An Integrated IMU/LiDAR Navigation System For GNSS-Denied Environments

Nader Abdelaziz and Ahmed El-Rabbany, Canada

Keywords: LiDAR SLAM; Kitware SLAM; GNSS/INS/LiDAR SLAM integration; Integrated navigation system.

SUMMARY

Traditionally, most navigation systems rely on GNSS/inertial navigation system (INS) integrated navigation systems, in which the INS can provide reliable positioning during short GNSS outages. However, for prolonged GNSS signal outages, the performance of the system will be solely dependent on the INS solution, which can lead to a significant drift over time. Consequently, integrating complementary onboard sensors is crucial. This study proposes a robust, loosely-coupled (LC) integration between the INS and LiDAR simultaneous mapping and localization (SLAM) using an extended Kalman filter (EKF). The integrated navigation system is tested on the raw KITTI dataset using both residential and highway datasets, which mimics various outdoor driving environments during a complete absence of GNSS signal. It is shown that the proposed IMU/LiDAR SLAM integrated system outperforms the sole use of the INS. The integrated system positioning results yielded an average reduction of the root-mean-square error in the east, north, and up directions of 94%, 67%, and 27%, respectively.

An Integrated IMU/LiDAR Navigation System For GNSS-Denied Environments

Nader Abdelaziz and Ahmed El-Rabbany, Canada

1 INTRODUCTION

There exist several challenges in the field of vehicular navigation research and development, of which providing accurate, robust positioning is a major one. That is, vehicular positioning demands navigation systems that provide an accurate position for all driving environments and weather conditions. In addition, the navigation system must achieve redundancy, such that should one sensor fail to operate, the system will still be functional. As a result, the use of a single sensor may not produce a robust navigation solution, even if such sensor provides accurate positioning. This emphasizes the need for multi-sensor integration to result in robust, accurate positioning (de Ponte Müller, 2017, Martínez-Díaz and Soriguera, 2018).

GNSS/INS integrated navigation systems are commonly adopted due to the complementary characteristics of GNSS and INS. Typically, the observations of the GNSS and INS are fused using a Kalman filter (Shin, 2005). That is, the INS provides the position of the vehicle through mechanization while receiving updates from the GNSS at a slower frequency to minimize the mechanization drift. The integration relies on the ability of the INS to provide the position of the vehicle at a high frequency. As a result, for closed-error scheme integration, the INS can provide reliable positioning while experiencing short GNSS signal outages. However, if the GNSS outage occurs for a prolonged amount of time, the system will rely on the performance of the INS, which is prone to a significant drift, especially when a low-cost micro-electro-mechanical system (MEMS) IMU is used (Abd Rabbou and El-Rabbany, 2015, Elmezayen and El-Rabbany, 2021, Elmezayen and El-Rabbany, 2020, Gao et al., 2021, Wang et al., 2018).

In order to improve the aforementioned performance of navigation systems, additional onboard sensors that can be used for navigation are required, which allows the system to sustain prolonged GNSS outages. LiDAR sensors are widely used for localization through simultaneous mapping and localization (SLAM) techniques. The basic idea of SLAM algorithms is to use a sensor to construct a map of the surrounding environment, while simultaneously keeping track of the location of the sensor.

Many studies proposed the integration of GNSS, INS, and LiDAR SLAM. In (Chang et al., 2019), an integration scheme was proposed, which integrates GNSS/INS with LiDAR SLAM based on graph optimization. In that study, the GNSS/INS results were matched with the relative pose of a 3D probability map. The system was tested during a one-minute outage of the GNSS signal. The RMS of the position in the east and north was reduced by roughly 80% compared to the GNSS/INS navigation solution.

In this paper, a loosely-coupled (LC) integration between GNSS/INS and LiDAR SLAM using an EKF is proposed. The proposed navigation system is tested in different driving environments (urban and rural) and scenarios (high and low driving speeds). In addition, the system provides reliable position and attitude information during GNSS signal outages.

2 SYSTEM ARCHITECTURE AND MATHEMATICAL MODELS

2.1 Full IMU Mechanization

The IMU observations are measured with respect to the body frame (b-frame), whose axes are defined as follows: the Y-axis is the forward direction, the X-axis is the transverse direction, and the Z-axis is the up direction. In addition, the IMU measurements are referenced to the navigation frame. Given the raw measurements of the accelerometer and gyroscopes of the IMU in the mechanization, the outputs are position (latitude, longitude, and altitude), velocity (east, north, and up directions), and attitude (roll, pitch, and yaw angles) (Noureldin et al., 2013).

2.2 LiDAR SLAM

The SLAM algorithm used in this study is the Kitware SLAM (KITWARE, 2020), which is based on the LOAM algorithm (Zhang and Singh, 2014). The LOAM algorithm is composed of three main stages, namely point cloud registration, LiDAR odometry, and LiDAR mapping. While Kitware SLAM uses the base architecture of LOAM, there exist some improvements. Firstly, running time is reduced due to the use of C++ libraries and tools designed for better computational performance. In addition, the algorithm is independent form robot operating system (ROS) and does not rely on hard-coded parameters. It can also run in Windows and Linux operating systems using LidarView software. Furthermore, it is more generalized such that it runs on several LiDAR sensors, including the Velodyne. Finally, the algorithm can process point clouds from multiple LiDAR sensors.

2.3 IMU/LiDAR Integration

In this paper, a LC integration between the GNSS, IMU, and LiDAR is adopted using an EKF, which results in an integrated navigation solution, as shown in Figure (1).

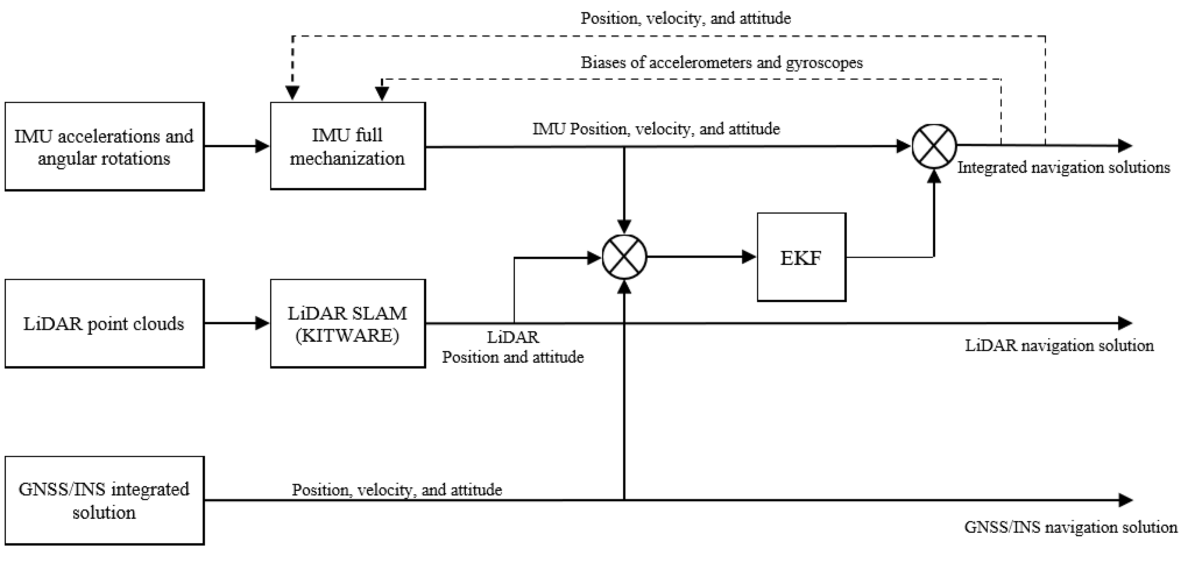

Figure (1): A block diagram for the GNSS/LiDAR/IMU LC integration

Raw IMU measurements of accelerations and angular rotations are used as input to a full IMU mechanization, which outputs position, velocity, and attitude of the navigation system. Meanwhile, the LiDAR point clouds are fed into the Kitware SLAM algorithm, which yields the position and attitude of the vehicle. These are used as the measurement update to the IMU mechanization output during the update stage of the EKF, which yields an integrated navigation solution. Subsequently, the updated errors are fed back into the IMU mechanization, which forms a closed-loop error scheme.

3 DATA SOURCE AND CASE STUDIES

The raw KITTI dataset is used in this study (Geiger et al., 2013). Two datasets of the raw KITTI dataset were used. The first one is a 2-minute-segment drive from the raw, residential KITTI datasets, 2011_09_30_drive_0018_sync, which features urban environments with dense features and slow driving speed. The second dataset is a 90-second-segment drive from the raw, road KITTI dataset, drive, 2011_10_03_drive_0042_sync, representing highway environments with sparse features and fast driving speed. These datasets formulate two case studies of GNSS signal outages for urban and rural environments.

For both case studies, the data experiences the same processing procedures. Firstly, the raw data of the IMU are fed as inputs into the full IMU mechanization. The stream of point clouds collected by the LiDAR sensor is processed using the KITWARE SLAM algorithm. Finally, the mechanization results and the LiDAR update are integrated using the EKF, which yields the integrated navigation solution.

4 ANALYSIS AND RESULTS

4.1 First Case Study—The Residential Dataset

The first case study represents a full GNSS signal outage along the whole trajectory of the vehicle. This is a 120-second outage, which processes all LiDAR frames of the residential dataset. Figure (2) illustrates the position errors in the ENU local frame. The first one uses the full IMU mechanization only without any update from the LiDAR SLAM. The second navigation solution is obtained through the LIDAR SLAM only. Finally, the third navigation solution is the integrated one resulting from the EKF. Similarly, Table (1) presents the position and attitude error statistics for the same three cases.

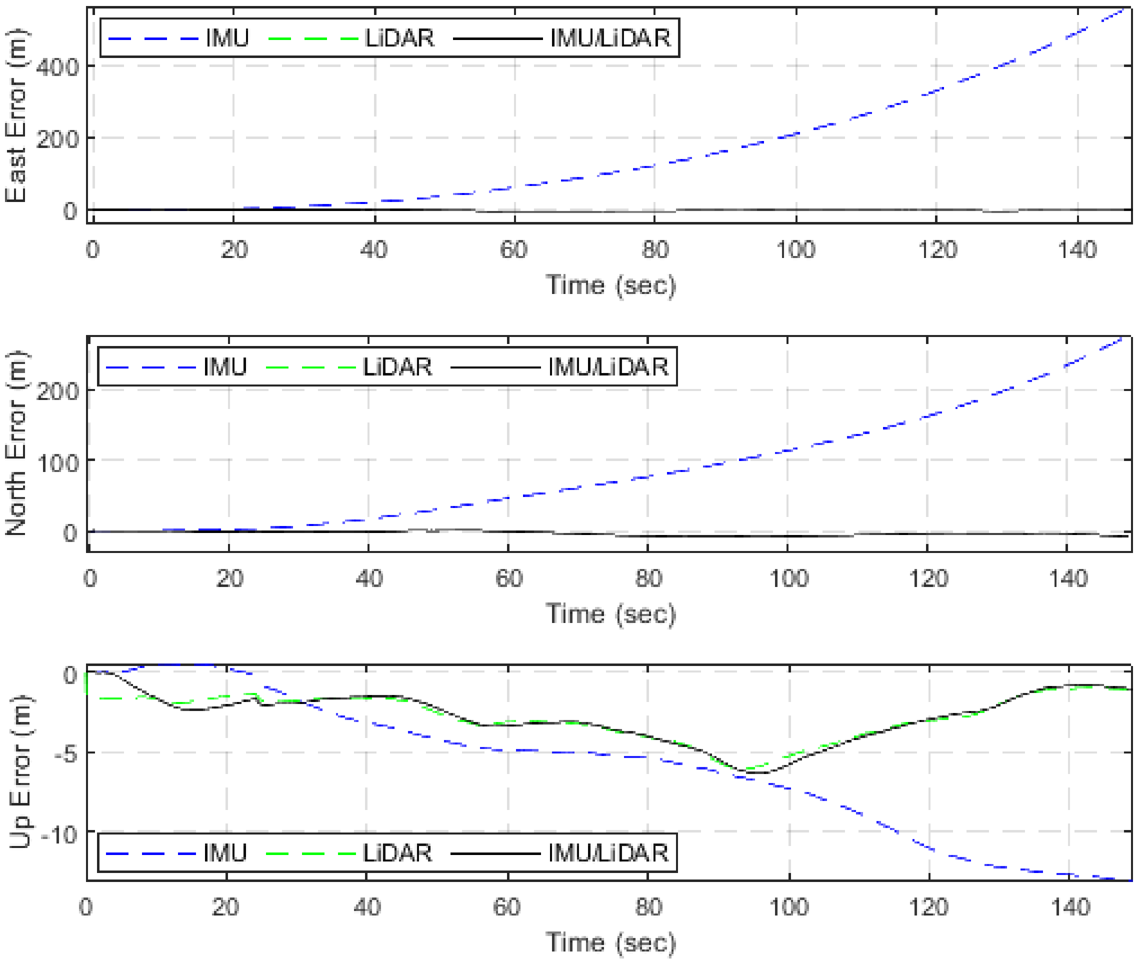

Figure (2): Residential dataset - complete GNSS signal outage: position errors (ENU)

Table (1): Residential dataset – complete GNNS outage: position error statistics (m)

	IMU			LiDAR			IMU/LiDAR		
	Mean	RMSE	Max	Mean	RMSE	Max	Mean	RMSE	Max
East	185.158	260.963	639.347	4.372	5.145	8.774	4.372	5.145	8.774
North	163.453	233.536	576.133	-2.212	2.572	4.625	-2.212	2.572	4.625
Horizontal	86.195	116.458	277.192	-3.426	4.456	8.528	-3.426	4.456	8.528
Up	5.949	7.236	13.127	2.836	3.155	6.100	2.813	3.207	6.357

It is noticeable from Figure (2) the large drift of the IMU mechanization over time, which indicates that it cannot be a sole, reliable sensor for navigation. However, the EKF integrated navigation solution exhibits significantly less error in comparison with the mechanization solution. The EKF converges to the measurement update, and thereby, the position solution is closer to the LiDAR SLAM solution.

The trajectories for the complete outage of the residential dataset are presented in Figure (3), where the mechanization, LiDAR SLAM, and EKF trajectories are compared to the ground truth.

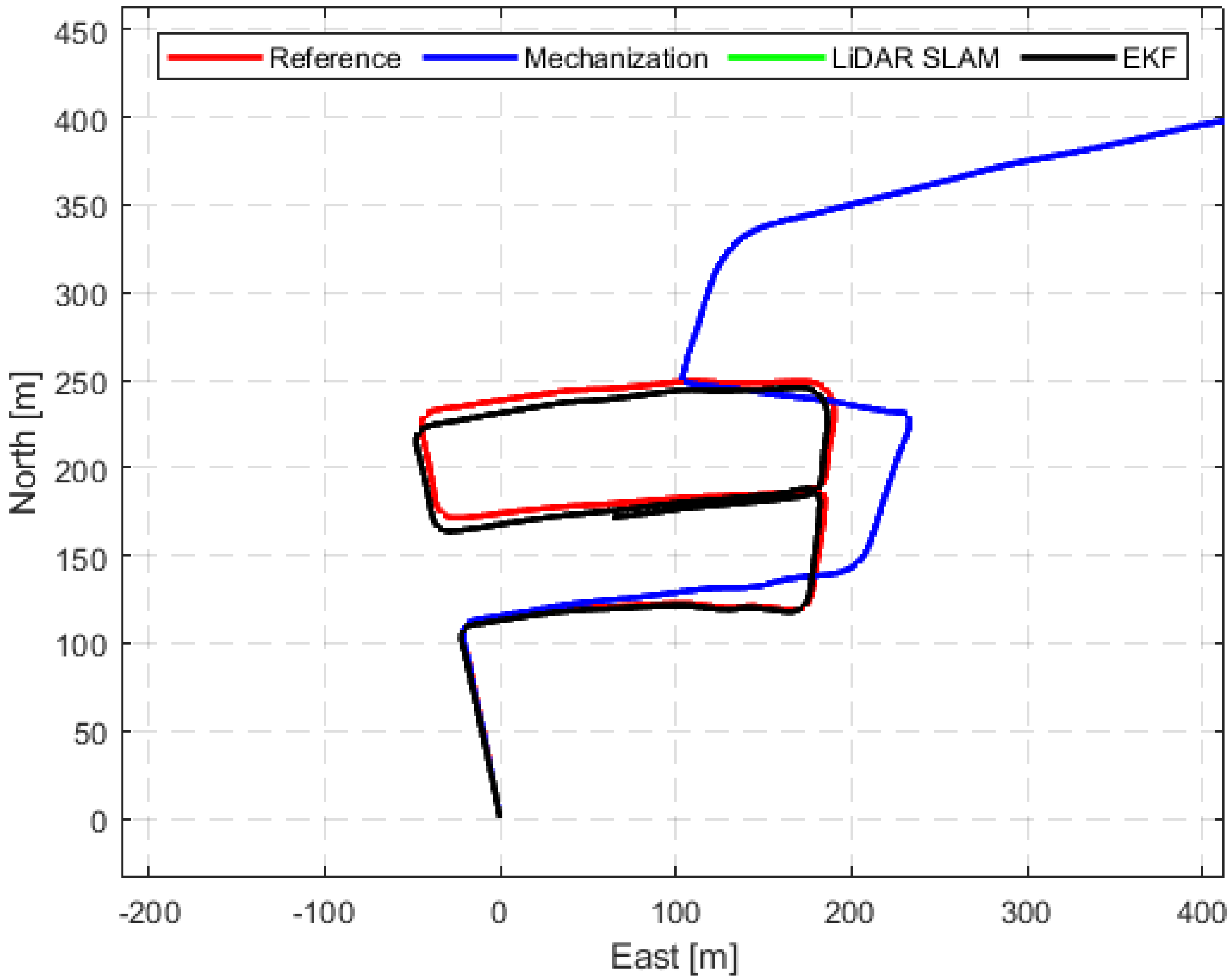

Figure (3): Residential dataset – complete GNNS signal outage: comparison of trajectories

4.2 Second Case Study—The Highway Dataset

The second case study utilizes the highway dataset, which features high driving speed and sparse-feature environments. Figure (4) represents the position, while Tables (2) quantify these errors numerically. Similar to the previous case study, the EKF converges to the position provided by the LiDAR SLAM navigation solution for the east and north directions. However, it converges the INS estimation for the up direction.

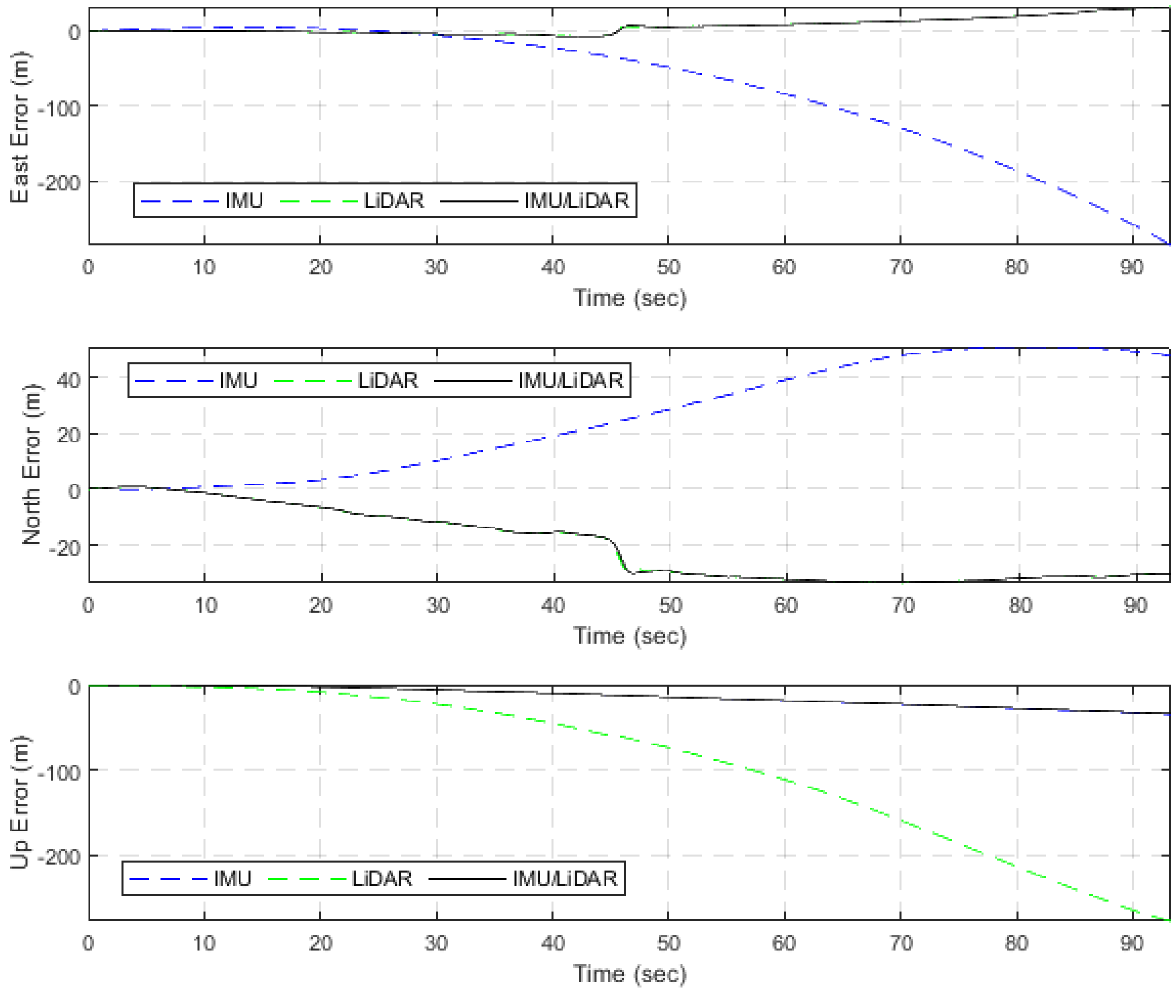

Figure (4): Highway dataset - complete GNSS signal outage: position errors (ENU)

Table (2): Highway dataset – complete GNNS outage: position error statistics (m)

	IMU			LiDAR			IMU/LiDAR		
	Mean	RMSE	Max	Mean	RMSE	Max	Mean	RMSE	Max
East	-73.02	111.17	284.67	5.90	12.09	31.68	5.87	12.08	31.62
North	25.81	32.29	50.88	-20.14	23.75	33.55	-20.15	23.76	33.52
Horizontal	79.98	115.76	288.56	22.45	26.65	43.80	22.45	26.66	43.78
Up	13.82	17.55	34.59	91.67	126.11	277.13	13.70	17.36	33.98

The trajectories for the complete outage scenario of the highway dataset are compared to the ground truth in Figure (5)

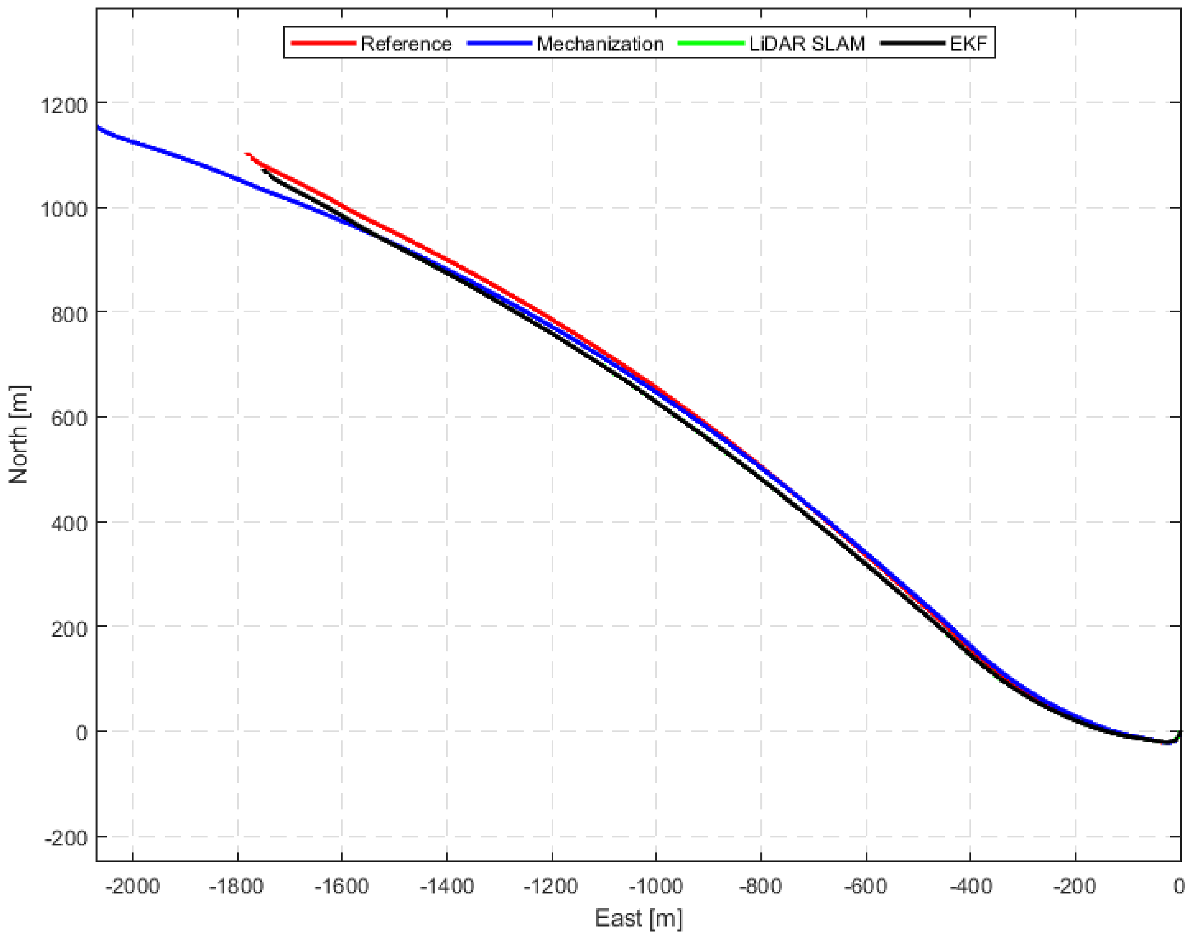

Figure (5): Highway dataset – complete GNNS signal outage: comparison of trajectories

5 CONCLUSIONS

In this paper, a loosely-coupled GNSS/INS/LiDAR SLAM integrated navigation system was proposed using an EKF. The dataset considered in this study is the raw KITI dataset, of which residential and highway drives were adopted. Two case studies were presented using residential and highway datasets. For each case, a full GNSS signal outage was simulated along with the full trajectory of the vehicle. The integrated navigation system yielded a navigation solution that outperformed the INS counterpart in both case studies, which is numerically quantified by an average reduction of the RMSE of 94%, 67%, and 27%, in the east, north, and up directions, respectively, for both cases studies combined.

REFERENCES

Abd Rabbou, M. and El-Rabbany, A. J. G. s. (2015). Tightly coupled integration of GPS precise point positioning and MEMS-based inertial systems. **19**, 601-609.

Chang, L., Niu, X., Liu, T., Tang, J. and Qian, C. J. R. S. (2019). GNSS/INS/LiDAR-SLAM integrated navigation system based on graph optimization. **11**, 1009.

de Ponte Müller, F. J. S. (2017). Survey on ranging sensors and cooperative techniques for relative positioning of vehicles. **17**, 271.

Elmezayen, A. and El-Rabbany, A. J. G. (2021). Ultra-Low-Cost Tightly Coupled Triple-Constellation GNSS PPP/MEMS-Based INS Integration for Land Vehicular Applications. **1**, 258-286.

Elmezayen, A. and El-Rabbany, A. J. J. o. A. G. (2020). Performance evaluation of real-time tightly-coupled GNSS PPP/MEMS-based inertial integration using an improved robust adaptive Kalman filter. **14**, 413-430.

Gao, B., Hu, G., Zhong, Y. and Zhu, X. (2021). Cubature Kalman Filter With Both Adaptability and Robustness for Tightly-Coupled GNSS/INS Integration. *IEEE sensors journal*, **21**, 14997-15011.

Geiger, A., Lenz, P., Stiller, C. and Urtasun, R. (2013). Vision meets robotics: The KITTI dataset. *The International Journal of Robotics Research*, **32**, 1231-1237.

KITWARE. (2020). https://gitlab.kitware.com/keu-computervision/slam. Accessed May 2020.

Martínez-Díaz, M. and Soriguera, F. J. T. R. P. (2018). Autonomous vehicles: theoretical and practical challenges. **33**, 275-282.

Noureldin, A., Karamat, T. B. and Georgy, J. (2013). *Fundamentals of inertial navigation, satellite-based positioning and their integration*. Springer-Verlag Berlin Heidelberg.

Shin, E.-H. J. U. r. (2005). Estimation techniques for low-cost inertial navigation. **20219**.

Wang, G., Han, Y., Chen, J., Wang, S., Zhang, Z., Du, N. and Zheng, Y. J. I.-P. (2018). A GNSS/INS integrated navigation algorithm based on Kalman filter. **51**, 232-237.

Zhang, J. and Singh, S. LOAM: Lidar Odometry and Mapping in Real-time. Proceedings of the Robotics: Science and Systems,

BIOGRAPHICAL NOTES

Nader Abdelaziz is currently a Ph.D. candidate in the Civil Engineering Department, Ryerson University, Canada. In addition, Mr. Abdelaziz holds the position of assistant lecturer at the Civil Engineering Department, Tanta University, Egypt. He obtained his Master of Science degree from the Faculty of Engineering, Tanta University, Egypt. Mr. Abdelaziz's Ph.D. research area focuses on multi-sensor integration for vehicular navigation. He received a number of awards in recognition of his academic achievements, including distinguished awards for academic excellence and research originality from Ryerson University and industrial partners. Furthermore, he received awards for best papers and posters at various conferences and professional events.

Dr. Ahmed El-Rabbany obtained his Ph.D. degree in GPS Satellite Navigation from the Department of Geodesy and Geomatics Engineering, University of New Brunswick, Canada. At present, Dr. El-Rabbany is a full professor at Ryerson University, where he leads research projects in the areas of satellite navigation and multi-sensor integration for navigation, mobile mapping, and unmanned aerial systems.

CONTACTS

Nader Abdelaziz

Ryerson University and Tanta University

350 Victoria Street, Toronto, Ontario, Canada M5B 2K3

(416) 979-5000

nader.abdelaziz@ryerson.ca

Ahmed El-Rabbany

Ryerson University

350 Victoria Street, Toronto, Ontario, Canada M5B 2K3

(416) 979-5000 ext. 556472; fax: (416) 979-5122

rabbany@ryerson.ca