An analysis tool for the contextual information from field experiments on driving fatigue

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Abstract. Elderly drivers will be more present on the road in the next few years. Mobility is fundamental for the elderly because it allows them to maintain an active lifestyle. But the elderly may suffer from cognitive, physical or sensorial decline due to aging. To help them to drive, context-aware systems can assess the status of a driver and warn him or her about hazards. We present a data analysis tool for car driving context information that includes data mining and statistical evaluation algorithms. We applied our system to data collected by sensors into an instrumented vehicle in realistic driving conditions. Results show that our tool is able to store the contextual information collected and to enable an interactive visualization of the data collected. Thanks to this tool, it is easier to share information among the scientists working on the data. Moreover, it makes it convenient to store data in the cloud.

Keywords: Context-awareness, Contextual information, Analytical tool, User modeling, Driving behavior analysis, Road safety

1 Introduction

Aging is a growing phenomenon in almost all countries of the world [1] and the percentage of people 65 and older will more than double between 2010 and 2050 [2]. For instance, there are five millions elderly in Canada and elderly drivers could represent nearly a quarter of the Canadian population of drivers in 2036 [3]. Such a demographic change will have an impact on various aspects of daily life, among them road safety. Indeed, aging has an impact on road safety. Elderly drivers are drivers aged 60 and older. Elderly drivers have their specific safety problems, for instance they have more car crash at intersections. In fact, they have the highest crash rates per vehicle distance of travel [4]. Aging has several consequences for society. Therefore, it is in the best interest to focus on this category of drivers.

In the last decade, there has been a growing interest in intelligent vehicles. A notable initiative on intelligent vehicles was created by the U.S. Department of Transportation with the mission of preventing highway crashes [5]. A range of new technologies allows monitoring and driver assistance, such as automatic speed controls or blind spot monitoring, to prevent motor vehicle accidents. Thus, such vehicles are equipped with multiple sensors that can recognize driver's current activities, and situate the vehicle in the environment. Through information provided by these sensors, it is possible to model the context of the users and vehicles; and use these models to assist the drivers and create new kind of driver-car interactions.

Context-aware driving systems can be especially useful to assist elderly drivers by providing adapted assistance that takes into account the driver's interaction capabilities, their cognitive capabilities, the driver habits; while taking into account the cognitive load inferred by such driving assistance [6]. By context-aware system, we mean the ability of a system to capture, model and use specific information about the environment surrounding the system, such as location, time, and user profile [7].

This paper presents a modeling tool for analyzing the driving context. To analyze contextual information, we used a web application and include data mining. The paper is structured as follow. Section 2 presents related works about elderly drivers, context-aware systems and driving behavior model. In Section 3, we present and describe our tool. Section 4 reports on the application of our tool to real data. Finally, Section 5 concludes the paper and presents perspective and future work.

2 Related works

Drivers have to respond rapidly to risks with good abilities like attention, perception, motor abilities, information treatment, etc. With aging, some physiological impairment appear and have negative impacts on driving skills [8]. The elderly suffer from cognitive, physical and sensorial decline. The cognitive skills are affected and lead to a longer reaction time, a diminution of attention, and a short memory [9]. Physical abilities are worsening with deterioration of psychomotor skills, development of arthritis, which causes neck problems, or also vulnerability of the body [10]. And sensory functions declines with a diminution of visual acuity, diminution of hearing or even, perceptual ability [9] [11]. These impairments are common among the elderly with normal aging. In addition, with diseases increasing, the elderly take medication that highlights the risk of accidents. Medication alters the driving skills and reduces sensorimotor performance (for example: decreased alertness, impaired vision, etc.) [10]. Therefore, some authors purpose license restrictions to manage elderly driver safety [12]. But driving cessation had adverse negative consequences [10,11] [13]. It is a stressful experience, which has an impact on quality of life. Elderly drivers want to continue to drive to maintain their independence, even more for elderly drivers living in rural or remote areas. Mobility is fundamental for elderly drivers because it allows them to maintain an active aging. Thus, it is in the best interests of societies to maintain elderly adults driving as long as they can safely do so.

So, driving is a complex and multitask processing that involves good perception and cognition from the driver. It is necessary to have an immediate and appropriate decision while driving. Driving task can be assisted by a context-aware system for vehicle control or vigilance. Context-aware system can detect the status of driver and prevent him about hazard.

Context aware system is defined as a system that uses context to provide relevant information and/or services to the user (relevancy is depending to the user's task) [14]. In 2005, Rakotonirainy [6] specify that context aware system assist the driver to have a safe behavior. These systems could reduce the amount of errors and the likelihood of accident. Indeed, driver errors are the consequences of 90% of the accidents and most of the accidents occur due to drivers' behavior [15]. Errors would be more prevalent in elderly drivers (or impaired drivers) because of a decreased ability to perceive or quickly interpret the information due to aging [16]. Driving errors are defined as an involuntary deviation from a rule or a norm. Planned actions fail to achieve the desired outcome [17]. Context-aware systems have not been used for applications for elderly drivers [13] although this system can improve vehicle control and prevent accident. Driving behavior is a complex interaction between the driver, the vehicle and the environment. For instance, the driver can have information about his/her physiological state (stress), the environment (traffic) and the car state (speed of traffic) [6]. To achieve an interaction reliable, different types of information are taken with different type of sensors and cameras and provide required information to the driver when it is necessary [18]. Sensors can be categorized into three types: physical sensors (i.e. light sensor, camera, audio sensors, accelerometers, location, temperature sensor, etc.), virtual sensors (i.e. software applications, network event sensors, etc.) and logical location sensors (i.e. combination between physical and virtual sensor) [19]. The best system combines all assistance functions to help the driver and produce good performance [18]. Context aware system's architecture is composed of a direct sensor access to provide sensing data, a middleware infrastructure to present information to users and a context server to manage the information's user and to save context information for a later use [20]. In sum, context aware systems improve driving with understanding the whole driving task (driver, environment and vehicle) and assist driver's decision to reduce road accidents.

But to assist the drivers, such system has to analyze the driver and predict when it is a normal and an abnormal behavior. Indeed, the main actor of the driving activity is the driver. So, there is a need to analyze the driver behavior in the context because the situation impacts on the type of actions [21]. Some cognitive models exist in the literature but they not take into account the context. Indeed, the benefits of context are the explanation of driving behavior and the improvement of the generalizability and reliability of existing driving behavior [21]. It is appropriate to develop behavior models for context aware system. This will help the driver to produce adapted driving actions. Driving behavior models incorporate cognitive state (attention) and behavioral state (motivation, belief or risk assessment). A model is designed for only one particular driving situation like fatigue [21]. Some researchers have developed context aware driving behavior models capable to explain and predict driver's behavior. In 2015, Bhattacharjee and Wankhede [22] develop a context-aware architecture for a driver behavior detection system able to detect four types of driving behavior in real-time driving (normal, fatigued, drunk and reckless driving). Different types of information are collected like speed of the vehicle, yawning angle, steering wheel angle and the vehicle's lane position. To capture static and dynamic aspects of the driver behavior, a dynamic Bayesian network is used. Results show an accurate detection of the abnormal driver's behavior. A context aware system has to integrate driver behavior model. Thus detect driver behavior, it is vital to collect contextual information about the driver, the vehicle and environmental context; then analyze with data mining methods. In the following section, we propose the description of a tool used to analyze the driving and the context, especially for elderly drivers.

3 Tool description

In the context of our research, we are using an instrumented vehicle, the LiSA (in french: *Laboratoire intelligent de Sécurité Automobile* or Intelligent Laboratory on Automobile Safety), a Nissan Versa 2008 (Fig.1). Among other, this car is equipped with a data logger AIM Evo4 which can collect the speed, steering movements, acceleration, braking, 3-axis acceleration and GPS location from the car embedded computer. LiSA also include an eye tracking faceLAB 5.0 system, a Microsoft Kinect (with a head tracking software [23]) camera and several other camera to monitor the driver. Finally, all the data is recorded by a computer installed on-board. Thus, LiSA is able to collect a wide range of contextual information.

Fig. 1. The LiSA' instrumented vehicle

To complete the contextual information with specific information on the user profile, we are using surveys during our experimentation to collect sociodemographic variables, such as their age, sex, driving experience, opinions toward safe driving, etc. Moreover, in the context of our last experiment [24], we collect the driver's level of perceived fatigue by using a scale ranging from '0' not at all fatigued to '10' very much fatigued at four times during the experimental session. Each participant was asked his or her level of fatigue just before starting driving (Time 1), after 15 minutes of driving once the experiment had started (Time 2), after 30 minutes (Time 3), and when the driving experiment ended (around 45 minutes) (Time 4). In the case of this experiment, the focus was measuring the level of perceived fatigue and not the physiological level of fatigue. The Table 1 presents an overview of the contextual information collected by LiSA.

Table 1. Contextual information collected by LiSA

Devices	Data collected
AIM Evo4	Time; Distance; Speed; RPM; Gears; Steering wheel rotation; 3-axis acceleration; GPS location (gyro, altitude, latitude, longitude, elevation, etc.)
faceLAB 5.0	Head position and rotation; Eye close (left, right, calibration); Eye gaze (left, right, rotation, calibration); Eye blinking (left, right, number, duration, frequency); PERCLOS; Saccadic eye movements; Pupil movements (left, right, diameter)
Microsoft Kinect	Head position and rotation; Blind spot check activity;
Surveys	Sociodemographic data; Opinion toward safe driving; Level of perceived fatigue;

To analyze these contextual information we built an analysis tool that include data mining and statistical evaluation algorithms that analyze the collected contextual information. The development of such tool was motivated by:

1. Building a development platform to test our algorithms on offline data, which could be later test on real-time data;
2. Getting a tool to stock the contextual information collected during our field experiments for each participants;
3. Building a tool that will allow an easy visualization of the data collected and could be used to make debriefing session with the participants.

Thus, we built this tool using a web application approach by adopting the Node web server technologies, the Javascript language and the MongoDB database. The choice of Node and the Javascript language was motivated by the high adaptability of Javascript language, where we can do server and client side computation. Most data mining and statistical analysis algorithms can be implemented in Javascript easily and developed algorithms can be translated into other languages (e.g. Java or Python) easily. Moreover, there is a huge selection of visualization API available in the community, which provided support for representing our data in graphs or diagrams.

For the database, MongoDB was an evident choice where the noSQL approach, which allows the indexation of data, provided by different sources in different formats (e.g. tabular data). To not loose any information provided by the sensors and their expressivity, we decide to upload the raw data into the MongoDB without any prior transformation. Afterwards, we had several transformations to do on raw data prior to their analysis. For instance, the time frames of the collected data are heterogeneous between sensors, with different sensing rates and time format. To make the data analysis easier, we made an algorithm that transform the data on the most common measure by aggregating the data from sensors with an higher sensing frequency by computing the average values. Another example is with the data provided by the faceLAB about the head position and the eye gaze. To match the cardinal position provided by the faceLAB with the car environment, we made a cardinal (translation) and a scaling transformation (in meters).

However, in the context of the field experiments (see next section), one of the key transformations required to the statistical analysis of the contextual information, such as the driving speed, is the noise reduction. All drivers are varying their speed depending of the driving contexts (obstacle, road topology, etc.). However, even in the case of monotonous driving in flat and straight lanes, the driving speed is varying a lot with several speed spikes at various intensity. Such small variations are not always related to the driver behaviors and can be related to environment and road conditions (Fig. 2) and can therefore be considered as noise. In this example, we are not interested in these small and frequent speed variations but in intentional variation of speeds, that we refer as speed spikes.

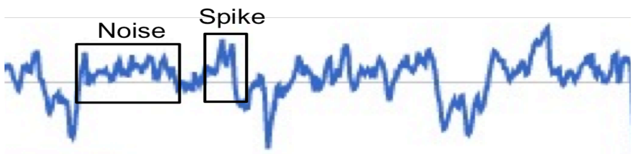

Fig. 2. Example of identified noise and valuable information (spike)

To remove this noises, we implemented a quasi-monotonic segmentation algorithm based on Lemire et al. [25] that reduces specific amounts of variation in a signal and keeps the variation in the data that are more significant (i.e. with a significant monotonicity). Intuitively, this algorithm segments a signal into pieces that are "quasi-monotonic" (mostly going up or down). A segment is said to be "quasi-monotonic" if we can approximate the data using a (truly) monotonic function that never deviates from the actual data by more than a small threshold. From a tolerance threshold, we can therefore construct a piecewise monotonic approximation of the original data. The segmentation and the piecewise monotonic approximation can be computed in linearithmic time (O(n log n)). Figure 3 presents an example of a speed signal that is processed by the segmentation algorithm, with the original signal and the signal processed with a threshold speed value of 10 kilometers per hour (this threshold can be set by the user). From this simplified approximation, we are able, for instance, to compute the number of speed spikes and compare it with the level of perceived fatigue, while ignoring variations that are not judged significant.

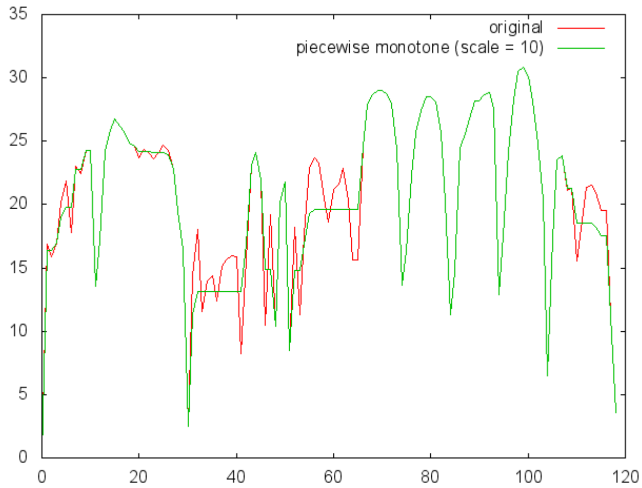

Fig.3. Speed signals with the segmentation algorithm

Moreover, for the evaluation of the drivers' behavior, we have implemented on the web application a serie of statistical tools that enable the evaluation of the contextual information per experiment segments. They compute average speeds, standard deviation and regression, as well as correlation quotient. These results (see next section for more details) were particularly used for the post-experimentation debriefing with the participants. We also developed an interface to link contextual information with geographical locations using the Google map API, while taking into consideration the temporal aspect of these data. This interface allows an easy exploration of the collected data and is used to validate specific events that occurred during the experimentations. This interface can also be used to visualize a participant experimentation through a playback function.

In summary, this contextual information analysis tool represents a multimodal platform that brings several benefits to the researches we conduct on road safety. Thanks to this tool, it is easier to share information among the scientists working on the data and it makes it convenient to store data in the cloud. The used technologies (Node.js and MongoDB) allow an easy implementation of contextual information analysis algorithms and give us the platform to test our algorithm on offline (real) data, before testing them within the technologies we are developing to assist the drivers in their tasks.

4 Results

This section shows the validity and effectiveness of our tool. We used our tool during a pilot evaluation with 20 participants, aged between 56 and 76 years old. The goal of the experiment was to evaluate the intrinsic evaluation/perception of the driving fatigue for elderly drivers and compare it with their driving behavior. During the experimentation, each participant drove around 50 kilometers on a close driving circuit with the LiSA car. During experimentation, field data were collected into the embedded computer of the LiSA then uploaded into the tool following the end of the driving period. During the pilot test, we collected an average size of contextual data for each participant of 29 MB, with 8 MB from the AIM evo4, 18 MB from the faceLAB and 3 MB from our Kinect's software, for 45 minutes of driving.

After the experimentation of each participant, it was possible to use the tool to visualize the collected data with its graphs (Fig. 4, 5, 6, 7) and maps (Fig. 8, 9). As we said in the previous section, the algorithm transforms data on the most common measure. For graphs (Fig.4), we included speed (blue line), the perceived fatigue level (red line) and linear regression of the speed (orange line) during the whole time driving. We add statistics information below the graphic with mean, variance, standard deviation, regression equation and regression correlation.

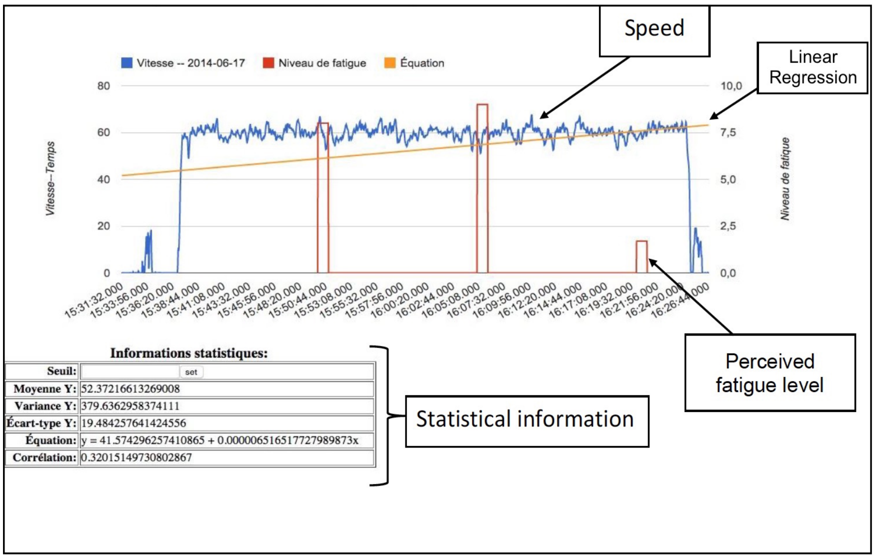

Fig. 4. Interface's explanation

For the speed's attribute, Fig.5 presents normal form and Fig. 6 presents the participant's experiment, segmentated in 3 sections. We proposed equation (in different colors) every 15 minutes and for each of them, statistics information (mean, variance, standard deviation, regression, etc.) (Fig. 6).

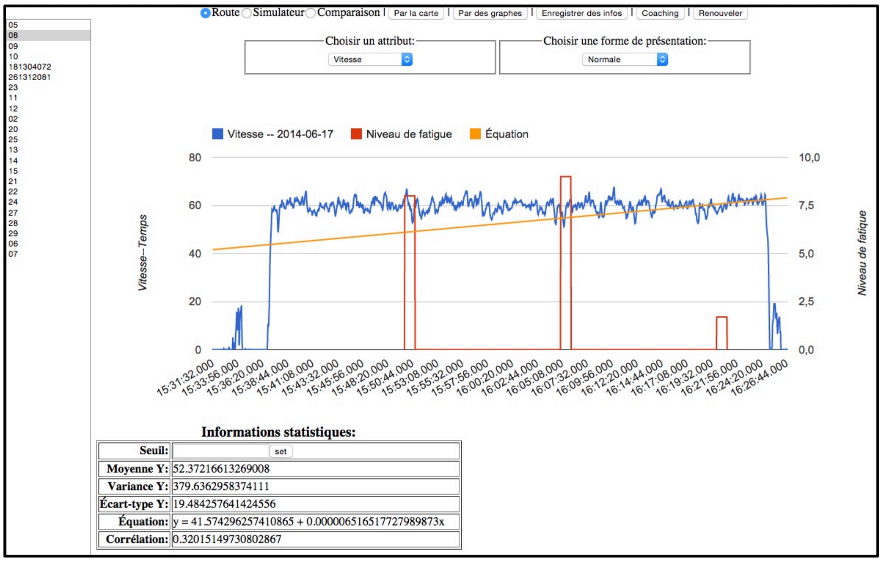

Fig. 5. Graph Interface - Normal speed

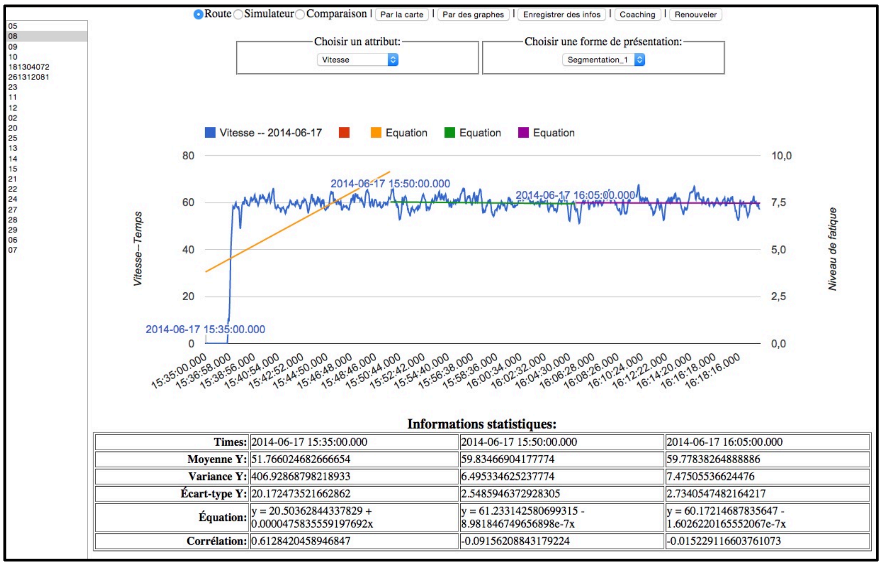

Fig. 6. Graph Interface - Segmentation of the speed

For the data provided about eye and head movements, Fig. 7 shows an example of blinking frequency (blue line) with the perceived fatigue level (red line) and the regression of blinking frequency (orange line) during all the experimentation. Likewise for the speed, statistical information are given below the graphic.

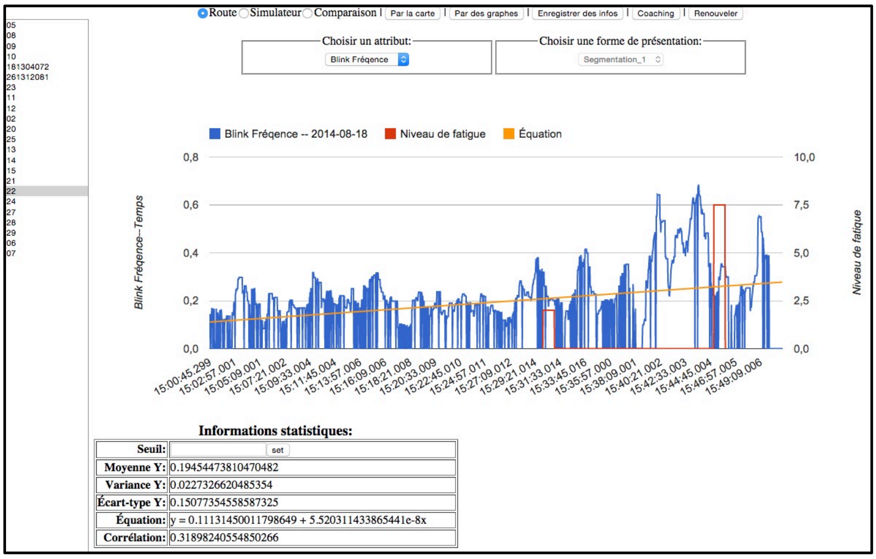

Fig. 7. Blinking frequency

Maps form (Fig. 8 and 9) gives contextual information with geographical localization using Google maps. It is possible to explore at any time all the information collected by the vehicle. Similarly, it can be used to validate a particular event that occurred during the experimentation.

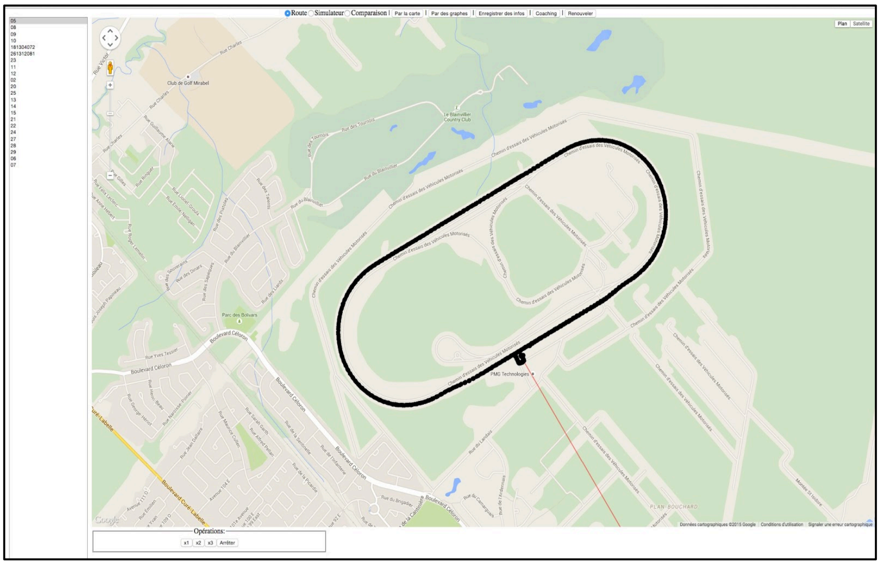

Fig. 8. Maps visualization

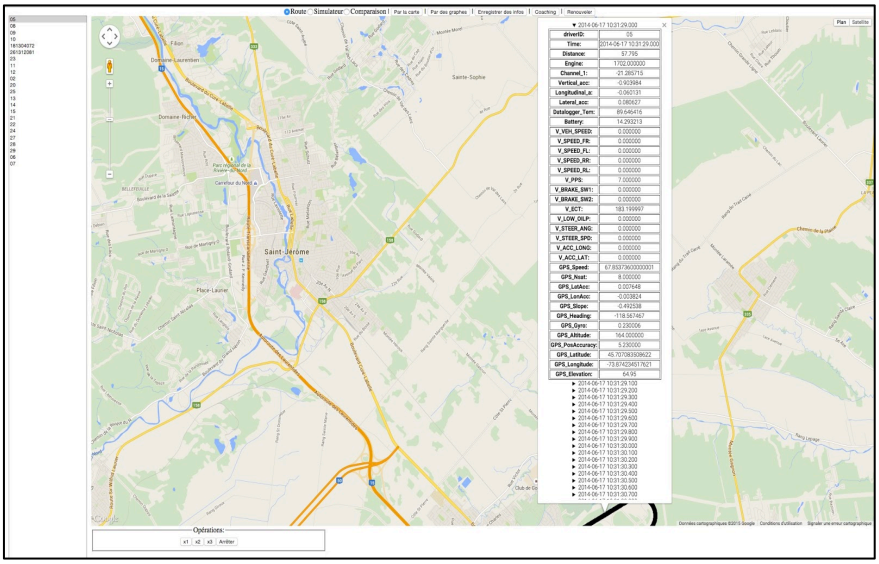

Fig. 9. Maps visualization and information

Finally, we propose a debriefing solution to help the driver after driving session (Fig. 10) to visualize their behaviors and talk about their perception of their driving fatigue versus the collected. It also includes participant's information (driving time, number of kilometers, mean speed and localization), curves (participant's speed, the speed limit and the perceived level of fatigue of the driver) and table (divided driving time per 15 minutes of driving with the mean speed of the participants and of his/her age group). We propose a comparison between the driver and his/her age group. We separated participants in two age groups: the 55-65 age group and the 66-76 age group.

At the moment, we propose this temporary solution but we still work on that part to improve the feedback. In addition, we will develop a comparison module between real driving condition and simulator driving condition in order to verify ecological validity.

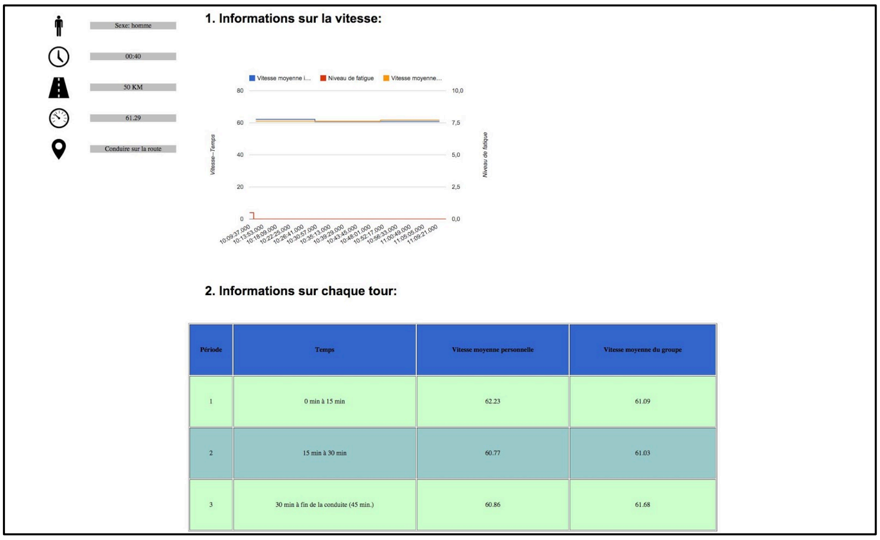

Fig. 10. Debriefing presentation

This tool shows promising results. From real data taken during experimentations, the tool allowed an interactive visualization of the collected data and an analysis by diagrams and maps for the driver.

5 Conclusion

In this paper, we presented a data analysis tool for car driving contextual information for elderly drivers. This category of drivers has impairments due to aging. To help them to drive safely, context aware system improve driving with understanding the whole driving task (driver, environment and vehicle) and assist driver's decision. The tool includes a web application approach with Node.js, JavaScript and MongoDB. These one allow an easy implementation of contextual information analysis algorithms and give us the platform to test our algorithm on offline data, before testing them within the technologies we are developing to assist the drivers in their tasks. We applied our system to collect data from the sensors of an instrumented vehicle (the LiSA) in realistic driving conditions. We used our tool during a pilot evaluation with 20 participants, aged between 56 and 76 years old. We evaluated the intrinsic evaluation/perception of the driving fatigue for elderly drivers and compare it with their driving behavior. Results show that our tool is able to store the contextual information collected and to enable an interactive visualization of the data collected for each participant. This contextual information analysis tool represents a multimodal platform that brings several benefits to the researches we conduct on road safety. If in our current experiments, the size of the collected data is relatively small; we can see that in our next projects, where the number of participants will increase substantially (100+) as well as the duration, the quantity of collected data will become more important. Moreover, we are planning to add other types of contextual information, such as physiologic data (e.g. heartbeat, EEG), which will even increase the quantity of data to manage and analyze. Our future work in this area will use this platform as an implementation and analysis base of contextual information.

Furthermore, it will be interesting to develop an algorithm able to categorized normal and abnormal driver behavior. Indeed, with the analyze tool, that is possible to monitor the behavior and alert the driver when there are change in driver's behavior for example.

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