Traffic Expression through Ubiquitous and Pervasive Sensorization

Smart Cities and Assessment of Driving Behaviour

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Abstract: The number of portable and wearable devices has been increasing in the population of most developed countries. Meanwhile, the capacity to monitor and register not only data about people's habits and locations but also more complex data such as intensity and strength of movements has created an opportunity to their contribution to the general wealth and sustainability of environments. Ambient Intelligence and Intelligent Decision Making processes can benefit from the knowledge gathered by these devices to improve decisions on everyday tasks such as planning navigation routes by car, bicycle or other means of transportation and avoiding route perils. Current applications in this area demonstrate the usefulness of real time system that inform the user of conditions in the surrounding area. Nevertheless, the approach in this work aims to describe models and approaches to automatically identify current states of traffic inside cities and relate such information with knowledge obtained from historical data recovered by ubiquitous and pervasive devices. Such objective is delivered by analysing real time contributions from those devices and identifying hazardous situations and problematic sites under defined criteria that has significant influence towards user well-being, economic and environmental aspects, as defined is the sustainability definition.

1 INTRODUCTION

Ambient Intelligence (AmI) is a very active area of knowledge and constitutes a multi-disciplinary subject which takes advantage of advances in sensing systems, pervasive devices, context recognition and communications. Nowadays, AmI applications can be found in fields ranging from home, office, transport, tourism, recommender and safety systems, among many others (Sadri, 2011). There is also a renewed concern towards the quality of living and well-being inside great cities. It is forecasted that most people will be living inside cities until 2050. If true, such statement would predict the increase of road traffic in cities that were neither originally designed nor prepared to handle such influxes of traffic. Current identification systems compromise direct evaluation and costly field studies to assess and evaluate the impact of the flux of traffic in certain cities. Additionally, simulation experiments provide possible scenarios under which some assessment can be made. However, the downside of simulations is the use of simplified models that are thought to mimic reality when in fact they may differ to some degree. Even more, the accuracy of these simulations is made by measuring the current state which in itself can include measurement errors and possible virtual scenarios under the realistic behaviours.

Ubiquitous Sensorization may be used to assess current traffic conditions, avoiding the use of costly field studies. The nature of those ubiquitous devices enables the possibility of direct analysis of driver behaviour and community habits (points of congestion, high speed areas and hazardous corners) assessed trough the statistical treatment of driving records. Such model has a direct impact diagnosing the current state of traffic and traffic behaviours to each route that may be used in modern GPS navigation systems as an additional parameter.

Approaches to real time safety assessment can be found in the research community, for instance in (Laureshyn, Svensson, and Hydén, 2010) and (Minderhoud and Bovy, 2001) a set of indicators is used to assess driving safety through the use of indicators. Such indicators take into consideration time of reaction, vehicle breaking time and whether or not there is a collision course. Yet, the analysis is still in real time, local to the surrounding area and activities such as identification of other vehicles within the nearby visible space. These capabilities are produced with the help of video interfaces and

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disregards other sources of information.

In the case of transport applications, an area also known as Smart Cars the AmI system must be aware of not only the car situation, but also the driver's intention, his physical and physiological conditions and the best way to deal with them (Rakotonirainy and Tay, 2004). The driver's behaviour is, thus, of key importance. Some authors have used machine learning and dynamical graphical models for modelling and recognizing driver's behaviours (Sun, Wu, and Pan, 2009). Examples of applications integrating AmI and ubiquitous principles in driving and traffic analysis were already purposed in the literature. In (Li et al., 2012), it is described a monitoring and analysis system to approach personalized driving behaviour, for emerging hybrid vehicles. The system is fully automated, non-intrusive with multi-modality sensing, based on smartphones. The application runs while driving and it will present personalized quantitative information of the driver's specific driving behaviour.

The quality of devices used to perform monitoring has a direct relationship to the quality of measurements, thus, in this case, they are the main source of measurement error which needs to be controlled and contained to known values of error in order to make this study effective to production use.

Other advantages include the possibility to increase information quality and create new routing algorithms in existing navigation systems taking into consideration aspects such as driver’s driving style or hazardous event rate during the routing and planning phase.

In (Paefgen, Kehr, Zhai, and Michahelles, 2012) a mobile application assesses driving behaviour, based on critical driving events, giving feedback to the driver. The Nericell system (Mohan, Padmanabhan, and Ramjee, 2008), from Microsoft Research, monitors road and traffic conditions using the driver’s smartphone and corresponding incorporated sensors, but it can also detect honking levels and potholes on roads. The I-VAITS project (Rakotonirainy and Tay, 2004) is an example that pretends to assist the driver appropriately and unobtrusively, analysing real-time data from the environment, from the car and from the driver itself, by the way the driver uses the different elements of the car, their movements or image processing of their face expressions. In (Bosse, Hoogendoorn, Klein, and Treur, 2008), in the context of a car safety support system, an ambient agent-based model for a car driver behaviour assessment is presented. The system uses sensors to periodically obtain information about the driver's steering operation and the focus of the driver's gaze. In the case of abnormal steering operation and unfocused gaze, the system launches proceedings in order to slow down, stop the car and lock the ignition.

In what refers to devices used, there are today a wide range of options that can be used. The most effective should be devices that are always present and can perform complex tasks while not requiring user’s direct attention. In such list, there are devices like smartphones, smartwatches, and intelligent wristbands. Those offer the advantage of accompanying user from one situation to another, but there are devices that can be used that are situation and local specific such as the internal computer of a car. In this last case the object itself becomes part of the car which might increase its production cost while on the other hand multi-purpose portable devices suffice to the work described.

Another important subject in these studies is the preservation of privacy, which may matter in order to make user trust the system. Privacy concerns can be included in many steps from the information collection and protection to the disclosure of aggregated information. Framework have been proposed in the literature to raise awareness to the potential causes that impair privacy. Martínez-Ballesté et. al (Martinez-Balleste, Perez-martinez, and Solanas, 2013) discusses a five dimensional framework to handle privacy which can be applied these projects. In this study, privacy concerns the identity of users, their queries in the system, their location, their footprint generated by sensors and the information they own. In the study portrayed in this article, privacy disclosure is maintained locally to the device the user holds and in the central server requires user’s token to access is own information. Aggregated results are disclosed coupled with different user and with no reference to user, location or records used. Though privacy issues are being addressed, as stated in the literature, in order to ensure privacy it is felt the need of a minimum community users which have to have overlapping routines to mask their own habits statistically.

2 TRAFFIC ASSESSMENT

Traffic assessment is directly related to trending topics such as smart cities and sustainable services. It is an increasing concern not only the quality of life of people inside big cities with millions of inhabitants but also its sustainability. Such concern has already derived the construction of sustainable development indicators and sustainable indicators that directly target this theme.

2.1 Road Traffic Analysis

2.1.1 Slow and Congested Sites

The definition of congested sites refers places in which traffic flow becomes affect by the overflow of cars that affect negatively usability of such roads to a point where the movement and flow becomes much slower than the norm of is even stopped.

Aside from the stressful environment the concentration of pollution gases in traffic jam can be a negative influence for one's health. The identification of traffic jams, and more importantly their avoidance can help mitigate its influence over the social dimension of sustainable driving. With the advent of the paradigm Smart Cities, health has become one of the topics of concern (Solanas et al., 2014). Smart assumption with information from vehicle configuration, speed and fuel can be used to grossly estimate the gas emissions to the atmosphere. Toxic emissions from vehicle exhaust fumes can be tracked both by the number of vehicles identified in a certain area and by the time the vehicle is present in such area. This can also be used to monitor air quality, even if grossly, it can give meaningful information to healthcare frameworks and help raise awareness for such problems in mobility and city planning.

2.1.2 Dangerous and Hazardous Routes

There are different approaches to identify hazardous routes or places. Depending on the approach results may vary which indicates that the analysis and classification of this parameter can become complex and include coverage problems, where the definition and identification process might miss classes of spots due to incomplete definition or incomplete detection systems.

Traditional approaches consider the number of accidents or the number of fines issued. In this case, they fail to identify situations like preponderance to aggressive driving, dangerous events such as high variance in velocity in short periods of time or dangerous maneuverers like high speed cornering sudden near full or full stops.

2.2 Driving Analysis

2.2.1 Driving Profiles

The usage of roads can be affected by driver's driving patterns. It is accepted that, if the majority of drivers have a predisposition to drive more aggressively in certain areas than others, then those areas are more dangerous. Our approach uses this thought to gather the driving records from a community of users and use them to calculate potential hazardous spots inside cities. Most evaluations are made using standard driving attributes, matured in the literature over a number of studies across different authors and projects. Thus, the list of most used attributes is:

- Time
- Average velocity
- Standard deviations of velocity
- Number of breaks
- Standard deviations of breaks
- Number of accelerations

With those measures, a complete profile can be designed and executed in applications that monitor current driver's performance. In (Ericsson, 2001), (Ericsson, 2000) other parameters were used to collect data from ordinary drivers in real traffic situations, such as wheel rotation, engine speed, ambient temperature, use of breaks and fuel consumption. In these studies, GPS data was also monitored, where each driving pattern was attributed to street type, street function, street width, traffic flow and codes for location in the city (central, semi-central, peripheral). It was concluded that the street type had the most influence on the driving pattern. The analysis of the 62 primary calculated parameters, resulted in 16 independent driving pattern factors, each describing a certain dimension of the driving pattern. When investigating the effect of the independent driving pattern factors on exhaust emissions, and on fuel consumption, it was found that there already studies with a common number of factors amongst the literature. As seen on table 1, there some studies across time that share the same factors.

Due to the decision to implement a pervasive system over mobile sensorizaion the work here described will account the attributes that are able to be collected by smartphone applications.

While these attributes characterize driving in a long term analysis, such strategy might miss spontaneous events that occur sporadically. An example of such is a sudden break with high intensity. In order to deal with these one-off events, other attributes are of relevance:

- Force exerted in the car
- Slope of the line connecting initial to final velocity during breaking and accelerating events

- Degree of the curvature of the road and force exacted in the car

Table 1: Attribute Study.

Attribute	Study References
Fuel Consumption	(Ericsson, 2001); (Mohan et al., 2008); (Kuhler and Karstens, 1978)
Velocity	(Ericsson, 2001); (Mohan et al., 2008); (Kuhler and Karstens, 1978); (Johnson and Trivedi, 2011)
Acceleration	(Ericsson, 2001); (Mohan et al., 2008); (Kuhler and Karstens, 1978); (Johnson and Trivedi, 2011)
Street Type	(Ericsson, 2001); (Mohan et al., 2008); (Kuhler and Karstens, 1978)
Trip Duration	(Ericsson, 2001); (Mohan et al., 2008); (Kuhler and Karstens, 1978); (Johnson and Trivedi, 2011)
Wheel Rotation	(Ericsson, 2001); (Kuhler and Karstens, 1978)
Motor Monitoring	(Ericsson, 2001); (Kuhler and Karstens, 1978)
Hour of day	(Ericsson, 2001); (Mohan et al., 2008); (Kuhler and Karstens, 1978); (Johnson and Trivedi, 2011)

This kind of analysis is only possible with a dedicated user community that constantly updates and makes use of the platform supporting these models. With the general availability of internet of things and the advent of portable and wearable devices with the ability to sense and store user locations, speed, gravitational force, sound and force among some examples.

2.2.2 Context Awareness

Aside from driving study, another complex analysis can be made with the help of context conditions. Such conditions include weather, traffic congestion and time of day, for instance. Each example can have significant influence on the safety and on the assessment of attributes related to driving. Aggressiveness and dangerous behaviour has different meanings in any of these conditions and while some concepts are broad enough to be used by all, others are situation specific meaning that what is dangerous in one situation might not be in another.

Usually, driving pattern is defined and associated to the speed profile of the driver, but it can be expanded to other variables, as gear changing, and big changes on the acceleration (Ericsson, 2001). In 1978, Kuhler and Karstens (Kuhler and Karstens, 1978) introduced a set of ten driving pattern parameters. Later, in 1996, André (André, 1996) reviewed those parameters, and reviewed some of the most common parameters such as action duration, speed, acceleration, idle periods and number of stops per kilometre. Experiments with communities are often used to provide real time analysis of geographic conditions and events, with examples of such in the Waze platform (Waze Ltd, 2014). However, they are the lacking features of historic analysis and historical supported suggestions.

The aim of this work is to focus on intangible and soft attributes which we define as attributes that are not directly observed by data records but rather computed with techniques from static analysis and machine learning processes. Such attributes should be used to find hidden patterns of road usage that might be missed in standard traffic flow simulations. Examples of such errors in simulation include driving aggravation due to unforeseen events even with normal traffic conditions.

2.3 Sustainable Driving

Traffic assessment is directly related to trending topics such as ubiquitous and pervasive methods that allow the balancing of economic, environmental and social factors needed for sustainable development. A new emerging and interdisciplinary area, known as Computational Sustainability, attempts to solve problems which are essentially related to decision and optimization problems in correlation to welfare and well-being. Due to its importance, some researchers have discussed and proposed quantification methods, and modelling process for sustainability (Todorov and Marinova, 2011), (Kharrazi, Kraines, Hoang, and Yarime, 2014).

Often, decision and assessment are based on measurements and information about historical records. Indicator design provides an explanation on why such decisions are being made and it often uses information fusion to create and update its values. From a technological point of view, indicator analysis uses different and sometimes nonstandard data which sounds feasible by technological data gathering software that collect, store and combine data records from different sources. In the case of transportation systems, the assessment of the impact of a given driving pattern is made over sustainability indicators, like fuel consumption, greenhouse gas emissions, dangerous behaviour or driving stress in each driver's profile.

A system to estimate a driver profile using smartphone sensors, able to detect risky driving patterns, is proposed in (Eren, Makinist, Akin, and Yilmaz, 2012). It was verified whether the driver behaviour is safe or unsafe, using Bayesian classification. It is claimed that the system will lead to fuel efficient and better driving habits. In (Healey and Picard, 2005), and in addition to car sensory data, physiological data was continuously collected and analysed (heart rate, skin conductance, and respiration) to evaluate a driver's relative stress. The CarMa, Car Mobile Assistant, is a smartphone-based system that provides high-level abstractions for sensing and tuning car parameters, where by developers can easily write smartphone applications. The personalized tuning can result in over 10% gains in fuel efficiency (Flach, Mishra, Pedrosa, Riesz, and Govindan, 2011). The MIROAD system, Mobile-Sensor-Platform for Intelligent Recognition Of Aggressive Driving (Johnson and Trivedi, 2011), is a mobile system capable of detecting and recognizing driving events and driving patterns, intending to increase awareness and to promote safety driving, and, thus, possibly achieving a reduction in the social and economic costs of car crashes.

3 EVALUATION APPROACH

In the work presented in this paper, the evaluation of city traffic is made using a platform named PHESS Driving. This platform inludes smartphone aplications, server backends for adminisrators and users and webpages for data visualization. Management is made either by platform managers or users of the platform in distinct, non-overlapping areas. Platform managers are responsible for the integrity of the data collected and the monitoring of processes while users can manage their own records (Fábio Silva, Analide, Gonçalves, and Sarmento, 2014).

This platform is responsible for synchronizing driving data from user's smartphones with a central server that analyses the behaviour of a community of users to deliver metrics and information about traffic and risky driving patterns in these areas. In figure 1, it is depicted the general flow of data used in the system. The user smartphone acts both as sensor collection device and as a display of information about user metrics. Internal metrics and indicators are supported at the server level which by coordination and conjunction of web services delivers processed information towards user's displays.

Assessment of metrics and indicators is made using data fusion processes detailed in sections 3.1 and 3.2. Such metrics and indicators provide the value added information of this system and have a preventive objective to warn the user about potential dangerous routes and avoid its use.

In order to provide a smart analysis for smart cities, the indicators are used in squares of terrain in city maps and the data used to classify that square is an aggregation of the indicators that fit geographically inside such square. For classification a three level classification was used from initial sample data present in the PHESS platform. In this sample data the focus was on outlier data present in over the 80% quartile representing the most extreme cases. Such cases are them flagged as yellow or red depending if they are between the 80% - 95 % or over 95% quartile respectively.

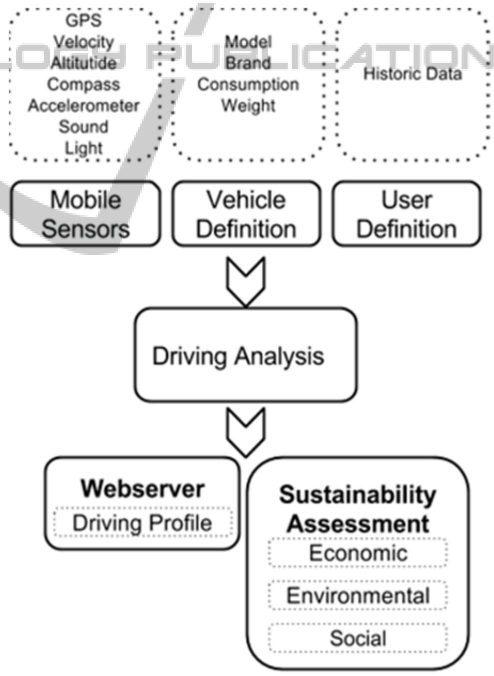

Figure 1: Conceptual architecture of the PHESS platform.

3.1 Driver Evaluation

In order to produce information about traffic flow and route safety it is necessary to gather information about relevant driving patterns in city areas. The focus of our analysis was derived from indicators accepted from the literature review and already present is the system PHESS Driving. Towards this effect it was considered:

- Intensity of acceleration and breaking;
- Number of breaking and accelerating events;
- Curve driving analysis;

The intensity of acceleration and breaking events is a challenging task. Due to the usage of mobile smartphones, sensor access is not easily controllable. Efficiency measures make data reading uneven in time meaning sometimes there is oversampling where others there is under sampling. In order to mitigate such problem the assessment is made using the linear slope from the line connecting an initial and final velocity as presented in equation 1. Such slope provides a mean to assess intensity that is independent of the size of the time interval.

$$\frac{v_f - v_i}{t_f - t_i} \tag{1}$$

The classification of the intensity of breaking is made using a green, yellow and red scale, derived from the initial sample as depicted in table 2.

Table 2: Indicator for slope of line between two different velocities.

Behaviour	Slope	Sample Coverage
Green	< 0.0017	80 %
Yellow	0.0017 – 0.0079	15 %
Red	> 0,7	5 %

Number of breaking and accelerating events are measured in time windows. Defining an event window is helpful because only accelerations and breaking inside such window are considered and can be analysed and compared between time windows. Table 3 provides information about classification for breaking and accelerating events.

Table 3: Indicator defined for acceleration and breaking events per 10 minutes.

Behaviour	Average	Sample Coverage
Green	< 42	80 %
Yellow	42 - 63	15 %
Red	> 63	5 %

Lastly, curve driving is a special event due to characteristic and driving difficulty. Due to car uneven handling, driving inside curvatures can present a risky task specially if driven at too much speed. For this analysis a special strategy is employed which monitor the degree trough smartphone sensors. Equation 2 demonstrates the formula used to track angle difference in the direction between two points. As the curvature becomes more intense the road curvature is identified as potentially more dangerous than others.

$$\begin{aligned} Dir = \tanh(\sin(\delta_2 - \delta_1) & \\ * \cos(\varphi_2), \cos\varphi_1 * \sin\varphi_2) & \\ - \sin\varphi_1 * \cos\varphi_2 & \\ * \cos\big(-(\delta_2 - \delta_1)\big) & \end{aligned} \tag{2}$$

In table 4 it is depicted the assessment made by the extended PHESS platform to the degree of curvature found using mobile sensorization.

Table 4: Indicator defined for assessing degree of curvature.

Behaviour	Average	Sample Coverage
Green	< 24º	80 %
Yellow	24º – 47º	15 %
Red	> 47º	5 %

3.2 Dynamic Modelling and Historic Information

There is information that is dependent on external conditions of traffic and not related with driving itself. The platform developed will try to assess external condition using context estimation from the data gathered. Again the strategy is made with the help of indicators. The indicators defined are:

- Road congestion;
- Road high speed.

In this case, the velocity recorded by users is aggregated inside each square of terrain. After an initial sample of the system the average speed is classified in a grid map identifying high speed squares and low speed, congested, squares. For such analysis it is considered the squares with average speed over the 80% quartile and the inverse for the selection of low speed squares.

Value added information produced in the system is published using a range of public web services. These web services provide public information about current traffic and driving conditions as well as, modelling analysis based on the historical data available in the platform.

4 RESULTS AND DISCUSSION

The model described in this article was tested as a complimentary module to the sustainability framework PHESS (Fabio Silva, Analide, Rosa, Felgueiras, and Pimenta, 2013). Its aims are to produce and generate knowledge that can be used to perform decisions and suggestions that have a direct impact on sustainability and the sustainability of user's actions. More than a responsibility framework, it is intended to increase awareness to sustainable problems that arise from user's own actions and road usage by drivers.

Taking into consideration a test city with a community of 10 users, it is possible to assess the sample metrics and indicators defined. The community of users was chosen from volunteers who recorded their driving routes during their daily habits without restrictions to the rate of recordings, duration of trips or locations. The nature of recording device was by definition their own android smartphones as long they were equipped with GPS, accelerometers, internet connection and able to install the application to gather driving records. Due to the strain on the recording device and their availability, cross-validation with approaches from other projects over the same information was not assessed in this study. Additionally, the unavailability of access to tools stated by research conducted in the community increases the difficulty comparing results with these studies. The nature of the results presented is also different relying on zone assessment instead of street assessment, due to the fact that street close to traffic jam tend to suffer the same problems as the main street. These results express areas according to the square granularity defined in the system and, as result may identify portions of a street englobing its assess routes within the same zone. Platforms such as Waze (Waze Ltd, 2014), currently do not do such assessment instead when indicated as congested, the full street is assigned a congested parameter and its assess routes are not automatically classified as well.

Nevertheless, the use of a decentralized capture devices presented no problems recording user's driving records. Analysing the flow of data, the bottleneck of the system should be the central server. However, during this experiments no problem was detected and measures to handle synchronization between device and central server can be mitigated with additional servers and load balancers.

The coverage of cities and metropolitan areas is dependent on the community. Not only its size, but also frequency, duration and length are determinant to allow users to produce information that can be used to assess cities. Its calculation is rather difficult, but considering the most popular and influential routes used by the vast majority of users, then small communities can produce meaningful results, which users can relate to. That was the case with our own experiments.

Statistical results from the data collected according to the principles defined in section 3 can be found in this section. Over table 5 and table 6, it is represented the summary of green, yellow and red evaluation according to each non-conformant behaviour defined in the system. In this specific case information about indicators in section 3.1 is used aggregating classification rounding the average classification in each square.

Table 5: Analysis of the indicator defined for acceleration per User per Trip.

Behaviour	Average Number of Accelerations and Decelarations	Standard Deviation
Green	38	3
Yellow	12	4
Red	3	8

Table 6: Analysis of Curvature and Intensity per User per Trip.

Behaviour	Average Curvature	Standard Deviation
Green	10	4
Yellow	12	3
Red	15	2

These results provide evidence that our initial sampling strategy to define green, yellow and red accelerations and curvatures hold in a real scenario. This means, the proportion of events classified is not excessively different from expected. A demonstrative example of the classification of events is made in figure 2 and its impact on the grid map on figure 3.

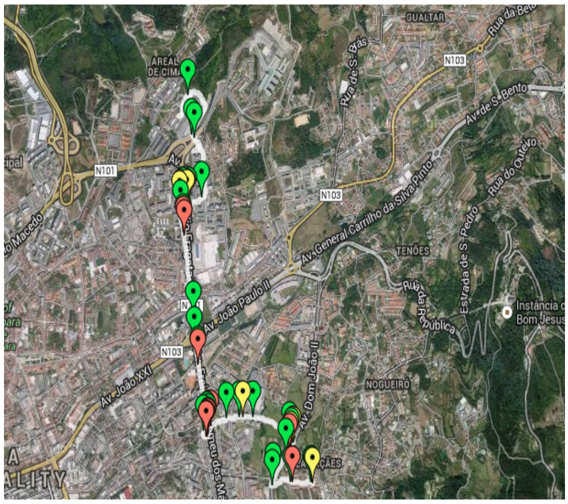

Figure 2: Individual Trip Event Classification.

In order to analyse the classification and demonstrate that the scale has been appropriated to detect a small but significant set of yellow and red events. Such detection mechanisms can be improved with more technical data about dangerous events or even adjust the quartiles used for classification, nevertheless the proposed approach provides satisfactory results.

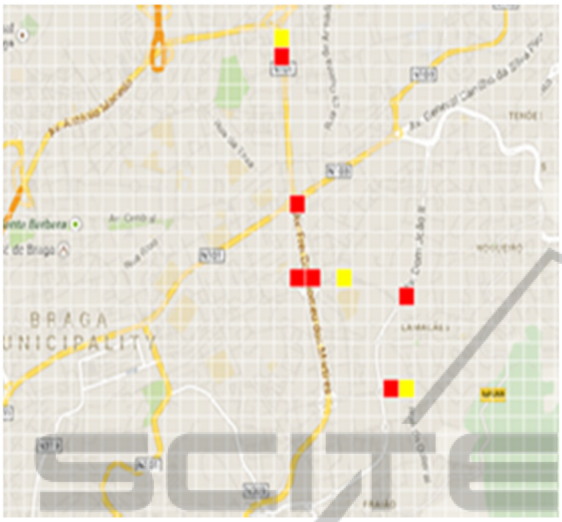

Figure 3: Individual Trip Impact on Community Map.

Each event is characterized in the map, and for the user it is possible to see the information relevant to that assessment. A set of filters with each indicator defined may alter the map zone classifications according to whether or not they are selected. Current available filters are acceleration and decelerations and curvature, as shown in the results of this paper. Speed information is available but as a heat map index as speed classification is dependent of traffic regulations directly enforced on each street. Due to this, the approach presented cannot accurately classify according to speed but it can clearly indicate faster zones than others.

On the other hand, figure 4 does not provide event level explanation but rather aggregations of the driving records of users that have been in such zones. The set of filter according to each indicator is also present but instead of providing information about individual records, they also use the aggregated values from the community of users in the same location.

The identification of only yellow and red locations over the grid helps mitigate privacy problem as it provides the user with relevant aggregated information but holds a significant portions of the data, green evaluations (±80% of the total records). Without this information it becomes more difficult individual user identification as the information not displayed may or may not exist in the system. Nevertheless, the critical information that can be used by drivers and for studies of mobility and transport planning is presented.

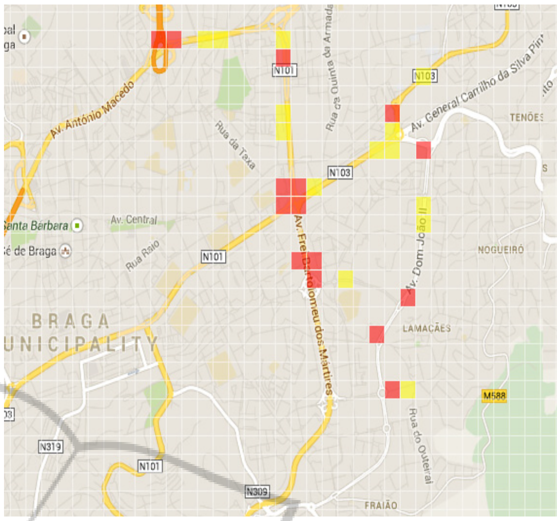

Figure 4: Aggregated User Data on Community Map.

The map covered by the classification results is within the expected range but varies according the time of day. However, the location of squares is preserved to allow direct comparison by time and day if necessary. Each square can have different averages, according to the time and classifications, Our approach, identifies such metrics on daily basis but the identified spots are within 10% to 15% of the visible map.

5 CONCLUSIONS

The use of pervasive devices already adopted by communities of users possess enough information and computing ability to build collaborative systems to tackle complex tasks. City traffic evaluation is one of such problems that are costly to audit and diagnose structural problem but can be simplified with crowd computing. Results are seem as satisfactory are reliable with the possibility to adjust according to specifics needs or needed improvement. The use of mobile sensors does constitute an additional effort to mitigate external influences such user involuntary movement, measurement and coverage errors. Nevertheless, the outputs generated in this platform were also found of relevance to the study of sustainability, where the intangible metrics and the structures employed to the indicator analysis pave the way to building sustainability assessing indicators able to join general purpose sustainability assessment frameworks such as the platform PHESS in discussion in this work.

In future iterations there are plan to update from grid analysis to road detection and road analysis becoming more accurate. Also, the validation of experiments on other cities are planned in order to prove both resilience and adaptation of the system. Integration of metrics found by this platform in common navigation systems are planned on the long term project, thus influencing routing options of people and acting as a true pervasive and ubiquitous object directing people away from dangerous situations into more comfortable and safe environments.

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