been tested in many random positions of the smartphone, always with consistent results.

This property allows the reorientation of the jerk vector considering time intervals long enough to construct the ellipsoid of data. The selection of the time interval, "Δt", responds to a trade-off. On the one hand it should be long enough in order to accurately define the ellipsoid of revolution (at least 2-3 minutes). On the other hand, it should not extend to more than one driving context, and therefore needs to be short. "$\Delta t = 5\ min$" has been selected, so that each sample include 3000 measurements (i.e. 5 min at 10 Hz). This selection allows obtaining an ellipsoidal shape with precision and also to identify univocally one driving context.

The main drawback of the method is that the longitudinal direction "x" cannot be differentiated from the transversal direction "y", and therefore "acceleration-braking" jerks cannot be isolated from "cornering" jerks. Only the "x-y" plane, parallel to the ground, can be identified. In spite of this, the jerk projection on the "x-y" plane is approximately circular (see Figure 2) implying similar magnitudes of these two jerk components. This means that the modulus of the jerk projection on the "x-y" plane could be a good indicator of the driving aggressiveness.

Figure 3 shows the cumulative distribution function (cdf) of the jerk measurements of three driving samples. Note that, from now on, by "jerk measurement" it is meant the modulus of the jerk projections on the "x-y" plane. These observations correspond to the same driver, travelling on the same route, but in a markedly calmed, medium-aggressive and aggressive driving. The three cdf's worthily distinguish each driving behavior.
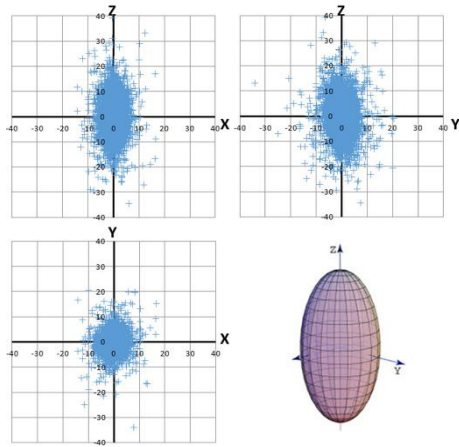
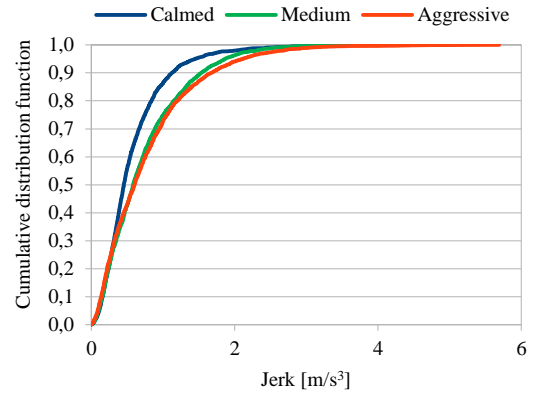Fig. 2. Jerk projections on coordinate planes in units of [dm/s³]

Fig. 3. Cumulative distribution function (cdf) of the jerk measurements of three driving samples

An indicator of aggressiveness (i.e. one value or a vector with different components) needs to be derived from the jerk's cdf. This selection should allow an easy identification of different aggressiveness patterns and clearly relate it to unsafe driving behavior. The mean jerk is an option. But probably, unsafe driving is more related to extreme jerks. Therefore, extreme value indicators, like the 99th, 95th, 90th or 85th percentiles, will probably perform better. The maximum jerk is discarded as an indicator because of its poor robustness, being largely affected by measurement errors.

2.3. Relating aggressiveness with safe driving

Safe driving behavior is established through surveying. The approach is based on the Driver Behavior Questionnaire (DBQ) as proposed in Parker et al. (1995), widely used in the study of driving psychology. According to Zapf and Reason (1994) the aim of this survey is to define a "theoretical classification of abnormal driving behaviors" through different types of factors. These include errors of action (i.e. Errors and lapses. The error in the translation between drivers' intention and their action due to the limited human capacity to treat and process huge amounts of data) and errors of intention (i.e. Mistakes and violations. The driver doing the wrong thing on purpose, either due to a mistake or due to a deliberate offense to traffic law).

Recently, Helman and Reed (2015) and Rowe et al. (2015) confirm the role of the DBQ survey as a valid measure of observed behavior in real driving and postulate that factors of the DBQ were significant independent predictors of crash involvement. The most common version of the DBQ has been used in the present research, consisting of 28 questions. The DBQ index is simply the mean of the grades (between 1 and 4) obtained. To establish the relationship between the DBQ indexes, obtained through the survey, and the indicator of the aggressiveness, obtained experimentally from the jerk measurements, multiple linear regression analysis is used. Results from this analysis provide a mathematical function that allows obtaining the DBQ index from the aggressiveness indicator. This derived DBQ index, suitably normalized between 0 and 10, will act as the safe driving grade that will provide feedback to the driver.

3. Pilot test and results

3.1. Experiment design

In order to test and calibrate the methodology, a pilot test was performed. The experiment required two activities for each participant: i) record his driving activity with the drivers' feedback mobile app, and ii) answer the DBQ

survey. The pilot was limited to car and motorbike drivers. A total of 7 drivers participated in the pilot test (6 men and 1 woman; 4 car and 3 motorcycle drivers). The age range was between 26 and 57 years old, being 35 the average. The average driving experience was 14 years, and their driving activity was related to both, commuting to work and leisure activities. Most of them have been involved in an accident in their driving life.

The data collection lasted two months, between March and April 2015. A total of 88 complete and valid intervals of 5 min. were recorded. "$\tau = 0.1s$" was selected as the time interval between measurements. The valid measurements implied a total length of approximately 305 km with an average speed of 41.63 km/h.

3.2. Driving contexts identification

In order to establish the driving contexts, the previous sample size was extended including authors' own driving measurements, using both motorcycle and car. This allowed achieving 469 samples "$(\bar{V}, P_s)$" averaged over 5 minutes. This means more than 39 hours of recording. Hierarchical clustering using the centroid method with Euclidean distance was applied. A grouping with 4 clusters was selected (see Table 1 and Figure 4).
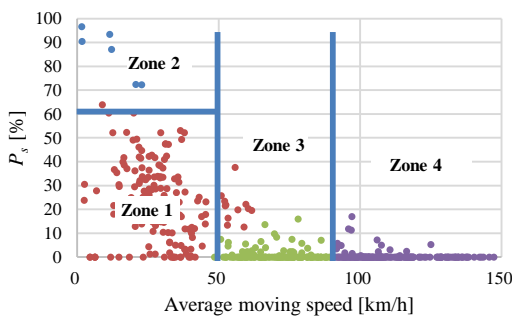

Fig. 4. Driving context identification.

Table 1. Boundaries of the different driving contexts.

Zone 1: $\bar{V}$<50km/h, P_s <60%; (Urban)	**Zone 3:** 50km/h<$\bar{V}$<90km/h; (Conventional roads/main arterials)
Zone 2: $\bar{V}$<50km/h, P_s >60%; (Congested)	**Zone 4:** $\bar{V}$>90km/h; (Freeway)

3.3. Driving aggressiveness indicator and DBQ results

Tables 2 and 3 summarize the Driving Aggressiveness Indicator, for car and motorbike drivers respectively. These are obtained from the cdf of the jerk measurements in each driving context. The DBQ results for each driver are also shown in the same tables. Cells are colored according to the magnitude of its value, in order to illustrate the existing correlation between the aggressiveness indicator and the DBQ results.

Table 2. Car drivers' pilot test measurements.

Z1	Jerk%85	Jerk%90	Jerk%95	Jerk%99	Mean	Mistakes	Lapses	Aggressive Violation	Rule Violation	Errors of Action	Deliberate Violations	DBQ Index
D1	0.824	0.969	1.186	1.735	0.460	1.13	1.25	1.00	1.33	1.19	1.17	1.18
D2	0.702	0.824	1.041	1.730	0.426	1.00	1.13	1.17	1.50	1.06	1.33	1.18
D3	0.769	0.969	1.365	2.730	0.441	1.67	1.33	1.00	2.00	1.50	1.50	1.50
D4	1.812	2.155	2.722	4.663	1.092	1.38	1.63	1.17	2.17	1.50	1.67	1.57
Z2	Jerk%85	Jerk%90	Jerk%95	Jerk%99	Mean	Mistakes	Lapses	Aggressive Violation	Rule Violation	Errors of Action	Deliberate Violations	DBQ Index
D2	0.656	0.808	1.079	1.741	0.334	1.00	1.13	1.17	1.50	1.06	1.33	1.18
D3	0.618	0.789	1.013	1.592	0.324	1.67	1.33	1.00	2.00	1.50	1.50	1.50
Z3	Jerk%85	Jerk%90	Jerk%95	Jerk%99	Mean	Mistakes	Lapses	Aggressive Violation	Rule Violation	Errors of Action	Deliberate Violations	DBQ Index
D1	0.967	1.094	1.282	1.728	0.623	1.13	1.25	1.00	1.33	1.19	1.17	1.18
D2	0.732	0.826	1.000	1.456	0.460	1.00	1.13	1.17	1.50	1.06	1.33	1.18
D3	0.715	0.838	1.073	1.731	0.425	1.67	1.33	1.00	2.00	1.50	1.50	1.50
D4	2.129	2.486	3.109	4.807	1.307	1.38	1.63	1.17	2.17	1.50	1.67	1.57
Z4	Jerk%85	Jerk%90	Jerk%95	Jerk%99	Mead	Mistakes	Lapses	Aggressive Violation	Rule Violation	Errors of Action	Deliberate Violations	DBQ Index
D2	0.818	0.910	1.078	1.487	0.522	1.00	1.13	1.17	1.50	1.06	1.33	1.18
D4	3.044	3.400	4.131	5.856	1.942	1.38	1.63	1.17	2.17	1.50	1.67	1.57

Table 3. Motorbike drivers' pilot test measurements.

Z1	Jerk%85	Jerk%90	Jerk%95	Jerk%99	Mean		Mistakes	Lapses	Aggressive Violation	Rule Violation	Errors of Action	Deliberate Violations	DBQ Index
D5	0.850	1.053	1.441	2.464	0.462		2.00	2.00	1.33	1.67	2.00	1.50	1.75
D6	0.626	0.766	1.046	1.764	0.368		1.33	1.33	2.67	2.00	1.33	2.33	1.83
D7	0.152	0.222	0.350	0.783	0.090		1.00	1.00	1.00	1.67	1.00	1.33	1.17
Z3	Jerk%85	Jerk%90	Jerk%95	Jerk%99	Mean		Mistakes	Lapses	Aggressive Violation	Rule Violation	Errors of Action	Deliberate Violations	DBQ Index
D6	0.850	1.053	1.441	2.464	0.462		1.33	1.33	2.67	2.00	1.33	2.33	1.83
Z4	Jerk%85	Jerk%90	Jerk%95	Jerk%99	Mean		Mistakes	Lapses	Aggressive Violation	Rule Violation	Errors of Action	Deliberate Violations	DBQ Index
D6	0.684	0.772	0.933	1.315	0.435		1.33	1.33	2.67	2.00	1.33	2.33	1.83

3.4. Driver feedback grade

With this extremely small sample size, little more than qualitatively suspecting the existence of correlation can be done. In spite of this, and only to illustrate the complete application of the methodology, linear regression analysis was performed in some of the contexts (see Table 4). Statistical robustness and significance of results are, of course, neglected. Despite these limitations, it was found that the best aggressiveness indicator is the 99th percentile of the jerks' measurements (i.e. "j_{99th}"). Therefore, the proposed regression model is of the form:

$$DBQ = A + B \cdot j_{99th} \tag{1}$$

Table 4. Linear regression analysis.

Driving Context	Type of vehicle	A (intercept)	B (coefficient)	R^2
Zone 1	Car	0.995	0.134	0.80
Zone 3	Car	1.132	0.093	0.51
Zone 1	Motorbike	0.972	0.366	0.74

Finally, the model is applied to the pilot drivers and normalized to values between 0 and 10, obtaining the feedback grades shown in Table 5.

Table 5. Feedback grades in the pilot test.

Car Driver	Grade	Motorbike Driver	Grade
D1	9,1	D5	7,1
D2	9,2	D6	7,9
D3	8,9	D7	9,1
D4	8,0		

4. Conclusions

One of the main problems regarding driving performance is the lack of feedback to the driver. This paper addresses the methodology behind a smartphone app that provides feedback to the driver in terms of a safe driving grade. The methodology is generic and can be used in any smartphone platform, provided that accelerometer and GPS measurements are available. No other source of information is needed. Aggressive and risky driving behavior is established by computing the jerk cumulative distribution function (cdf). This is related to safe driving by regression analysis with respect to the results of the DBQ (i.e. the Driving Behavior Questionnaire). A pilot test of the methodology allowed identifying four different driving contexts (i.e. urban, congested, conventional road/main arterial and freeway), and calibrating the correlation between the 99th percentile of the jerks' cdf and the DBQ results in some of them. The small sample size of the pilot test, with only 7 drivers, prevents any kind of statistical significance of the data presented herein. The feedback grades for the 7 drivers are only obtained for illustrative purposes.

The presented method needs to be refined. Further research will include looking for solutions that eliminate the need of using GPS data. This would reduce significantly the smartphones' battery consumption. An extensive pilot test would be necessary to establish robust correlation models between the jerks' cdf and the DBQ results. Finally, a method for normalizing the obtained grades, accounting for possible bias in the answers to the survey needs also to be investigated.

The ultimate objective of the driver feedback app is to ease the drivers' learning and self-assessment, so that they can gradually improve their performance and monitor the evolution. This will have an effect on the human factor in driving, the main cause of traffic accidents, avoiding near accident situations and finally, reducing accident rates. Other applications and sub products are also possible. These might include the establishment of detailed cause-effect relationships between aggressive driving and the associated risk, valuable information in order to improve road safety as well as for insurance companies, applications for vehicle fleet management, geolocation of dangerous spots in a road network or as a tool for objective proving driving behavior, in order to qualify for premiums in vehicle insurances or for being retrieved the driving license after a revocation.

Acknowledgements

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