A Framework for Adaptive Resolution Geo-Referencing in Intelligent Vehicular Services

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***Abstract*— Future smart cities are profoundly looking forward to providing services that assure daily competent functionality. Efficient traffic management and related vehicular services are crucial aspects when considering the city's decent operation. The significant presence of the vehicular and smartphone sensing and computing capabilities within and amongst the vehicles open the door towards robust vehicular and road services. The retrofitted present and future vehicles will be able to provide accurate real-time information about the road conditions and hazards, driver behaviour, and traffic. Adequate geo-referencing is remarkably demanded in order to preserve robustness while providing vehicular services. Present and widely spread global positioning systems (GPS) receivers are providing low-resolution position update at 1 Hz, which is not sufficient at high speeds. Also, alternative high data rate geo-referencing technologies may face self-contained or environmental-based performance limitations. In this paper, we propose an adaptive resolution integrated geo-referencing framework that augments GPS and inertial sensors to provide accurate localization and positioning for road information services. Also, we examine the effectiveness of the proposed system in geo-referencing for selected real-life road services.**

Keywords*— *Intelligent Vehicular Services, Vehicular Sensing, GPS, Inertial Sensors, Integrated Navigation Systems, Sensor Fusion

I. INTRODUCTION

Intelligent vehicular services have witnessed significant advancement due to the growth of the sensing, communications and computing systems and architectures [1]. Being equipped with or connected to these technologies, land vehicles are now capable of creating and interpreting big data. These sensed data enable valuable information about both the vehicle operation and regarding the interaction with the surrounding environment [2]. The vehicular services involve crowd management, monitoring road hazards and conditions, driver's behaviour assessment, and participating in reporting the traffic congestion levels [3].

In order to assure efficient performance of intelligent road services, an accurate geo-referencing is always required. Accordingly, most of the vehicular services lack the access to the required adequate geo-referencing of the detected events as they rely only on GPS. Generally, in urban areas and downtown cores, the localization accuracy dramatically deteriorates due to GPS satellite signal blockage and multipath [4, 5]. Moreover, complete outages also occur while driving under bridges or in tunnels.

To overcome GPS positioning systems challenges, inertial navigation systems (INS) are integrated with GPS receivers to provide accurate and continuous positioning [6]. The low-cost MEMS-based inertial sensors (accelerometers and gyroscopes) that are embedded in INS systems in land vehicles and ubiquitous smart devices are not susceptible to the same challenges of GPS. However, stand-alone INS solutions are liable to long-term position drifts and errors due to inertial sensors biases and noises. For example, uncertain and erroneous geo-referencing of the monitored anomalies again will distract the efforts required for road maintenance process[7, 8]. Other positioning technologies such as vision, Lidars and radars may suffer from environmental aspects such as fog, rain and snow that limit their performance. Also, some of these sensors such as Lidars are not affordable yet in terms of cost, and the high computational capabilities that are in some cases, beyond the requirements of ubiquitous vehicular services [9].

Consequently, most of the commercial GPS receivers are operated at 1 Hz. At high speeds, a position update of 1 Hz is not sufficient and lead to a low-resolution geo-referencing which limit the information quality regarding the monitored road hazards [7]. In many systems, standalone GPS receivers are used to localize the anomalies with an update rate of 1 Hz [10, 11, 12, 13]. The other systems used the GPS receivers embedded in the smart devices to locate the anomalies [14] and also with an update rate of 1 Hz. Although, for accurate and high-resolution road anomalies geo-referencing, a GPS receiver with an update rate of 5 Hz was used in [8].

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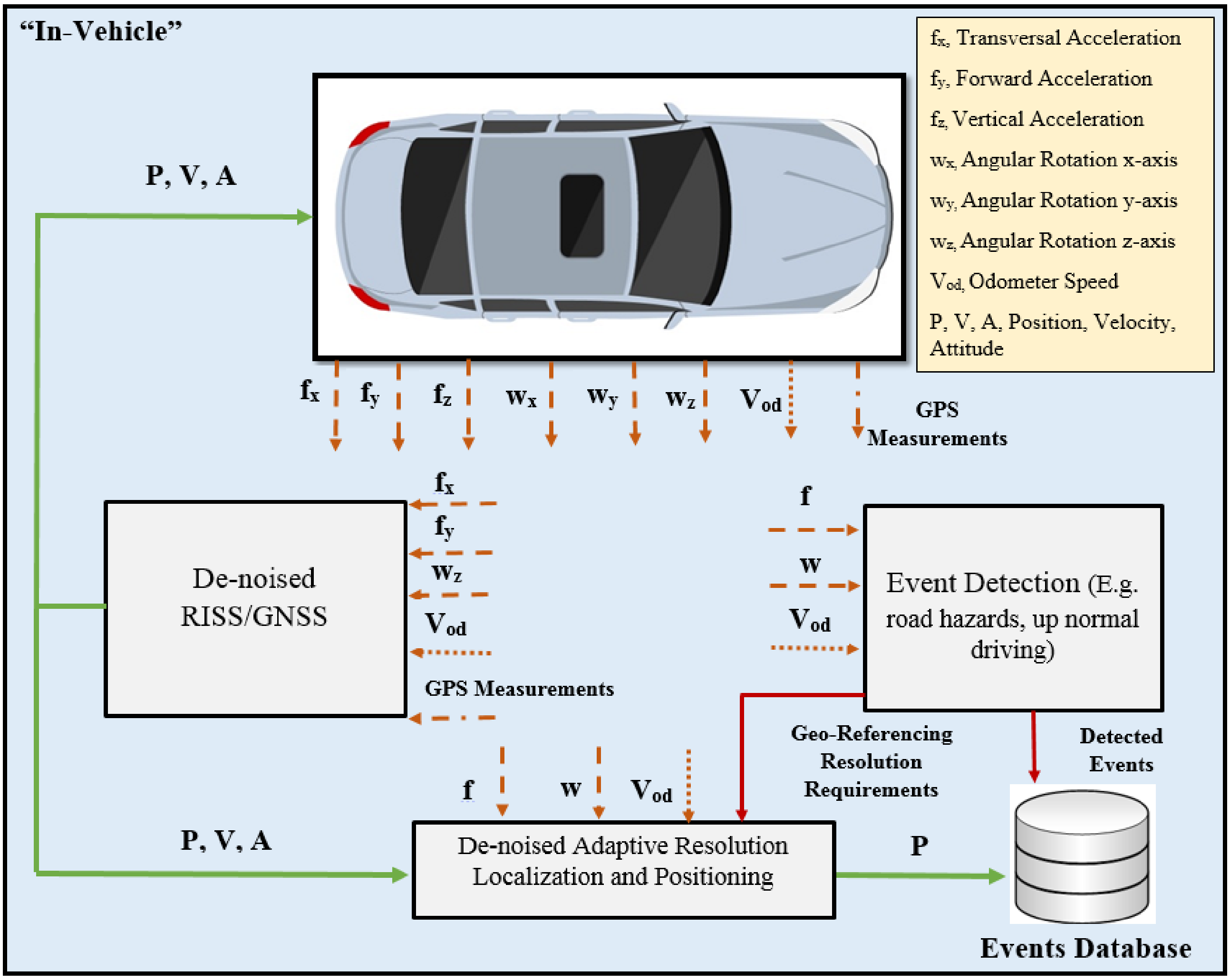

Figure 1 Framework for Adaptive Resolution Integrated Geo-referencing

Also, for monitoring driver behavior or even for accident-related assessments, automotive insurers require access to high-resolution positioning information during these events to help with their assessments and consequent decisions [15]. Nevertheless, most of the GPS data are always collected from either standalone GPS receivers or the ones within the smartphones were both are operated at 1 Hz. This low data rate position lacks the required resolution while assessing a detected up normal driver behaviour. Consequently, there is a notable demand for adaptive high data rate positioning for intelligent vehicular services.

In this paper, we propose a novel adaptive data rate positioning and localization framework. The system first augments the GPS by fusing its corresponding location measurements with a de-noised reduced inertial sensor system (RISS) at 1 Hz. The obtained accurate position is then fed to a RISS or a full mechanization module when triggered by a road event that requires a higher resolution geo-referencing or positioning. Accordingly, the mechanization module or RISS utilizes the output of the RISS/GPS module along with the inertial sensor measurements to provide high-resolution position information regarding the detected events. The monitored events and their corresponding location information update a database for reporting or further analysis purposes.

The paper is organized as follows: the framework for the adaptive resolution localization and positioning is introduced in section II. A practical-based real driving test case used to show the framework capabilities is followed in section III. The paper contributions and findings are summarized in section IV.

II. ADAPTIVE RESOLUTION GEO-REFERENCING FRAMEWORK

In this section, we present the proposed adaptive resolution geo-referencing framework and discuss its structure and specific components. Also, we provide a description of the conducted processes and the information flow.

Accordingly, as shown in Figure 1. the framework uses the inertial sensors and GPS receivers within the land vehicles or the ones embedded in the smartphones. The inertial sensors are used to collect information that describes the vehicle motion dynamics that can be used in both navigating the vehicles and in extracting information for intelligent road services. On the other hand, GPS receivers are utilized to collect location measurements (position, velocity). In the following subsections, we illustrate the system modules and operation.

A. Integrated De-noised RISS/GPS

As mentioned earlier in the paper, GPS positioning technology has two significant challenges while being adopted for vehicular services. The first is the GPS receivers suffer from partial or complete outages during various driving scenarios and area [6]. The other challenge is that the broad majority of the commercial receivers are operating at 1 Hz, which is low-resolution location information for some vehicular services. In contrast to GPS, INS that is a self-contained technology relies on inertial sensors to provide positioning that can be available at high data rates. The main drawback of the INS technology is the rapidly growing position error in short periods due to sensors biases, noises and errors [5].

In literature, there were many techniques used in fusing GPS and INS to leverage both advantages while also avoiding their drawbacks. The Kalman filtering (KF), in specific, was widely used in integrating GPS and INS because of its computational efficiency and robustness [16]. However, in extended outages, the performance of the integrated navigation systems may deteriorate because of the inertial sensors noises and errors. In our system, as shown in Figure 1, we utilize a denoised RISS/GPS integration systems to obtain an accurate positioning solution at 1 Hz [16, 17].

In our system, we utilize a wavelet packet sensor de-noising technique to enhance the quality of the raw inertial sensor measurements [18]. The wavelet packets analysis has the capability of decomposing the signal into multi-frequency levels that separate the noises from the frequencies of the vehicle motion. Also, wavelets packets can separate eliminate the high-frequency noises and keep the high-frequency components that are describing road hazard or dangerous driving events, as shown in Figure 1. In this work, we use 5 wavelet packet decomposition levels of the Daubechies family. Besides, for thresholding, we adopt a soft thresholding technique (Stein unbiased risk estimator). This thresholding mechanism is chosen to minimize the thresholding risk [17, 18].

The RISS [6], is consisted of the gyroscope that measures the angle rotation around the z-axis, the forward and the transverse accelerometers, and an odometer. The main advantages of using the RISS compared to the full inertial measurement unit (IMU) is when the pitch and roll angles are calculated using accelerometers the biases or noises of the two omitted gyroscopes are avoided. The vehicle velocity is calculated using the forward speed measured by the odometer that gives the advantage of avoiding any uncompensated noises or biases of two accelerometers [6].

Afterwards, the de-noised sensor signals, along with the odometer measurements, are used in the mechanization process. The navigation state vector of 3D RISS is given by $x = [\varphi, \lambda, \Omega, v_e, v_n, v_u, r, p, A]^T$ where φ is the latitude, λ is longitude, Ω is the altitude, v_e is the velocity in the direction of east, v_n is the velocity in the north direction, v_u is the up velocity, r is the roll angle, p is the pitch angle, and A is the azimuth. The pitch angle is given by the following:

$$p = sin^{-1}\left(\frac{f_y - a_{od}}{g}\right) \tag{1}$$

Where f_y is the forward acceleration, a_{od} is the vehicle acceleration calculated using the vehicle acceleration gathered by the odometer, and g is the gravitational acceleration. The roll angle is obtained as follows:

$$r = -\sin^{-1}\left(\frac{f_x + v_{od}\omega_z}{g \cos p}\right) \tag{2}$$

The transversal acceleration is f_x, the vehicle speed computed from the odometer measurement is v_{od}, the angular rotation around the vertical Z-axis is ω_z. Besides, the azimuth angle is calculated as follows:

$$\dot{A} = -\left(\omega_z - \omega_e \sin\varphi - \frac{v_e \tan\varphi}{R_N + \Omega}\right) \tag{3}$$

h is the altitude and R_N is the normal radius of the earth curvature. Moreover, the three velocities can be transformed from the forward velocity and computed as follow:

$$v_e = v_{od} \sin A \cos p \tag{4}$$
$$v_n = v_{od} \cos A \cos p \tag{5}$$
$$v_u = v_{od} \sin p \tag{6}$$

The latitude φ, the longitude λ, the altitude $\Omega, and\ R_M$ the meridian radius of curvature can be calculated as follow:

$$\dot{\varphi} = \frac{v_n}{(R_m + \Omega)} \tag{7}$$

$$\dot{\lambda} = \frac{v_e}{(R_N + \Omega)\cos\varphi} \tag{8}$$

$$\dot{\Omega} = v_u \tag{9}$$

In this system, we use the extended Kalman filter (EKF) closed-loop process to integrate the GPS and INS. The EKF outperforms the KF as the linearization is carried out on the corrected RISS outputs. In addition to the bias compensation of the gyroscope measurements achieved by the EKF. Accordingly, accurate positioning can be achieved. Further details and the mathematical model of the EKF 3D RISS/GNSS can be accessed in [6, 17]. The output of this stage in terms of position velocity and attitude (P, V, A) is obtained at 1 Hz. For general navigation purposes, this data rate of accurate position is suitable for navigating the vehicles in urban canyons and downtown cores. Also, the (P, V, A) is used as the initialization for the adaptive resolution positioning component when triggered by a monitored event.

B. Monitoring Road Hazards, Driver's Behaviour and Geo-Referencing Requirments

Nevertheless, detecting and monitoring road conditions and driver's behaviour are key examples of the vital vehicular services of the smart cities. In general, the systems provide such services use the inertial sensors and the GPS receivers within the vehicles to provide the road quality assessments and driver behaviour analysis [11, 15]. However, the typical low-resolution location updates provided by the GPS commercial receivers are not useful [7].

At high speeds, for example, for a highway with the speed limit of 100 km/h, the vehicles travel around 28 m/s. With the GPS update of 1 Hz, a location stamp can be achieved with a resolution of 28 meters. Geo-referencing the road anomalies or ice accumulation requires a higher resolution localization in order to precisely report these events. Also, the high-resolution continuous positioning may be required for assessing driver behaviour who may be involved in a crash event. In such a case, a 1 Hz position update will not provide the required resolution of continuous positioning [7, 15].

In the proposed system, as shown in Figure 1, the event detection component collects the inertial sensor linear accelerations and angular rotations measurements at a data rate of 100 Hz, and the vehicle speed at 1 Hz. With the aid of predetermined measurement thresholds, the event detection module is informed of a road anomaly or irregular driving event. For a consecutive time windows of 1 second each, the inertial measurements are de-noised using the wavelet packet decomposition process that was mentioned earlier in the paper. Afterwards, machine learning techniques are used to detect and classify the type of the occurred road anomaly or driver behaviour.

For efficient reporting and further analysis, detected road events, specifically, the ones that occurred at high speeds may need additional location information. Regarding the road hazards, the event detection module can decide the exact time instant the road even has started. Also, the vehicle speed is monitored to guide with the position resolution requirement. For instance, a position update with a resolution of approximately 1m is required in most of the cases. Then, a time-stamped request is sent to the adaptive positioning and localization module along with the required rate to request the required position information. On the other hand, in the case of a dangerous driving scenario, a continuous high position resolution is required during the time window of 1 second. The position update rate is also decided with the aid of the vehicle speed during the intended time window.

C. *Adaptive Resolution Localization and Positioning for the Vehicular Services*

In this subsection, the adaptive resolution geo-referencing module is presented. The event detection module first triggers this module. Once a road event is detected, the detecting module sends a detailed request of the required positioning or localization resolution. The details include the time window or windows that a higher position resolution is required. Also, the event detection component clarifies the nature of the required location information. For road anomalies, the event detection module sends the exact time instant where the event has started and requests a high-resolution geo-location for the monitored event while also considering the vehicle speed.

For irregular or dangerous driving scenarios, the event detection module first set whether the event occurred in a one or more than a one-time window. Accordingly, it sends the time-stamped windows that require a higher resolution continuous positioning. The adaptive rate geo-referencing then requests the (P, V, A) information of the time window or windows that need additional location information.

The adaptive geo-referencing module can utilize a RISS or full mechanization procedures to provide a higher resolution position. For this work, we describe the RISS procedures that are similar in concept to the full mechanization where additional details can be accessed in [6]. RISS is like the INS systems that use the inertial sensor measurements to present information about the moving platform's velocity, position and attitude in a dead reckoning (DR) manner. In DR, the linear accelerations and angular rotations are used to determine the present vehicle position with the knowledge of its last position. In the case of RISS used in higher resolution positioning module, the RISS/GPS provides the module with (P, V, A) of a specific time window to be used in initializing the RISS module. Afterwards, the RISS utilizes the inertial measurements with the upsampled odometer speed to predict the high-resolution position requested by the event detection module. The detected event and its location information are updating the database, as shown in Figure 1.

III. CASE STUDY

In this section, we present a case study of a real-life driving experiment held in the city of Kingston, ON. In this scenario, the vehicle was travelling at a speed of 50 km/hr. This speed indicates that the RISS/GPS module can provide a position resolution of 15 m/sec. During the driving experiment, the event detection module with the aid of the inertial sensors was able to detect a severe manhole that disturbed the vehicle motions, as shown in the accelerometers measurements in Figure 2.

The integrated RISS/GPS module has determined the position of the monitored manhole at points 1 and 2 in Figure 3. Accordingly, the low-resolution position of 1 Hz has led to a misleading geo-location for the monitored event. As shown in Figure 2, the inertial sensors were logged at 100 Hz. Using pre-set measurement thresholds, the event started at the sample no.30. Thus when a significant change of the vertical acceleration measurements was detected. This implies that the event approximately occurred at one-third of the time window of one second. Taking into consideration that the vehicle was travelling at 50 km/hr, the event detection module requests a higher resolution point position at 10 Hz. Moreover, it specifies that the requested point position is the one corresponding to the sample no.30.

The adaptive resolution positioning component then requests the (P, V, A) information at the time window number 1that is shown in Figure 3. In addition, the odometer measurement at time windows number 1 and 2 are used in an

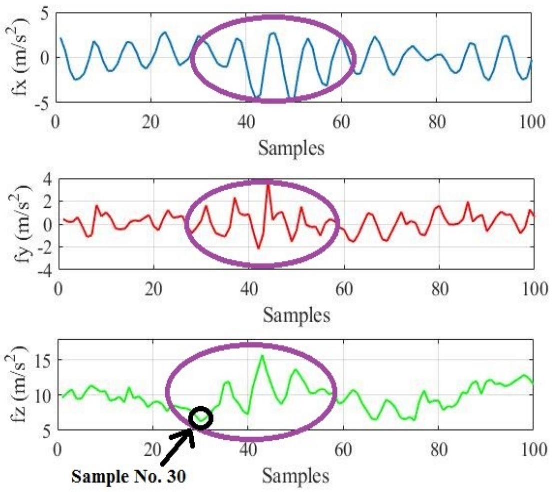

Figure 2 Three Axis Accelerometer Measurements for a Detected Road Anomaly (Manhole)

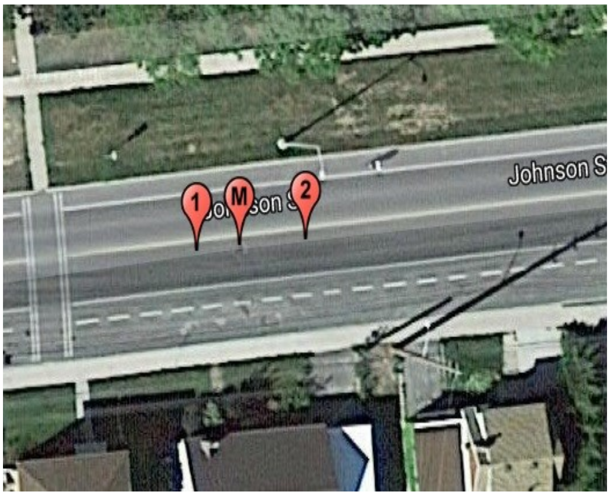

Figure 3 Adaptive Resolutions Geo-Referencing of a Road Anomaly (Manhole)

upsampling process to get a speed update of 10 Hz. The (P, V, A) of time window no. 1 is used to initialize the RISS module and leveraging the Equations 1-9 that are used to predict the point position corresponds to the sample no. 30, where the manhole was detected. As shown in Figure 3, the predicted high data rate manhole position is more accurate than the position of the time window no.1 and no.2 that are shown in Figure 3. The presented case study shows the significance of the proposed framework for geo-referencing vehicular services, such as monitoring road conditions.

IV. CONCLUSION

Intelligent vehicular services are in the core interest of the future smart cities due to their direct effect on residents' safety and the daily city operation. Accurate and dynamic geo-referencing is a significant component in most of the vehicular services. However, relying only on GPS commercial receivers that operate at 1 Hz and suffer from the well know GPS operation challenges can limit the effectiveness of such vehicular services. On the other hand, the other positioning technologies have either performance limitations or comes at a high cost. In this work, we proposed a dynamic framework that is capable of providing adaptive data rate localization and positioning information for the vehicular services. The system fuses the inertial sensors measurements with GPS measurements to present detailed location information of the monitored road hazards or driver behaviour. This location information, along with their corresponding detected events update a database that can be used for reporting or further analysis and investigations by municipalities or authorities.

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