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Location Detection of Vehicular Accident Using Global Navigation Satellite Systems/Inertial Measurement Units Navigator

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***Abstract*—**Vehicle tracking and accident recognizing are considered by many industries like insurance and vehicle rental companies. The main goal of this paper is to detect the location of a car accident by combining different methods. The methods, which are considered in this paper, are Global Navigation Satellite Systems/Inertial Measurement Units (GNSS/IMU)-based navigation and vehicle accident detection algorithms. They are expressed by a set of raw measurements, which are obtained from a designed integrator black box using GNSS and inertial sensors. Another concern of this paper is the definition of accident detection algorithm based on its jerk to identify the position of that accident. In fact, the results convinced us that, even in GNSS blockage areas, the position of the accident could be detected by GNSS/INS integration with 50% improvement compared to GNSS stand alone.

***Keywords*—**Driving behavior, integration, IMU, GNSS, monitoring, tracking.

I. Introduction

RECENTLY, vehicle accident fatalities rate has been one of the main concerns in fleet managements. More than 2000 fatalities and 11000 serious injuries per year have been reported by health agency of Canada, which impose expenses around 100 billion dollars per year to government [1]. Driver behavior monitoring helps to develop the pricing solutions of insurance companies based on driver habits, place of traveling, and other factors [2].

Reliability requirement of location based services (LBS) is based on global navigation satellite systems (GNSS). However, perfect conditions affected by multi path errors cannot be achieved when driving in severe environments [3]. A helpful key to obtain a trustable navigation algorithm is to integrate the GNSS data with Inertial Measurement Units (IMUs) which are self-governing navigation devices.

Kalman Filter (KF) is a method to fuse IMU and GNSS which can determine the optimal estimation of the system with minimum mean and square errors [4], [5]. This paper has designed a KF-based GNSS/IMU to have a full coverage in GNSS outages. In KF-based GNSS/IMU fusion, IMUs can recognize the location, velocity, and heading of the moving vehicle by utilizing inertial navigation mechanization process. [6], [7].

The raw data of IMUs have to be exploited in dynamics condition. Also, accident detection technologies are the technologies to trigger and activate Supplemental Restraint System (SRS) like airbags and seatbelts used in different vehicles [8]. This paper proposed to use different inertial sensors to detect an accident by two important factors in driving, which are the deviation in velocity and heading of the vehicle. If the proposed accident detection algorithm can recognize that an accident is happened, the GNSS/IMU navigation system can present the location of the accident.

The paper is organized as follows: Section II presents the GNSS/IMU integration process. Sections III and IV give the proposed methods which are used in this paper as well as the analysis of experimental results. Section V presents the conclusions of this paper.

II. GNSS/IMU Integration Process

This section presents details on background of techniques and ideas used in this study. More specifically, the main algorithm will be considered in this paper is integration of GNSS and IMU to have a full coverage for navigation system, and detection of accident based on dynamic of the moving vehicle.

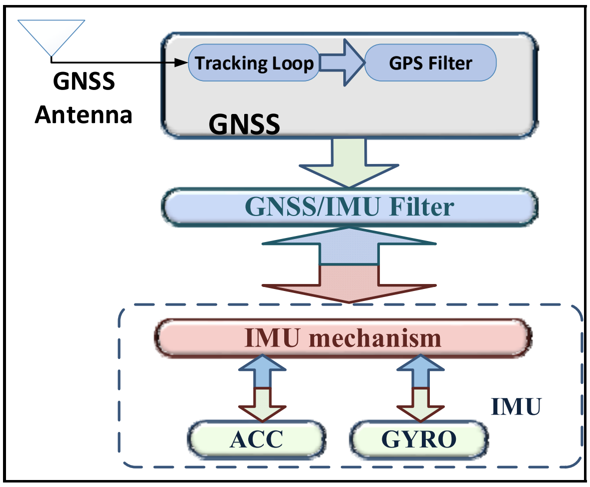

Fig. 1 Loosely coupled GNSS/IMU integration

Integration of IMUs and GNSSs through loosely coupled structure, not only maintains independency and redundancy of stand-alone GNSS and IMU solutions, but also it can provide more robust navigation solution [9]. Loosely coupled structure presents a closed-loop architecture that allows the correction of certain errors of the IMU system. This structure is generally

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preferable in the GNSS/IMU integration as being composed of three distinct entities, which are the stand-alone GNSS solution, the stand-alone IMU solution, and the GNSS/IMU solution.

GNSS/IMU integration model is presented in Fig 1. This model contains errors of location, speed, and heading [10]. GNSS/IMU integration can reduce the errors with this error model [11]. The block diagram of KF is shown in Fig. 2.

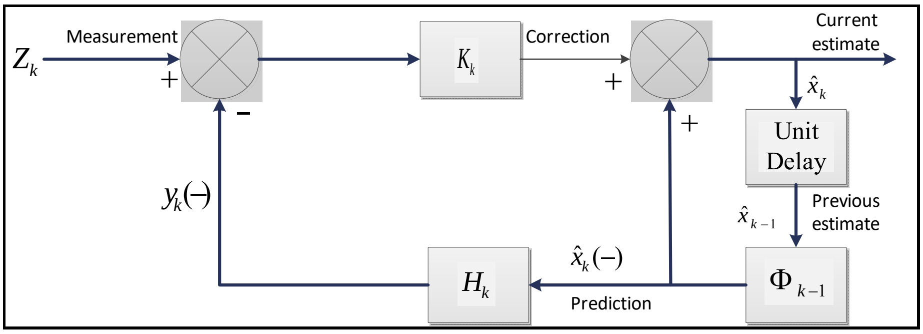

Fig. 2 A block diagram of Kalman filter

III. Proposed Methods

This paper proposes to combine two independent and complementary solutions in a global accident detection system to provide stable and accurate positioning of car accident even in severe urban environments. The proposed solutions consist of augmenting the navigation solution with combined GNSS and IMU using KF and exploiting the inertial sensor to estimate the dynamics of vehicle to extract the accident. Fig. 3 shows how two solutions are combined in this study. This section presents details on these proposed solutions.

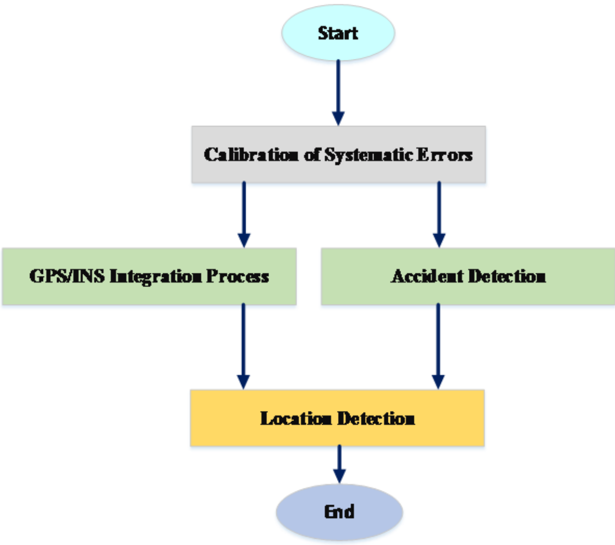

Fig. 3 Flowchart of the auto-accident detection

A. Dynamic Model of GNSS/IMU Integration

Equations of dynamic model of GNSS/IMU integration are related to process of the navigational information using accelerometers and gyroscopes. So, the global model used in this paper is based on (1) [12], [13]:

$$\begin{bmatrix} \dot{R}_b^n \\ \delta\dot{\underline{V}}^n \\ \delta\dot{\underline{P}}^n \end{bmatrix} = \begin{bmatrix} R_b^n(\underline{\Omega}_{ib}^b - \Omega_{il}^l) \\ \underline{f}^n + \underline{g}^n - (\underline{\Omega}_{en}^n + 2\underline{\Omega}_{ie}^n) \times \underline{V}^n \\ T.\underline{V}^n \end{bmatrix} \tag{1}$$

The attitude of the moving body inside the IMU algorithm is obtained by integrating the propagation equation of the direction cosine matrix which is shown with $\mathrm{R_b^n}$. $\underline{\Omega}_{ib}^b$ can be obtained by the gyroscopes, and Ω_{il}^l can be calculated by $\mathrm{R_b^n}$. $\mathrm{R_b^n}$ is obtained by $\mathrm{R_b^l} * \mathrm{R_l^n}$. In the mentioned equation, $\mathrm{R_l^n} = \mathrm{R_n^l} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & -1 \end{bmatrix}$ and $\mathrm{R_b^l}$ can be calculated by (2) [14]:

$$R_b^l = \begin{bmatrix} \cos\theta\cos\psi & -\cos\phi\sin\psi + \sin\phi\sin\theta\cos\psi & \sin\phi\sin\psi + \cos\phi\sin\theta\cos\psi \\ \cos\theta\sin\psi & \cos\phi\cos\psi + \sin\phi\sin\theta\sin\psi & -\sin\phi\cos\psi + \cos\phi\sin\theta\sin\psi \\ -\sin\theta & \sin\phi\cos\theta & \cos\phi\cos\theta \end{bmatrix} \tag{2}$$

The KF determines the general problem of trying to estimate the state of a discrete time controlled process that is clarified by the linear dynamic model presented by (6) and a measurement model in (4):

$$x_k = A_{k,k-1}x_{k-1} + B_{k-1}w_{k-1} \tag{3}$$

$$z_k = C_k x_k + v_k \tag{4}$$

where A_k, B_k, and C_k are the transition, noise model, and observation matrices, respectively. $z_k$and x_k are the measurement and error state vectors. w_k and v_k represent the system and measurement noises, respectively, with the uncorrelated and zero mean random processes [15]:

$$\begin{gathered} E[w_k v_j^T] = 0 \\ w_k \sim N(0, Q_k) \\ v_k \sim N(0, R_k) \end{gathered} \tag{5}$$

and the covariance matrices are:

$$E[w_k w_j^T] = \begin{cases} Q_k & ,j = k \\ 0 & ,j \neq k \end{cases} \quad (6)$$

$$E[v_k v_j^T] = \begin{cases} R_k & ,j = k \\ 0 & ,j \neq k \end{cases} \quad (7)$$

There are two steps in KF process. The first step is the prediction of the system model [15]:

$$\hat{x}_{\bar{k}} = F_{k,k-1}\hat{x}_{k-1} \quad (8)$$

$$P_{\bar{k}} = F_{k,k-1}P_{k-1}F_{k,k-1}{}^T + G_{k-1}Q_{k-1}G_{k-1}{}^T \quad (9)$$

The measurement update is considered as [15]:

$$K_k = P_{\bar{k}}H_k^T(H_k P_{\bar{k}} H_k^T + R_k)^{-1} \quad (10)$$

$$\hat{x}_k = \hat{x}_{\bar{k}} + K_k(z_k - H\hat{x}_{\bar{k}}) \quad (11)$$

where K_k, P_k, and $\hat{x}_k$ are the Kalman gain, covariance update, and state update, respectively.

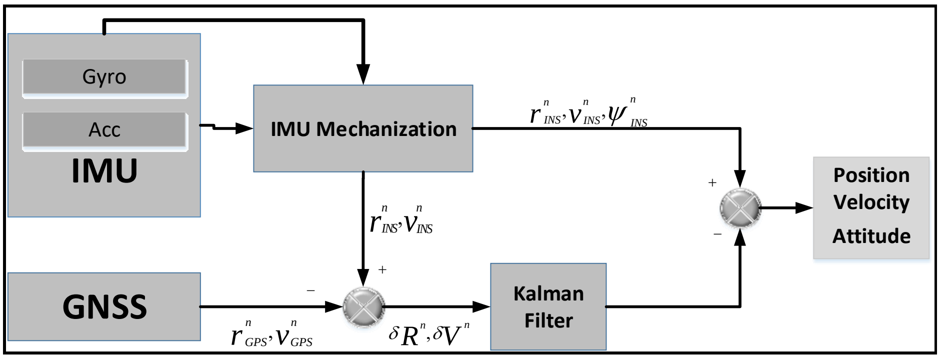

Fig. 4 GNSS/IMU integration system used in this study

B. Accident Detection

The proposed accident detection algorithm in this paper is based on several experimental tests which are carried out in real environment using TRAXXAS as a simulated real car. Different controlled accidents are designed for rear, front, left, and right accidents. A sample of these accidents is presented in Fig. 5. These figures show different kinds of accident in terms of acceleration of x, y, and z. Also, Fig. 6 shows the absolute value of acceleration during the designed accident. As one can see, there are at least a big peak when an accident was happened. Fig. 7 presents the absolute value of jerk which is derivative of absolute value of acceleration. As it is illustrated in this figure, the jerk threshold is 0.39 m/s^3 to determine if an accident is happened.

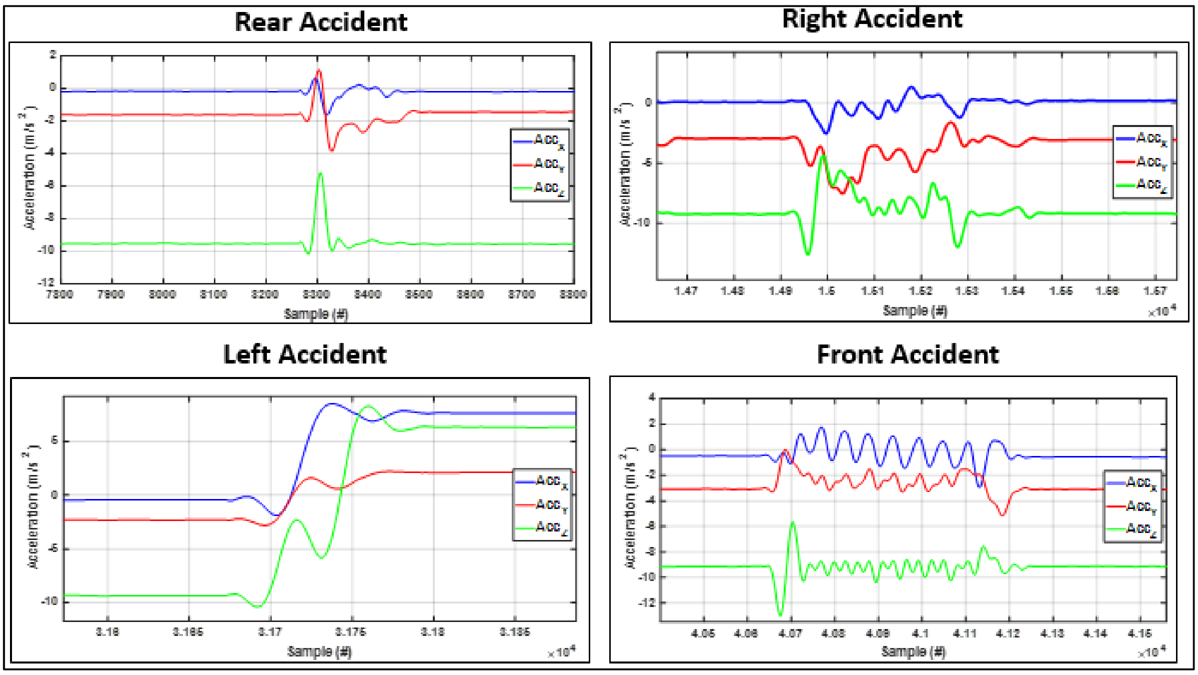

Fig. 5 Acceleration in x, y, and z for different accidents with TRAXXAS

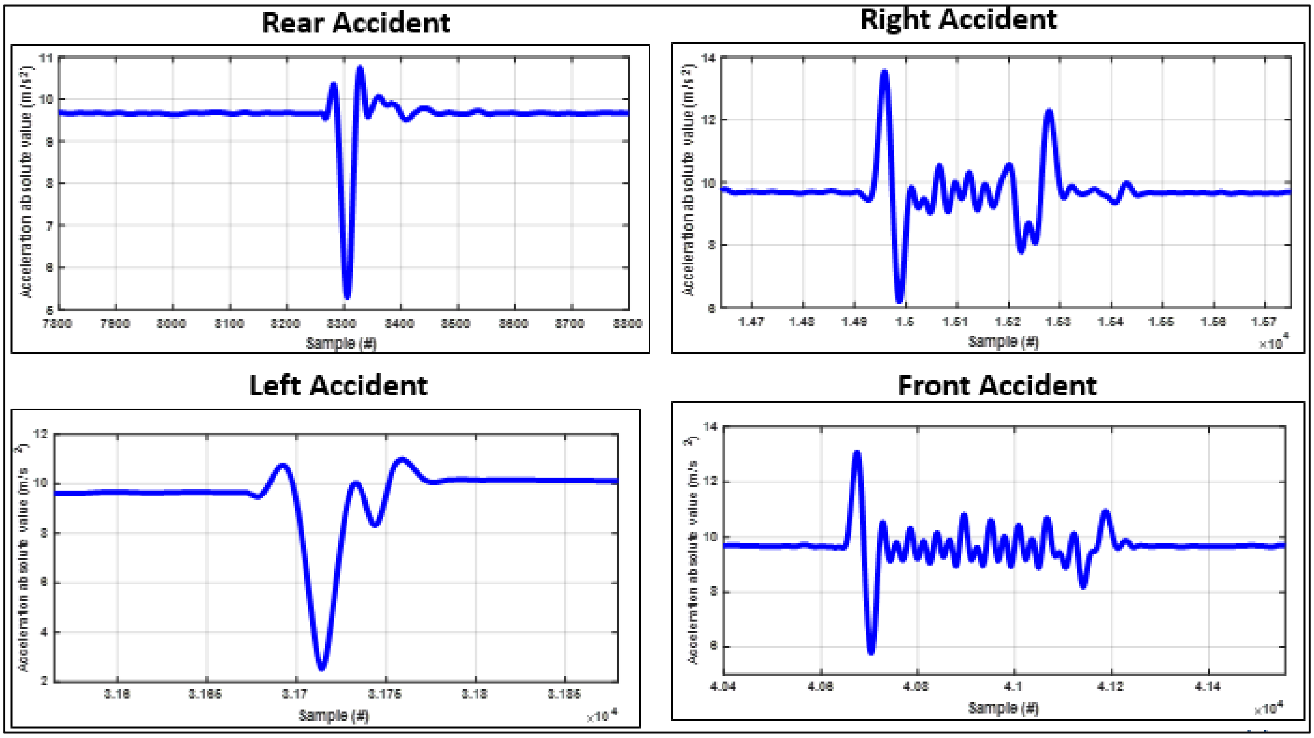

Fig. 6 Absolute value of acceleration for different accidents with TRAXXAS

Also, several experimental tests were carried out in real environment using a real car. Different accidents were considered for rear, front, left, and right accidents. A sample of these accidents is presented in Fig. 8. These figures present the different kind of accidents in terms of acceleration of x, y, and z. Also, Fig. 9 presents the absolute value of acceleration during the accidents. There is at least a big peak when an accident was happened. Fig. 10 presents the absolute value of jerk which is derivative of absolute value of acceleration. As one can see in this figure, the jerk threshold is 20 m/s^3 to determine if an accident is happened in real car.

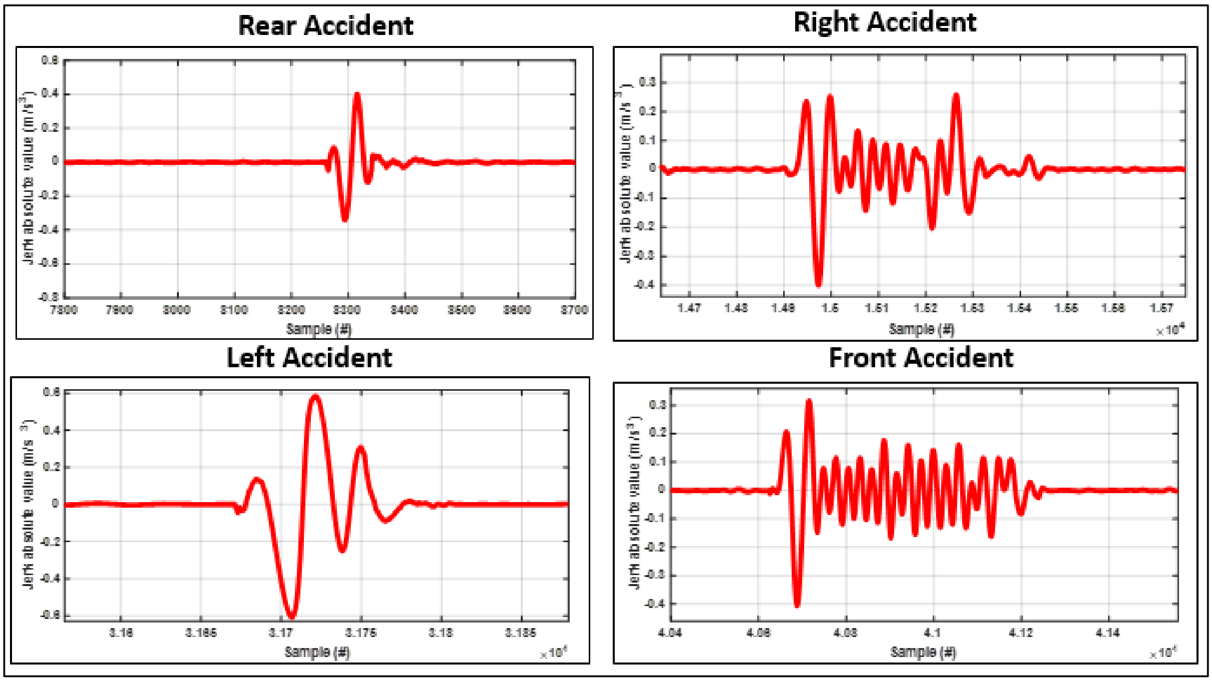

Fig. 7 Absolute value of jerk for different accidents with TRAXXAS

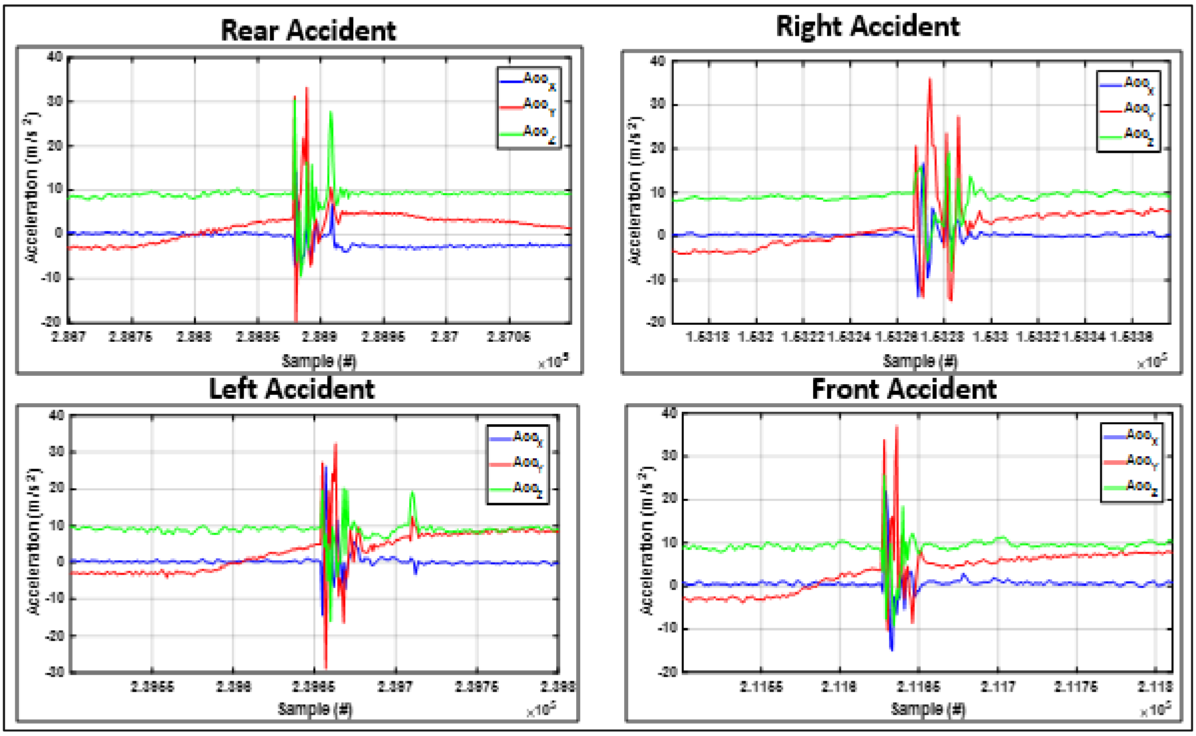

Fig. 8 Acceleration in x, y, and z for different accidents with real car

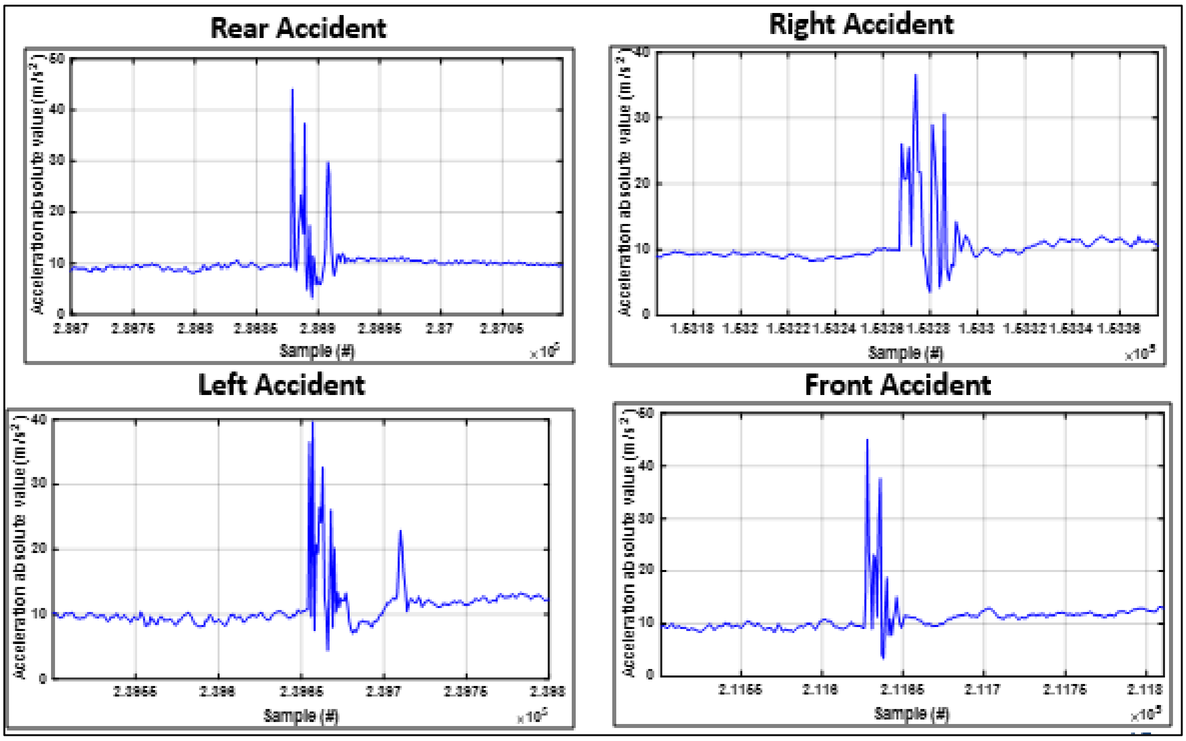

Fig. 9 Absolute value of acceleration for different accidents with real car

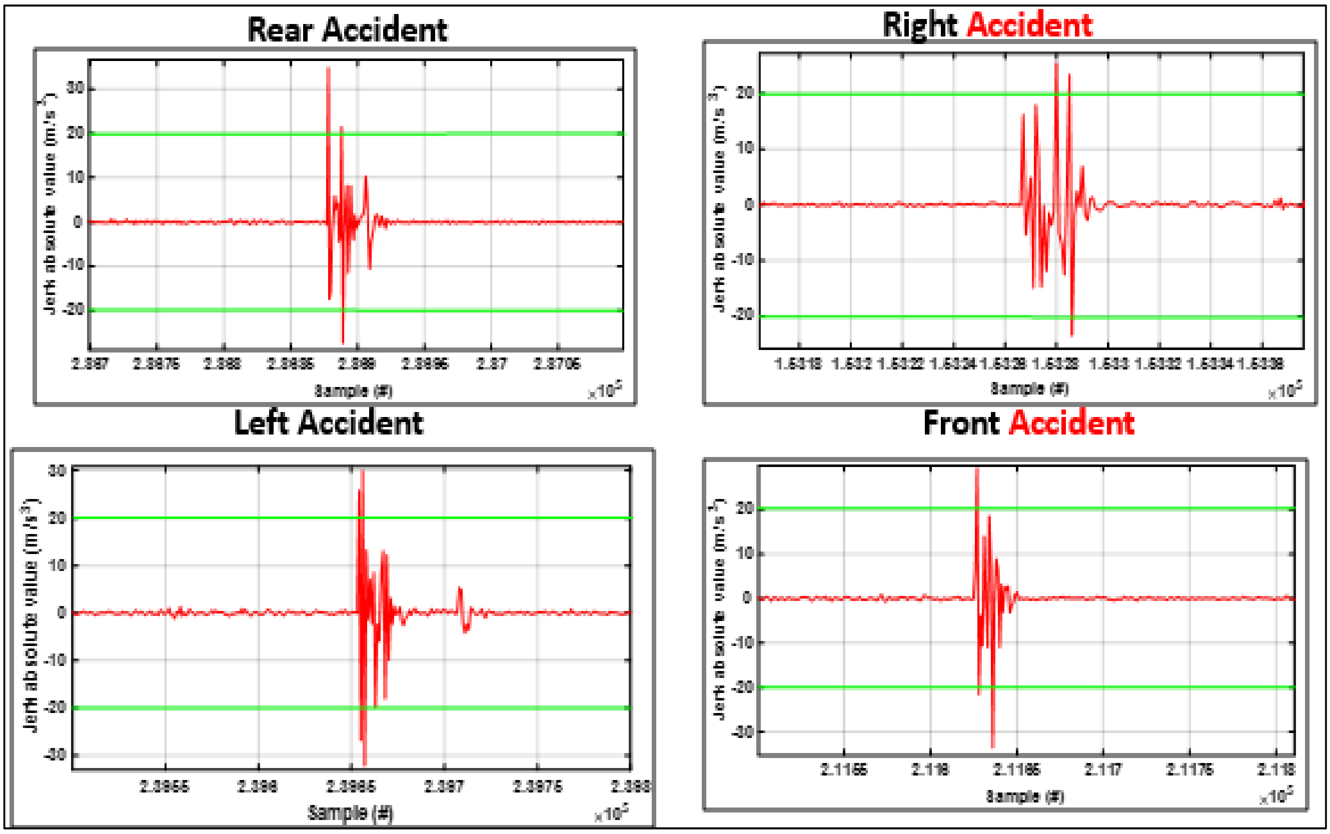

Fig. 10 Absolute value of jerk for different accidents with real car

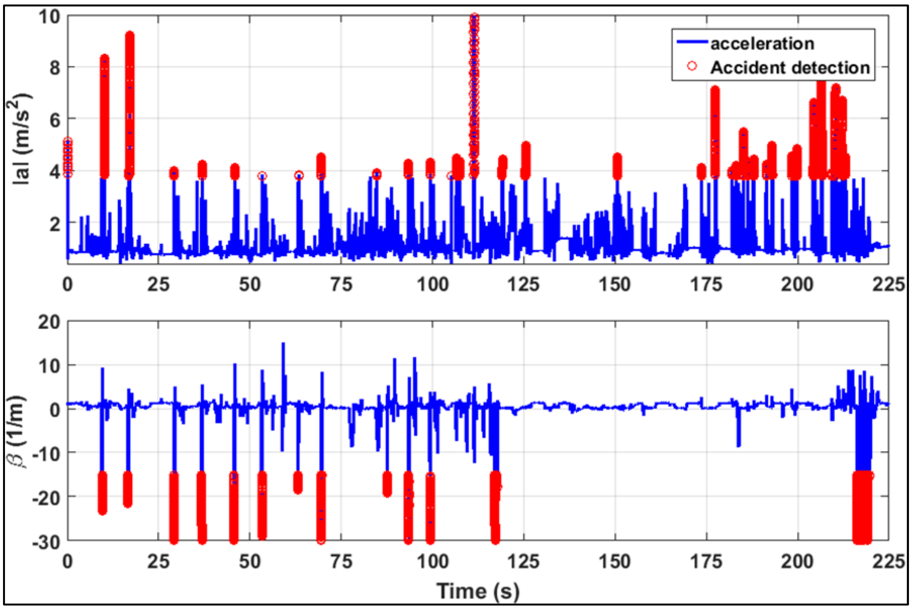

Fig. 11 Accident detection based on acceleration and curvature of the vehicle

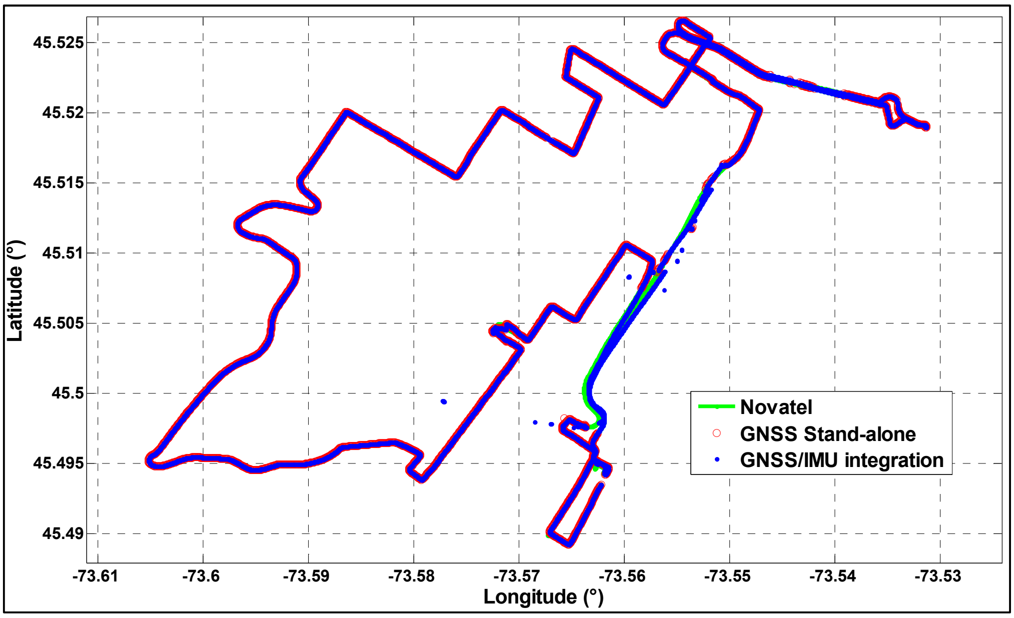

Fig. 12 Comparison of GNSS stand-alone and GNSS/IMU integration for the second scenario

IV. Experimental Results

The data which were obtained for analysis of the accident detection consist of accelerometers, gyroscopes, magnetometers, and a temperature sensor. [16]. The proposed solution was implemented for a road-test in different scenarios. The results were evaluated against a reference solution provided by Novatel SPAN technology to validate the proposed method and to assess the overall performance during the GNSS outages. Scenario #1 is a trajectory which was recorded in an ideal environment to assess the accident detection algorithm. Scenario #2 is a trajectory which was performed in harsh environment to evaluate the navigational systems in difficult situation.

Scenario #1 was chosen in order to allow the GNSS receiver to obtain optimum visibility throughout the trajectory. This scenario thus provides a control navigation solution for the different algorithms allowing to quantify their performances in an ideal environment. The trajectory was carried out on the Griffin town of Montréal, specifically in the municipalities of Chalet de Mont-Royal.

Fig. 11 presents the accident detection algorithms based on both acceleration and curvature of the moving vehicle. According to proposed model in accident detection, if the absolute value of acceleration is more than 3.7 m/s^2 and curvature of the vehicle is more than 15°, an accident is detected. After the accident is detected, the position of the accident reveals on the map.

Scenario #2 was performed in an urban freeway, in downtown area with lots of skyscrapers. Scenario # 2 can evaluate the impact of a harsh environment on GNSS/IMU navigation solution. Fig. 12 illustrates the horizontal positioning results for the trajectory of both algorithm configurations of GNSS stand-alone and GNSS/IMU integration. In this figure, green color presents the solution of Novatel SPAN as the reference, red color dots present the GNSS stand-alone solution, and blue color shows the GNSS/IMU integration solution.

V. Conclusion

This paper proposes a solution for the analysis and the diagnosis of car accidents and location-of-collision detection system based on GNSS/IMU integration. The accident detection and navigation system algorithms utilized set of raw measurements obtained by various sensors. These algorithms can detect car accidents based on the capabilities of intelligent systems. The models consider GNSS/IMU-based navigation algorithm, calibration of navigational sensors, a de-nosing method as long as vehicle accidents. Even in harsh environment, the place of an accident can be recognized.

Acknowledgment

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