Driver behavior assessment based on loosely coupled GPS/INS integration in harsh environment

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***Abstract*—Commercial location-based services use mainly the Global Positioning System (GPS) receiver data to develop the driver assistance and monitoring systems. Nevertheless, the GPS receiver has a lot of problems, and the important one is the signal availability in harsh environment such as urban canyon, tunnel and bridge. To overcome this drawback, the Inertial Navigation System (INS) comes to aid the GPS receiver using Kalman filtering to compute precise the position, velocity and acceleration in these environments.**

This paper matches the two complementary areas which are: GPS/INS integration and Driver Behavior Assessment (DBA). In the literature, these two fields have been deeply investigated separately. However, an accurate analysis of the driver behavior requires precise and available data (position, velocity and acceleration) even in harsh environment. This paper presents a new method for driving behavior assessment based on the loosely coupled GPS/INS integration that allows a precise results, especially in case of GPS outages which can be modeled in the driver behavior assessment part. This assessment uses the belief theory, to fuse risk information given from the Driver, Vehicle and Environment entities, and the fuzzy theory to reduce the complexity of the fusion problem. The obtained real test results show good performance of the developed algorithms as well as the risk models. In addition, the presented results show the capability of the belief theory to model the GPS outages and the quality of signals.

I. Introduction

Over the last few years there has been a growing interest in the development of new insurance premium models based on the driver behavior, such as Pay How You Drive (PHYD) and Pay Where You Drive (PWYD). Insurance companies, such as Dejardins, with its Ajusto program in Canada, offers new pricing models based on the vehicle location and the quality of driving using the GPS receiver data. Supervising the driving behavior has three major advantages. The first one concerns the fleet manager who can follow the driving quality of his drivers while they are on the road. This helps to motivate them to obtain more rewards and to decrease the accidents or incidents. Consequently, the fleet manager saves money on insurance. The second benefit is the reduction of the greenhouse gas emissions. In the near future, insurance companies will rewards drivers who save their CO_2 emissions. The third advantage is the improvement of the tear and wears of the vehicle and increases its lifetime thanks to the optimal use of the fleet.

Driver behavior assessment in harsh environment is a very difficult and complex task due to the involvement of distinct interconnected parameters of different types. The first question is how to take into account simultaneously all of these different types of parameters and their uncertainty. In [1], Derbel and Landry use the Belief and Fuzzy theories to estimate the driver behavior in case of different critical driving situations. The Belief theory is used to fuse the risk information between the different computed risks at each entity level. These risks are divided into three types: Driver risk, Vehicle risk and Environment risk. The Fuzzy theory is used to reduce the complexity of the fusion problem. In their work, they evaluate the driver behavior only when there is a GPS signal, which represents the drawback of their work.

Low-cost GPS suffers from signal block and outages, especially in harsh environment, such as tunnels and urban area, where the number of satellites in view is less than 3. In this case the GPS signal remains poor and/or unavailable, so, the navigation solution is affected as well as the evaluation of the driver behavior. Then, the insurance charge based on the GPS receiver data is biased. To overcome this problem, many researchers proposed to assist the GPS receiver by other systems such as the INS to compute an accurate vehicle position, velocity and orientation using Kalman Filtering. There are multiple methods to integrate the GPS receiver and INS data and the most common ones are the loosely coupled, tightly coupled and ultra-tightly coupled. The loosely coupled integration will be detailed later in this paper while more information on the two other methods can be found in [2].

The basic Kalman filter deals with linear problems while the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Particle Kalman Filter (PKF) handles non-linear problems [3]. The EKF uses the linearized measurement and the state equations and the Jacobian matrices. So, the choice between these types of Kalman filter depends on the problem constraints and raises the question on how to choose the best filter for insurance applications in order to provide the vehicle position and velocity for DBA system in case of GPS outages.

Figure 1 presents the methodology of the presented work. In case of GPS outages, the loosely coupled GPS/INS integration system is switched on. Meanwhile, the driver behavior is evaluated locally at the Driver, Vehicle and Environment entity and then globally by fusing the obtained local risks. To evaluate these risks, the Driver entity utilizes the age and gender of the driver and the Environment entity uses position, time of the day, day of the week and month of the year while the Vehicle entity risk is based on the following parameters: position, velocity and lateral and longitudinal accelerations.

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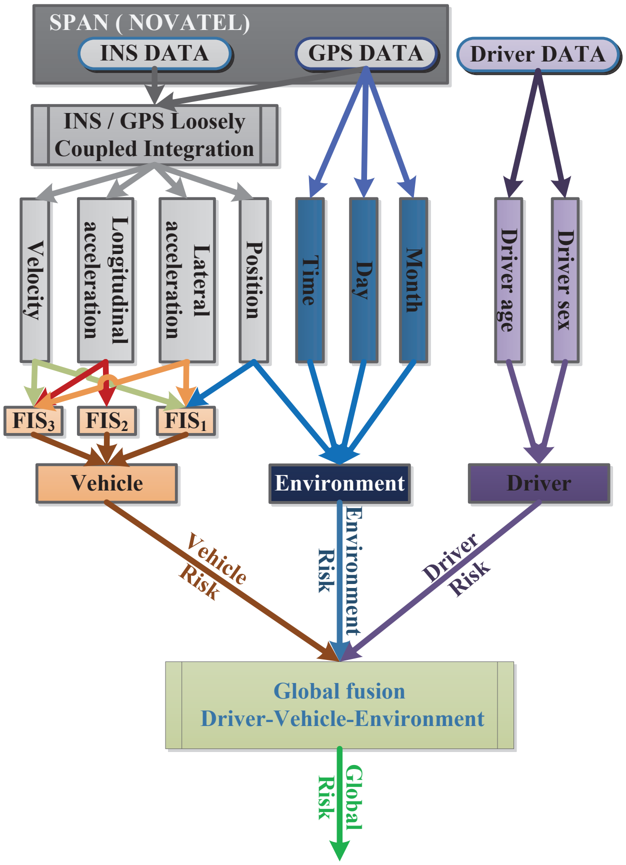

Fig. 1: Diagram for driving risk assessment based on the GPS/INS loosely coupled integration

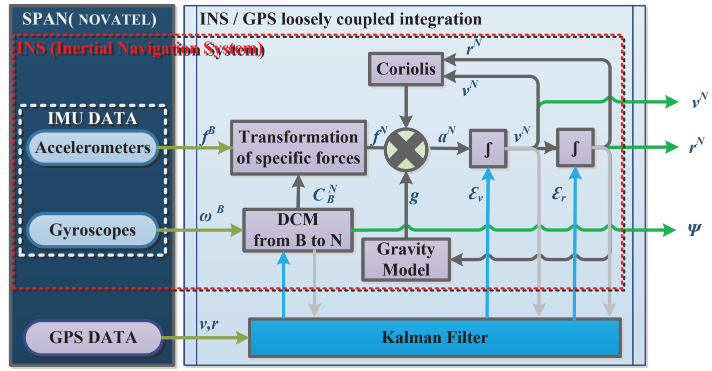

Fig. 2: Loosely coupled GPS/INS integration diagram

In this paper, Section II details the loosely coupled GPS/INS integration algorithm and Section III presents the methodology used to evaluate the driver behavior. Before concluding in the Section V, Section IV tests and validates our developed models for GPS/INS integration and for risk assessment using two scenarios. The first one defines a sample while the second scenario evaluates the driver behavior during driving period.

II. Loosely coupled GPS/INS integration

The main causes of the GPS outages are low signal strength and multi-path which occur in harsh environment such as urban canyon and tunnels. The GPS and INS are complementary since they have different errors characteristics and measure different quantities. The GPS can provide the position and velocity while the accelerometer measures the specific forces and the gyroscope gives the attitude rate.
Loosely-coupled integration allows the independence and redundancy of GPS and INS solutions to be maintained in addition to provide a more robust coupled navigation solution. Indeed, integration by loosely coupling has a closed loop architecture which allows the correction of certain error parameters of the INS system [2]. In the literature, there are other methods of GPS/INS integration such as the tightly and ultra-tightly coupled algorithms. In this paper, we are concentrated on the loosely coupled GPS/INS integration because of its real time use benefits. Figure 2 presents the architecture of the loosely coupled loosely-coupled GPS/INS integration algorithm which uses the GPS and the INS data of the SPAN (Novatel). These data are already calibrated and highly precise and also considered as reference for our future works. The presented work is used to validate our developed loosely coupled GPS/INS integration algorithm together with the driving risk models. The choice of the use of the belief theory comes to model the outages of the GPS, especially in harsh environment.

The architecture presented in the Figure 2 uses a Kalman filter to couple the GPS and INS solutions (position and velocity) in order to estimate the position, velocity and attitude errors of the INS solution. It illustrates also the typical architecture of INS with its related components. The INSs are fully autonomous systems able to compute the position, velocity and attitude of the vehicle based solely on the linear acceleration and angular rates given by the inertial sensors (gyroscopes and accelerometers). The data from the Inertial Measurement Unit (IMU) provides the specific forces, in the body frame, which are transformed to the North-East-Down (NED) frame. The components of force of gravitational attraction, of centripetal force and of acceleration of Coriolis are removed from the vector of specific forces in order to obtain only the acceleration of the mobile according to the navigation frame. The Gravitational and Coriolis accelerations can be estimated using mathematical models as function of the vehicle position and velocity. Then, the acceleration is integrated one time to obtain the velocity and a second time in order to have the position of the mobile [4]. Thus, this model is used to estimate nine error states of the navigation system given by the following array:

$$\delta x = \left[\psi^N \;\; \delta v^N \;\; \delta r^N\right] \tag{1}$$

where δx is the state vector error, ψ the attitude error, δv the velocity error and δr the position error.

The error propagation model used for GPS/INS integration by loosely coupling is based on the ψ angle error propagation model. Thus, the continuous representation of the developed system is given by the following equation:

$$\delta \dot{x} = F\ \delta x + G\ \eta_p, \tag{2}$$

where η_p is the system noise vector, F the transition matrix of the state vector characterizing the propagation of the state parameters, and G the matrix characterizing the link between the noise and the state parameters. The equation (1) can be written as

$$\begin{bmatrix} \dot{\psi}^N \\ \dot{v}^N \\ \dot{r}^N \end{bmatrix} = \begin{bmatrix} -(w_{IN}^N \times) & 0 & 0 \\ -(C_B^N f^B)\times & (w_{EN}^N + 2w_{IE}^N)\times & 0 \\ 0 & I & -(w_{EN}^N \times) \end{bmatrix} \begin{bmatrix} \psi^N \\ v^N \\ r^N \end{bmatrix} + \begin{bmatrix} 0 & -C_B^N \\ C_B^N & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \eta_f \\ \eta_w \end{bmatrix} \tag{3}$$

where $w_{IN}^N = w_{EN}^N + w_{IN}^N$ the angular velocity of the Earth centered Earth Fixed frame **E** compared to the Earth centered Inertial frame **I** projected along the axis of the frame **N**, w_{EN}^N the transport rate, η_f the accelerometer noise, η_w noise of the gyroscope, C_B^N the Direction Cosine Matrix (DCM) crossing from Body frame **B** to Navigation frame **N**, f^B the specific force vector of the accelerometers and $(x\times)$ the antisymmetric matrix formed from the state vector **x**

$$(x\times) = \begin{bmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{bmatrix} \tag{4}$$

The noise vector of the system consists of the measurement noise of the inertial sensors. Thus, the associated covariance matrix is defined such that:

$$\begin{bmatrix} \sigma_{\eta_f}^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{\eta_f}^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{\eta_f}^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{\eta_w}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{\eta_w}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{\eta_w}^2 \end{bmatrix} \tag{5}$$

where $\sigma_{\eta_f}^2$ the variance of the accelerometer noise and $\sigma_{\eta_w}^2$ the variance of the gyroscope noise. The parameters $\sigma_{\eta_f}^2$ and $\sigma_{\eta_w}^2$ can be computed through a statistical analysis of the raw measurement form the inertial sensors.

$$\begin{bmatrix} \delta v^N \\ \delta r^N \end{bmatrix} = \begin{bmatrix} 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} \psi^N \\ \delta v^N \\ \delta r^N \end{bmatrix} + \begin{bmatrix} \eta_V \\ \eta_R \end{bmatrix} \tag{6}$$

The measurement error vector of this system consists of the position and velocity errors provided by the GPS receiver. However, in order to simplify the implementation of the filter, this covariance matrix associated with the measurement noise is considered to be constant and it is defined as follow:

$$\begin{bmatrix} \sigma_V^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_V^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_V^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_R^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_R^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_R^2 \end{bmatrix} \tag{7}$$

where σ_V^2 and σ_R^2 are the variance of the velocity and position measurement, respectively.

III. DRIVER BEHAVIOR ASSESSMENT (DBA)

In the last decade, active safety attracted more attention from research teams due to the increase of the number of road accidents. For several years, great effort has been devoted to active safety systems that incorporate solutions based on the information provided by the three entities Driver, Vehicle and Environment. Nonetheless, the choice of the parameters is the main issue of these active safety applications due to the problem of their types, uncertainty and interconnection between parameters. However, some of parameters remain very important. In the Driver entity, accident statistics depends on the driver age and gender. From the Environment point of view, the driving place, the time of the day, the day of the week and the month of the year influence the accident statistics. The vehicle responses to driver inputs are the main and important factors that affect the driver safety.

A. *Belief theory for information fusion*

Traditional methods use the Hidden Markov Model (HMM) [5] and Neural Network (NN) to estimate the driver behavior. This paper presents a new approach to manage the different aspect of the driving behavior estimation by adopting a two level of information fusion matched by the use of the fuzzy theory. This technique, presented in the Figure 1, is an effective way to improve the computation time and reduce the complexity of the fusion problem. The information fusion is based on the Belief theory which is called also Dempster-Shafer theory of evidence [6], [7]. The advantage of this theory is the capability to characterize the uncertainty of the results through the upper (Plausibility) and lower (Belief) bound of the probability of an element of a subset. This probability is also called the Basic Probability Assignment (BPA), which is determined using the fuzzy measure designed to model the parameters related to the DVE system. In fact, this relationship between fuzzy and belief measure plays the crucial role to reduce the computation time and offers the possibility to model the risk involved by each parameter. The three Fuzzy Inference Systems (FISs) given in the Figure 1 could be used for real time assessment of the risk involved by the Vehicle entity parameters. The risk is classified as 'Low', 'Medium', 'High' and between each of couple of them.

The Belief theory is based on four steps. The first one is "modeling" where the frame of discriminant Θ is defined. The referential subset 2^{Θ} contains all the possible risk propositions and given by

$$2^{\theta} = \{\emptyset, LR, LR \cup MR, MR, MR \cup HR, HR, HR \cup LR, \in \qquad (8)$$

where LR, MR, HR designate the "Low Risk","Medium Risk" and "High Risk" respectively, $\emptyset$ represents the conflict between sources and Θ the ignorance of the risk (the union of all hypotheses). The risk of an event is qualified over the sets of the referential subset using the Basic Probability Assignment (BPA), which is the second step of the Belief theory. This task is the hardest one in this theory. In this paper, the Fuzzy theory is used for two reasons: the first one is the availability of the statistics that can be used to develop the fuzzy model. The second reason is that the fuzzy theory can be used to reduce the number of inputs in each entity of the system DVE and then it reduces the complexity of the fusion problem when using the Belief theory.

The third step is the combination between the different risk information from the sources weighted by the BPA. The sixth version of the Proportional Conflict Redistribution (PCR6) defined by Martin in [8] is used in this framework. This algorithm has been already tested and compared by Derbel and Landry in [9] to the first developed algorithm of combination proposed by Dempster and Shafer in [7].

The decision step, which is the last one, could be made through three functions: credibility, plausibility and pianistic probability. The Belief function, which is used in this work, is defined as follows:

$$Bel(X) = \sum_{Y \subseteq X, Y \neq \emptyset} m(Y) \qquad (9)$$

where m is the mass or the BPA and X and Y the propositions.

B. Environment entity and Open Street Map (OSM)

The risk related to the Environment entity is based on the position of the vehicle and the time, day and month of driving. These parameters are given from the GPS and updated in every time step. The position of the vehicle (longitude and latitude) is used to determine the district of driving based on the Open Street Map data. An algorithm has been developed to determine the district, the street and the maximum allowed velocity from the GPS data at each time step for each position data. The drawback of using OSM is the insufficient number of the available data for some cities (e.g. Montreal). Then, the driving street and the maximum velocity are unavailable. To overcome this problem, an interpolation function has been developed. It adds a number of points (positions) to the OSM database between each pairs that are considered as references points and defines the limits of each street. To optimize the processing time, only the box that contains all the positions given by the GPS is used.

IV. Experimental tests and results

A. Loosely coupled GPS/INS integration

In order to verify the validity of the proposed GPS/INS integration algorithm given by the Figure 2, an experimental

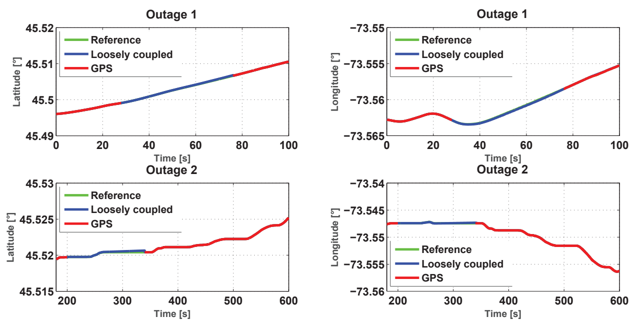

Fig. 3: INS/GPS integration algorithm performances in terms of positioning

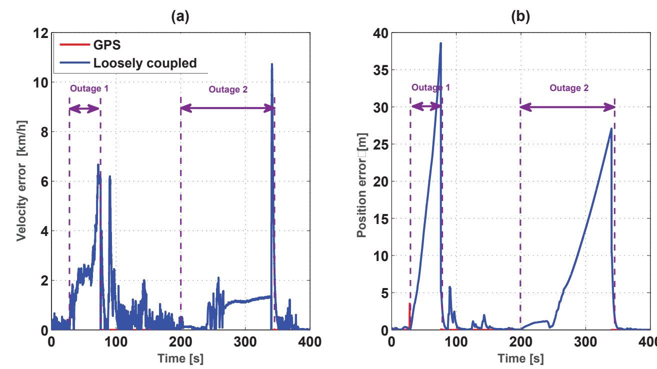

Fig. 4: Position and velocity errors

test is carried out. The trajectory of the test is given by the Figure 7.

Figure 3 presents the positions given by the GPS in red, the reference positions in green and the obtained positions from the developed INS/GPS integration algorithm in blue. It shows that the GPS is not able to determine the vehicle positions in the tunnels, represented by circles in the Figure 7, which agrees with the literature results. Using our developed loosely coupled GPS/INS integration algorithm, we are able to determine the vehicle position in case of GPS outages using the INS only (Figure 3). Once the GPS receiver signal is available, the Kalman filter updates the errors and the position of the vehicle. This could be concluded from the Figures 4a and Figures 4b where the position and velocity errors increase during the GPS outage time. This Figure presents the errors between the velocity (Figure 4a) and position (Figure 4b) given by the developed INS/GPS integration algorithm and the reference.

The error analysis cannot be complete without focusing on the cumulative error in terms of position, presented in Figure 5, during the mission. This Figure shows that the navigation solution is better in case of the outage #2 (Ville Marie tunnel) than the one of outage #1 in terms of cumulative position error. In fact, the outage #2, which is characterized by low velocities and long stopping times, lasts longer than the outage #1, which corresponds to a highway. The duration of the two outages can be shown in Figure 4.

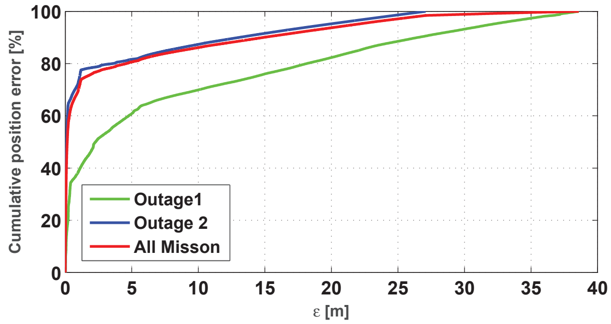

Fig. 5: INS/GPS integration algorithm performances in terms of cumulative position errors

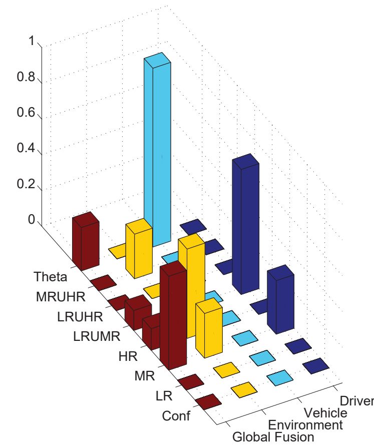

Fig. 6: Driver behavior results related to the scenario #1

We note that the GPS generates a large position error when the vehicle is in the stop mode.

B. Driver behavior assessment

1) Scenario #1: The first scenario considers a sample data and then the evaluation of the driver behavior is made microscopically. This scenario is designed to test the developed risk model as well as the loosely coupled INS/GPS integration algorithm. We assume that the 32 years-old male driver drives at 4pm on Monday in May 2016 in the 'Ville-Marie' district of Montreal (Canada).

According to the developed driver risk model, based on his age and gender, the Driver entity distributes the masses over the propositions MR (m(MR)=0.3) and LR ∪ MR (m(LR ∪ MR)=0.7) as shown in the Figure 6.

The 'Ville-Marie' district is qualified by a medium risk based on the statistics of the number of accident given by Gilbert and Halsey-Watkins in [10]. So, the masses related to the driving place assigns the total mass to the medium risk MR proposition (m(MR)=1). Nevertheless, the masses related to the hour of driving and the month of driving are given to the high risk HR proposition (m(HR)=1) while the masses related to the day of driving is totally assigned to the MR ∪ HR proposition (m(MR∪HR)=1).

Based on the PCR6 combination rules and the maximum of basic probability assignment decision criteria, the local masses related to the Environment entity is distributed over the propositions MR (m(MR)=0.25), HR (m(HR)=0.5) and MR∪HR (m(MR∪HR)=0.5. This obtained local fusion result confirms that the PCR6 reproduces all the risk obtained by each parameters as discussed by Derbel and Landry in [11].

The GPS signal is unavailable since the vehicle is in the tunnel. In this case, the mass related to the Vehicle entity is totally assigned to the proposition Θ. In fact, we consider that there is a risk but we cannot determine it since the velocity and position of the vehicle are unavailable and then the FISs FIS_1 and FIS_2 in the Figure 1 cannot be activated.

As shown in the Figure 6, the global fusion algorithm using the PCR6 distributes the masses over the propositions MR (m(MR)=0.5250), HR (m(HR)=0.1212), LR∪MR (m(LR∪MR)=0.1114) and Θ (m(Θ)=0.2424). Using the PCR6 all the risk propositions obtained at the local fusion level are reproduced at the global fusion level. The mass assigned to the Vehicle entity is transformed to a mass of 0.2424 over the proposition Θ. That is to say, the evaluation of the driver behavior over the other possible propositions has a belief of 0.7576. In our case of study, if the mass over Θ is not null means that the system was not able to identify a part of the driving behavior.

2) Scenario #2: The experimental test is performed by a 32 years-old male driver who drives at 3pm in Montreal (city in Canada). The trajectory contains two GPS outages as shown in the Figure 7. The GPS data are given by the red line in this Figure. We note that the red lines inside the outage places, described by circles, denote the interpolated data between the last and the first available GPS data before and after the availability of the GPS receiver signal, respectively. In case of the GPS outage and without use of the LCI algorithm, the district of driving is given by the last available position.

The experimental test vehicle Dodge 2012 is equipped with a SPAN Novatel which contains a high precision INS and GPS receiver to collect data (e.g. position, velocity, acceleration). We used these high precision sensors to validate our developed models in this framework and study the impact of the GPS outages on the evaluation of the driver behavior intended to serve the insurance companies. We note that the outages obtained in the presented scenarios are created manually.

This section studies the impact of outages on the evaluation of the driver behavior macroscopically. The macroscopic evaluation, as the term indicates, utilizes the mean of the parameters which is the mass in this case of study. At each time step, the masses over the propositions given by the equation (8) is computed at the local and global fusion levels. At the end, the mean of the masses obtained at the global fusion results is computed.

Figure 8a presents the mean of the masses given at the global

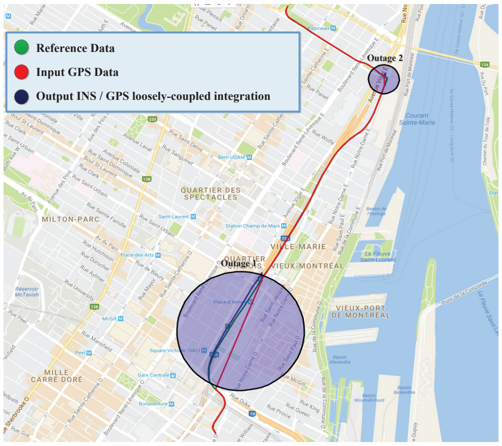

Fig. 7: Test trajectory

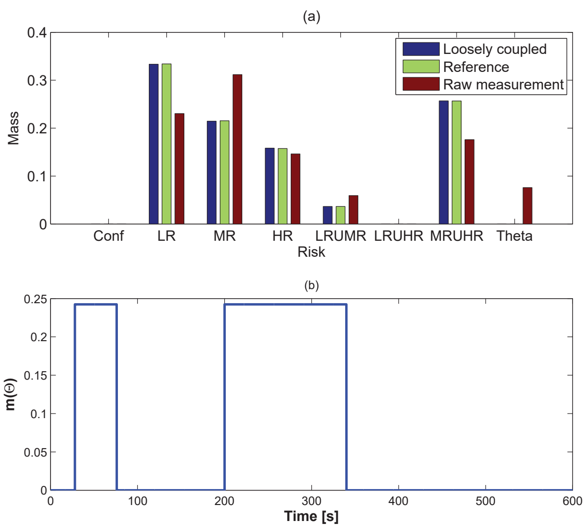

Fig. 8: Driver behavior results related to the scenario #2

fusion level using the raw measurement (data with outages), reference (SPAN Novatel) and the data obtained through the loosely coupled integration step using the raw measurement. Table I summarizes these results and compares the obtained masses. The originality of our methodology lies in the fact that there is no conflict between information sources since the mean mass over this proposition is null (m(Conf)=0) according to Figure 8 and Table I.

Using raw measurement data, the GPS outages involve a mean mass over the proposition Θ ($m(\Theta)$=0.0760). Figure 8b presents the variation of the mass over the proposition Θ over time. The maximum value assigned to $m(\Theta)$ is 0.2424 where the minimum is 0. In that Figure, when the mass is not null means that there is a GPS outage and/or some parameters, required to assess the driver behavior, are missed. So, the insurer can take into account this information when computing the insurance premium of the client.

TABLE I: Mean masses over the risk propositions using the reference, raw measurement and loosely coupled INS/GPS integrated data

	Reference	Raw	Loosely coupled
Conf	0	0	0
LR	0.3335	0.2305	0.3335
MR	0.2146	0.3117	0.2146
HR	0.1584	0.1463	0.1584
LR ∪ MR	0.0365	0.0594	0.0365
MR ∪ HR	0	0	0
LR ∪ HR	0.2570	0.1761	0.2570
Θ	0	0.0760	0

V. Conclusion

This paper has clearly shown the impact of GPS outages on the evaluation of the driver behavior. It has presented a GPS/INS integration system followed by a Driver Behavior Assessment (DBA) system. Summing up the results, it can be concluded that the DBA has been sensitive to the GPS outages. In addition, the most important finding of this paper is the validity of the developed risk models of the DVE system since there is no conflict between sources, even in case of GPS outages.

Acknowledgment

This research is part of the project entitled Vehicle Tracking and Accident Diagnostic System (VTADS). This research is partially supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), École de technology supérieure (ÉTS) within the LASSENA Laboratory in collaboration with two industrial partners namely iMetrik Global Inc. and Future Electronics.

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