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Collaborative Navigation: Supporting PNT System Operational Anomaly Detection

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Abstract: Modern Positioning, Navigation, and Timing (PNT) systems heavily rely on Global Navigation Satellite Systems (GNSS). Meanwhile, GNSS-based PNT systems are increasingly becoming susceptible to unintentional and deliberate Radio Frequency (RF) interference. In particular, as technology keeps advancing and hardware is becoming so inexpensive, it takes a modest effort to disrupt the normal operation of almost any PNT systems, thus posing an extreme threat to autonomous transportation systems that rely on precise PNT. As communication capabilities are expanding, a group of vehicles can easily share data when they operate in close vicinity. This gives opportunity to position and navigate the vehicles based on a jointly computed navigation solution, which is usually called collaborative navigation, resulting in a potentially more accurate and reliable operation. In this study, the feasibility and performance potential of collaborative navigation on the detection and mitigation of GNSS-based PNT system operational anomalies are evaluated on some real data and simulated anomaly scenarios. By incorporating an outlier detection method based on least squares adjustment, the collaborative navigation has shown to be able to maintain the differences to the reference solution to within 0.2 m, 0.5 m, and 3.0 m for the biased case, noisy case, and anchor case, respectively, for all test vehicles.

Keywords: Cooperative navigation, Localization, Positioning Systems, Fault Detection, Information and sensor fusion.

1. INTRODUCTION

Modern Positioning, Navigation, and Timing (PNT) systems heavily rely on Global Navigation Satellite Systems (GNSS). Meanwhile, GNSS-based PNT systems are increasingly becoming susceptible to unintentional and deliberate Radio Frequency (RF) interference. In particular, as technology keeps advancing and hardware is becoming so inexpensive, it takes a modest effort to disrupt the normal operation of almost any PNT systems, thus posing an extreme threat to autonomous transportation systems that rely on precise PNT.

Finding protection against any interference to PNT systems is happening on multiple levels. Modernization of Global Positioning System (GPS) has introduced new signals to provide significant capabilities to increase protection at signal and receiver level. In parallel, the proliferation of GNSS systems in the past decade has substantially increased the signal availability, so PNT systems using all the potentially available signals can exploit the benefits of redundancy. Nevertheless, there are limits on what can be done against RF interference in PNT systems, and therefore, using totally independent sensor technologies is mandatory to detect malfunctioning and potentially offering mitigation to some extent.

As communication capabilities are expanding, a group of vehicles can easily share data when they operate in close vicinity. This gives opportunity to position and navigate the vehicles based on a jointly computed navigation solution, resulting in a potentially more accurate and reliable operation. This method, usually called collaborative navigation (or cooperative navigation), is considered here for detecting any malfunctioning of a GNSS-based PNT system, such as hardware problem, jamming or spoofing.

1.1 RF interference and mitigation

RF interference has become a serious threat to the GNSS navigation systems. Even though the GNSS signals have been designed to withstand a certain level of interference through Direct Sequence Spread Spectrum (DSSS) technique, they are so weak at the receiving end on Earth that most modern electronic equipment interferes with them at close range (Humphreys, 2017). The open GNSS signals to civil users are especially vulnerable due to their open structure and lacking encryption and authentication (Gao et al., 2016; Humphreys, 2017). The jamming, either unintentional or deliberate, will block the genuine GNSS signal from being tracked. The spoofing fools the receivers with counterfeit signal to produce precise but erroneous solution (Humphreys, 2017).

The effects of simple spoofing attacks on GNSS receivers integrated in Android smartphones are investigated in (Rustamov et al., 2020). A portable spoofer was developed with a Software Defined Radio (SDR) and a low cost front-end. The spoofer was placed within 1-3 m from the test smartphones under open sky. It broadcast spoofing signals over GPS L1 band as if received one day ago at a different location that was 144 km away. The carrier-to-noise density ratio (C/N_0), Automatic Gain Control (AGC), and time of signal transmission and reception from the test smartphones were analyzed. The results show that during the spoofing period, tracking of the real signals from low elevation satellites is lost; the fake signal is not acquired but the real signals of satellites with the same satellite vehicle identification number as the fake satellite is lost too. The position outputs deviate a few meters during spoofing that is blamed to loss of lock to some GPS satellites. Actually, the test smartphone uses a multi-constellation GNSS chip that has been claimed to be able to reach 30 cm accuracy in open environment (Moore, 2017).

Varying methods to protect GNSS receivers from jamming and interference are summarized in (Gao et al., 2016) into four main categories: inertial aiding, spatial filtering, time-frequency filtering, and vector tracking. Deep integration of Inertial Navigation System (INS) and GNSS will improve jamming-to-signal (J/S) ratio, system accuracy, and high dynamic performance. Spatial filtering uses antenna arrays to point the receiver antenna beam towards the GNSS satellites and away from jammers. Time-frequency filtering methods are based on GNSS signal conditioning and filtering. Vector tracking achieves enhanced tracking robustness under degraded conditions by utilizing the fact that signal channels are coupled through the shared receiver states of position, velocity, and time. Inertial aiding and vector tracking improve the receiver robustness by lowering the minimum required C/N_0 level for receiver acquisition and tracking; whereas, the incident interfering signals are suppressed before entering the receiver in the spatial and time-frequency filtering approaches (Gao et al., 2016).

1.2 Collaborative navigation

Collaborative Navigation entails a concept of a group of platforms, referred to as network nodes, navigating collectively (as a network) and supporting each other's positioning solution to obtain higher accuracy and availability for all platforms. Early works have been focused on integrating the inter-nodal range/bearing measurements or locally generated maps (Roumeliotis and Beke, 2002; Bryson and Sukkarieh, 2009; Grejner-Brzezinska et al., 2009). In fact, a similar concept, community relative navigation, was studied before GPS was established, and can be traced back at least to the 1970s (e.g., Rome and Stambaugh, 1977; Widnall and Gobbini, 1982; Schneider, 1985).

Recent technology advancements have made the inter-nodal measurements, especially the range measurements, more accurate and affordable than before. Inter-nodal range can be measured with a radio signal in a wireless sensor network through RSS (Received Signal Strength), TOA (Time of Arrival), TDOA (Time Difference of Arrival), and AOA (Angle of Arrival) techniques, or with optical sensors through computer vision techniques (Grejner-Brzezinska et al., 2009). Among them, Ultra-Wide Band (UWB) ranging technology, with a broad bandwidth available for time transfer and centimeter level ranging capability, is of particular interest to positioning and navigation applications (MacGougan et al., 2009). Moreover, the UWB transceivers mounted on the nodes form an ad-hoc network that can provide a datalink among the nodes without any additional infrastructure and aid the INS/GNSS solution by giving accurate inter-nodal range measurements (Vydhyanathan et al., 2009).

The benefits of cooperative navigation have been demonstrated through simulation in (Grejner-Brzezinska et al., 2009). The result shows that, for repeated 60-second GPS gaps, separated by 10-second signal availability, cooperative navigation can maintain the accuracy at 1-2 m level for nodes only equipped with consumer grade Inertial Measurement Unit (IMU). In the simulation, a decentralized Extended Kalman Filter (EKF) was used to integrate all the measurements. Similar research is presented for cooperative navigation concept verification prototype in (Vydhyanathan et al., 2009), in which all nodes were equipped with GPS, Micro-Electro-Mechanical Systems (MEMS) inertial sensors, barometric altimeter, and UWB transceiver. The results show that with UWB aiding, a horizontal position accuracy of ± 0.5 m, horizontal velocity accuracy of ± 0.28 m/s, and orientation accuracy of $\pm 0.3°$ for roll and pitch and $\pm 6.3°$ for heading were obtained for the mobile node during several second GPS outages (Vydhyanathan et al., 2009).

An outlier detection algorithm for collaborative navigation is presented in (Xiong et al., 2021). The algorithm models the GNSS measurements and inter vehicle range measurements into common and specific parts and excludes the faulty measurements with a greedy search strategy. The test results show the algorithm has a better detection of GNSS faults than tradition Receiver Autonomous Integrity Monitoring (RAIM) and good sensitivity to the faulty UWB range measurements.

1.3 Contributions

This study investigates the detection and mitigation of GNSS-based PNT system operational anomalies on individual vehicles in the context of collaborative navigation. The contributions can be summarized as follows.

(1) Establishment of a framework for collaborative navigation to integrate individual vehicle's GNSS or INS solutions, inter-vehicle ranges, and ranges to infrastructures.
(2) Demonstration of the effectiveness of collaborative navigation in detecting and mitigating PNT system operational anomalies on individual vehicles in post processing mode.
(3) Utilization of a least squares adjustment based method for outlier detection in collaborative navigation.
(4) Analysis of the theoretic limitation of the "anchor" concept that relies on the navigation solution of an anchor vehicle and ranges to other vehicles.

2. METHODOLOGY

This study adopts centralized EKF to integrate GNSS or INS solutions of individual vehicles and range measurements among vehicles and from a vehicle to beacons along the road. A least squares adjustment based method is used to detect outliers in GNSS or INS solutions of individual vehicles before the EKF measurement update.

2.1 Collaborative navigation based on range measurements

The range measurement is a function of the positions of the vehicles involved. After linearization, it has the following form.

$$r_{ij,t} - r^0_{ij,t} = [\boldsymbol{J}, -\boldsymbol{J}][\boldsymbol{x_i}, \boldsymbol{x_j}]^T + e_{ij,t}, \tag{1}$$

where $r_{ij,t}$ is the range between vehicle i and j at epoch t, $r^0_{ij,t}$ is the computed range from the approximate coordinates, $\boldsymbol{J}$ is the Jacobian coefficient vector, $[\boldsymbol{x_i},\ \boldsymbol{x_j}]$ are (unknown) correction vector to the approximate coordinates of the ith and jth platforms, and $e_{ij,t}$ is the error term.

The collaborative navigation can be implemented in a central Extended Kalman Filter (EKF), in which the communication and range measurements between the vehicles are assumed. The centralized architecture allows near-optimal behaviors in well-understood environments. The state model can be described as follows.

$$\boldsymbol{x_k} = \Phi_{k,k-1}\boldsymbol{x_{k-1}} + G_k\boldsymbol{w_k}, \quad \boldsymbol{w_k} \sim \mathcal{N}(\boldsymbol{0}, Q_k), \tag{2}$$

where $\boldsymbol{x_k}$ is the state vector, $\Phi_{k,k-1}$ is the state transition matrix, $\boldsymbol{w_k}$ is a Gaussian, zero-mean, white noise vector with a covariance matrix of Q_k, k and $k-1$ are time instants.

The linearized observation model is as follows.

$$\boldsymbol{y_k} = H_k\boldsymbol{x_k} + \boldsymbol{v_k}, \quad \boldsymbol{v_k} \sim \mathcal{N}(\boldsymbol{0}, R_k), \tag{3}$$

where the observation vector $\boldsymbol{y_k}$ may include the GNSS or INS solutions of individual vehicles as well as Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) ranges, R_k is the variance of the observation error vector $\boldsymbol{v_k}$.

Following (Jekeli, 2001), the EKF solution can be expressed in the following equations.

$$\boldsymbol{\hat{x}_k^-} = \Phi_{k,k-1}\boldsymbol{\hat{x}_{k-1}}, \tag{4}$$

$$P_k^- = \Phi_{k,k-1}P_{k-1}\Phi_{k,k-1}^T + G_kQ_kG_k^T, \tag{5}$$

$$\boldsymbol{\gamma_k} = \boldsymbol{y_k} - H_k\boldsymbol{\hat{x}_k^-}, \tag{6}$$

$$K_k = P_k^-H_k^T(H_kP_k^-H_k^T + R_k)^{-1}, \tag{7}$$

$$\boldsymbol{\hat{x}_k} = \boldsymbol{\hat{x}_k^-} + K_k\boldsymbol{\gamma_k}, \tag{8}$$

$$P_k = (I_n - K_kH_k)P_k^-(I_n - K_kH_k)^T + K_kR_kK_k^T, \tag{9}$$

where $\boldsymbol{\hat{x}_k^-}$ is the a priori expected value of the state vector, P_k^- is the error covariance of the expected state, $\boldsymbol{\gamma_k}$ is the innovation vector, K_k is the Kalman Gain matrix, $\boldsymbol{\hat{x}_k}$ is the a posteriori estimate of the state after the measurement update, and P_k is the a posteriori covariance of the state vector.

2.2 Least squares adjustment based detection method

Generally, the innovation vector as in equation (6) in EKF is exploited to detect the measurement faults, as the normalized-innovation-squared test statistic employed in (Maaref et al., 2018; Zhu et al., 2020; Xiong et al., 2021). Meanwhile, it is found in the study that the innovation based method has higher false alarm rate for the same detection threshold. Hence, least squares adjustment is adopted to detect any anomalies in individual vehicle's GNSS or INS solutions in collaborative navigation.

There is a rank deficiency problem in least squares adjustment based on range measurements only. As an example, to localize a quadrilateral from lengths among its corners on a plane, the rank deficiency is three. There are some methods to solve the rank deficiency problem. A straightforward one would be reducing the number of unknown parameters, that is, treating the GNSS or INS position of some vehicles as known and removing the corresponding corrections from the parameter list. This method will be used in the anchor case later for cross validation. The issue with the method is there will be no chance to detect any errors in those GNSS or INS positions in collaborative navigation.

Among some other methods, Minimum Norm Least Squares Solution (MINOLESS) is selected in this study because the solution norm is minimized among all possible (biased) solutions. The adjustment method can be described with the following equations (Schaffrin and Snow, 2017).

$$\boldsymbol{y} = \underset{n\times m}{A}\xi + \boldsymbol{e}, \boldsymbol{e} \sim (\boldsymbol{0}, \sigma_0^2P^{-1}), rk(A) < \{m, n\}, \tag{10}$$

$$\underset{n\times m}{E}\boldsymbol{\xi} = \boldsymbol{0}, \text{with } AE^T = 0, R(A^T) \overset{\perp}{\oplus} R(E^T) = R^m, \tag{11}$$

$$N = A^TPA, \tag{12}$$

$$\boldsymbol{c} = A^TP\boldsymbol{y}, \tag{13}$$

$$\boldsymbol{\hat{\xi}} = (N + E^TE)^{-1}\boldsymbol{c}, \tag{14}$$

$$D\{\boldsymbol{\hat{\xi}}\} = {\sigma_0}^2(N + E^TE)^{-1}N(N + E^TE)^{-1}, \tag{15}$$

where the rank of the coefficient matrix A is less than its dimension (n, m). With the introduction of "inner datum constraints" in equation (11), the columns of E^T form a basis for the nullspace of A, and the orthogonal direct sum of rangespaces of A^T and E^T is in the m-dimensional real space R^m. Equation (14) and (15) represent the estimate of parameters and its covariance, respectively.

Locations derived from the least squares adjustment are then compared to GNSS or INS solution of individual vehicles against a threshold to detect any anomalies. The detected faulty GNSS or INS solution can then be downweighted or simply excluded from participating in the measurement update of EKF. Without the effects of faulty GNSS or INS solutions of individual vehicles, the collaborative navigation will be more accurate and reliable.

3. TEST DATASET

A real dataset was collected at a parking lot of The Ohio State University and included four vehicles. The anchor vehicle A was equipped with GNSS receivers, high-end and MEMS IMU sensors, cameras, laser scanners, as well as UWB transmitters to measure the ranges to other vehicles and UWB beacons along the road. Three other vehicles, B, C, and D, were equipped with GNSS receivers and multiple UWB transmitters. The GNSS receivers were operating in standard point positioning mode. Two networks of UWB devices independently measured the V2V ranges using different channels. UWB transmitters on the right side of the four vehicles formed Network 1 (NET1), whereas the left side sensors formed Network 2 (NET2). Ten UWB beacons were deployed along the road to enable the range measurements from vehicle A to get the V2I range measurements. The UWB beacons were regarded as the infrastructure of the road and their locations had been accurately surveyed. The vehicles were driven in formation in the test with most of time A and B being side by side and in the front, followed by C and D. Fig. 1 and Fig. 2 show the scene of data collection and a trajectory of the anchor vehicle, respectively. More information about the data collection campaign can be found in (Retscher et al., 2020).

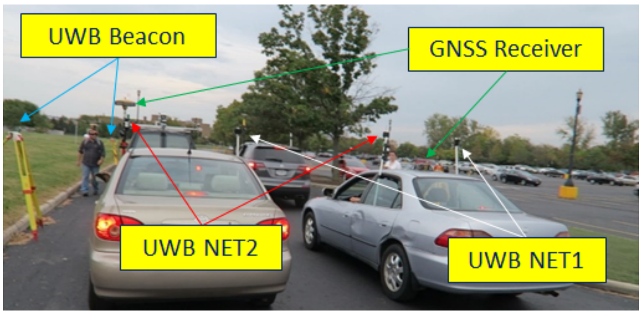

Fig. 1. The scene of data collection.

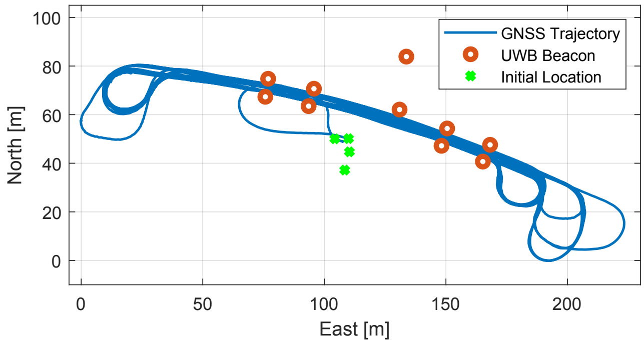

Fig. 2. GNSS trajectory of vehicle A, UWB beacon locations, and the initial locations of the four vehicles.

A period of 42.6 seconds (214 epochs) of data were selected for this study. As the UWB success rate was below 50%, V2V ranges were simulated from GNSS solutions with a standard deviation of 0.05 m. For the same reason, V2I ranges were also simulated at the same level of accuracy from the known locations of UWB beacons and vehicle A's GNSS solutions.

4. TEST RESULTS

Centralized integration architecture is adopted for this study by assuming the GNSS solution of four vehicles as well as the V2V and V2I range measurements are available to a central EKF without any communication delay. GNSS solutions of four vehicles, V2I ranges from A, and V2V ranges among four vehicles are the measurements for the EKF. The state vector includes two dimensional positions, velocities, and accelerations of these four vehicles.

The least squares adjustment based detection method as described above is used for the fault detection of GNSS solutions of individual vehicles.

4.1 Collaborative navigation

The collaborative navigation results are depicted in Fig. 3 and 4 and are used as reference for the test scenarios discussed below. Since the GNSS solutions are from standard point positioning, the differences between collaborative navigation and GNSS solutions are at sub-meter level as shown in table 1.

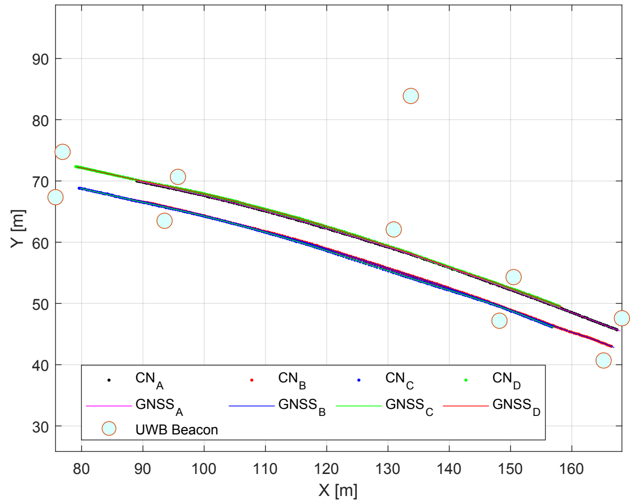

Fig. 3. Trajectories of collaborative navigation solution.

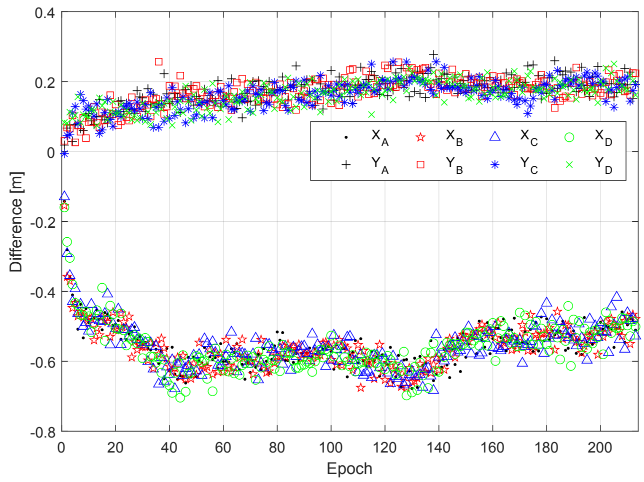

Fig. 4. Differences between collaborative navigation and GNSS solution.

Table 1. Statistics of norms of differences between collaborative navigation and GNSS solution [m]

Vehicle	Min	Max	Mean	Std.
A	0.14	0.74	0.58	0.07
B	0.16	0.72	0.58	0.06
C	0.17	0.70	0.58	0.06
D	0.14	0.71	0.58	0.07

4.2 Constant bias to one vehicle's GNSS solution

As for a spoofing attack case like in (Rustamov et al., 2020), a constant bias of 1.0 m is added to each component of vehicle D's GNSS solution starting from the 57th epoch for 100 epochs, and then it is used to derive the collaborative navigation with the other vehicles' GNSS solution as well as V2I and V2V ranges. As seen from Fig. 5 and table 2, using the information of other vehicles and the range measurements, the position error of vehicle D has been restricted to less than 0.2 m. After the bias-added periods, the solution gradually converged back to the reference solution.

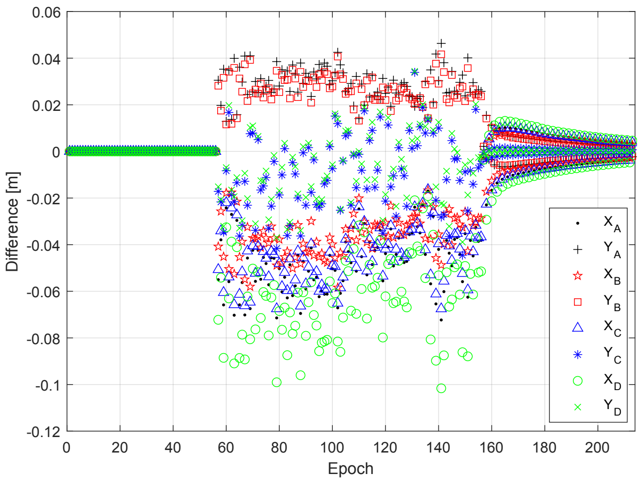

Fig. 5. Differences between collaborative navigation for the biased case and reference solution.

Table 2. Statistics of norms of differences between collaborative navigation for biased case and the reference solution [m]

Vehicle	Min	Max	Mean	Std.
A	0.00	0.09	0.03	0.03
B	0.00	0.07	0.02	0.02
C	0.00	0.08	0.02	0.02
D	0.00	0.11	0.03	0.03

Obviously, any added biases larger than 1.0 m in GNSS solutions will be detected with precise inter-vehicle range measurements.

4.3 Noisy GNSS solution of one vehicle

To investigate the situation that the GNSS receiver produces noisy positioning results due to interference, random noise with zero mean and variance of 1.0 m is added to each component of the GNSS solution of vehicle D. The collaborative navigation solution for this case is presented in Fig. 6 and table 3. The collaborative navigation clearly helps decrease the position error for vehicle D with the maximum 2D distance to the reference solution being below 0.5 m. Comparing to the result of the constant bias case above, the increased noise level creates challenges for detecting and mitigating GNSS anomalies.

In the meantime, if decreasing the weight of D's GNSS solution for the whole duration of the affected periods before deriving the collaborative navigation, the offsets of D's solution can be controlled around 0.1 m, as shown in Fig. 7 and table 4. Obviously, techniques in the RF domain, such as C/N_0 monitoring and received power monitoring as in (Humphreys, 2017), should be combined to detect and mitigate the anomalies for this case.

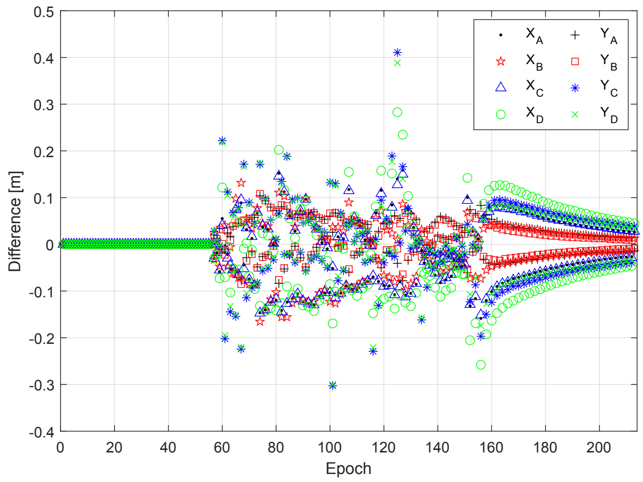

Fig. 6. Differences between collaborative navigation for the noisy case and reference solution.

Table 3. Statistics of norms of differences between collaborative navigation for noisy case and the reference solution [m]

Vehicle	Min	Max	Mean	Std.
A	0.00	0.18	0.05	0.05
B	0.00	0.20	0.04	0.04
C	0.00	0.43	0.07	0.07
D	0.00	0.48	0.08	0.07

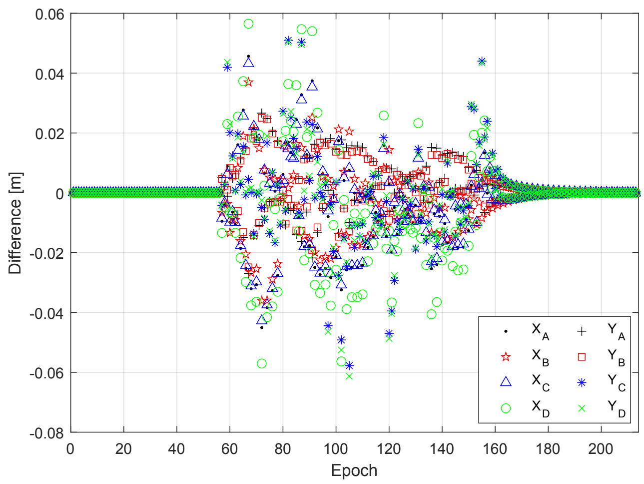

Fig. 7. Differences between solution of always-downweighting for noisy case and the reference solution.

4.4 GNSS outages for three vehicles

In the presence of strong interference, most of the GNSS receivers may lose tracking of the satellite signals and produce no positioning results. There are some high-end, interference resistant GNSS receivers, however, that may still be able to position. This case is also investigated by assuming the GNSS solution is only available on vehicle A and thus trying to derive the navigation solution for the other vehicles with the V2V range measurements. The results are plotted in Fig. 8 and tabulated in table 5, in which it can be found that the differences to the reference solution are less than 1.2 m for B and 3.0 m for C and D. It demonstrates that the collaborative navigation can generate the navigation solution for the other three vehicles during the outage periods, which is rather unreal in single platform navigation without aiding from other sensors, such as IMUs and odometers/speedometers. However, the solution differences seem to be larger than expected at first glance, considering the V2V ranges are simulated from the GNSS solutions.

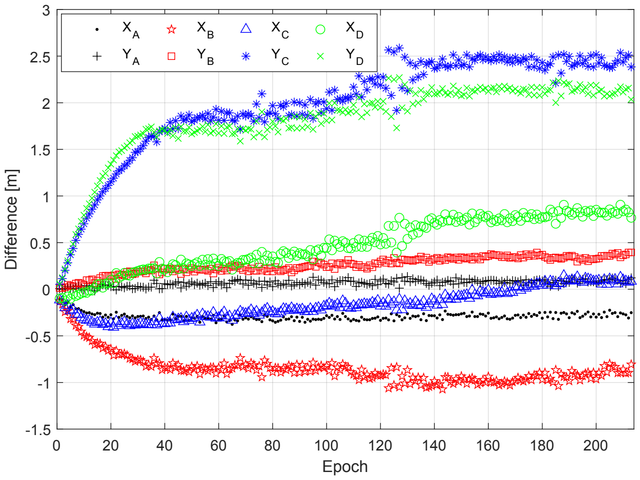

Fig. 8. Differences between collaborative navigation for anchor case and reference solution.

For cross validation, a least squares adjustment has also been used to estimate the positions of the vehicles. In the computation, the coordinate corrections of vehicle A are excluded from the parameter list and the number of unknowns is reduced to six. Meanwhile, as explained before, the rank of the coefficient matrix A in equation (10) is still rank deficient, which makes the estimation an ill-posed problem. Accordingly, it is not a surprise to find from Fig. 9 that the maximum differences of a single coordinate component are close to 400 m.

Table 4. Statistics of norms of differences between always-downweighting solution for noisy case and the reference solution [m]

Vehicle	Min	Max	Mean	Std.
A	0.00	0.05	0.01	0.01
B	0.00	0.04	0.01	0.01
C	0.00	0.06	0.01	0.01
D	0.00	0.08	0.01	0.02

Table 5. Statistics of norms of differences between collaborative navigation for anchor case and the reference solution [m]

Vehicle	Min	Max	Mean	Std.
A	0.10	0.39	0.30	0.04
B	0.13	1.12	0.89	0.17
C	0.13	2.59	2.00	0.52
D	0.11	2.40	1.89	0.45

The difficulty in location estimation for the anchor case can also be illustrated geometrically as in Fig. 10. Consider rotating the quadrilateral $ABCD$ about its corner A to two different locations. The location of A has not changed, neither have the lengths among all four corners, but the locations of the other corners are totally different. Therefore, for this anchor case, knowing the location of the anchor vehicle and the V2V ranges is not adequate to accurately determine the location of all vehicles.

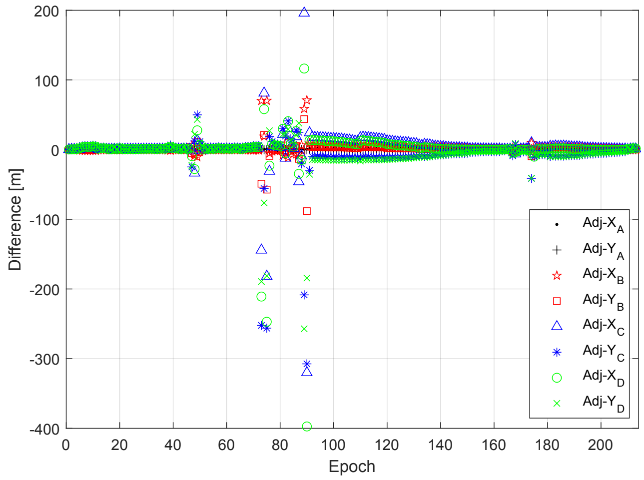

Fig. 9. Differences between adjustment for anchor case and reference solution.

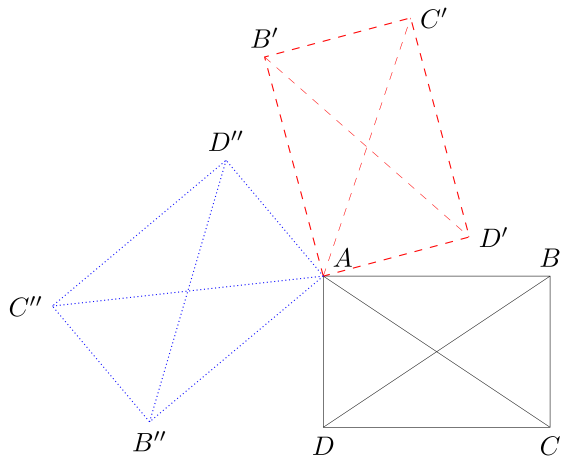

Fig. 10. Rotating a quadrilateral around one corner A won't change the location of A and lengths to other corners.

5. CONCLUSION

The feasibility and performance potential of collaborative navigation on the detection and mitigation of GNSS-based PNT system operational anomalies are evaluated on some real data and simulated anomaly scenarios in this study. The collaborative navigation is based on the GNSS solution of four vehicles as well as ranges among vehicles and from one vehicle to beacons along the road. A least squares adjustment based method is used to detect outliers in GNSS solutions before the EKF measurement update.

The effectiveness of collaborative navigation in detecting and mitigating PNT system operational anomalies on individual vehicles are demonstrated in three simulated cases.

For a simulated spoofing attack in which one vehicle's GNSS solutions are deviated 1.0 m constantly in all components, collaborative navigation can keep the solution differences to the reference solution from clean data to below 0.2 m for all affected epochs.

For a simulated interference case with increased noise level, by adding white noises with a variance of 1.0 m to each component of one vehicle's GNSS solution, the vehicle's total position difference to the reference solution can be contained to below 0.5 m in collaborative navigation. If combining interference detection techniques from RF domain, the navigation performance could be further improved.

In the anchor case, it is simulated that all lower-end receivers lose positioning capabilities due to strong interference and the collaborative navigation has to rely on the GNSS solution of one anchor vehicle and V2V ranges. The collaborative navigation can generate the navigation solution within 3.0 m differences to the reference solution for the other three vehicles during the outage periods, which is rather unreal in single platform navigation without aiding from other sensors. However, due to the inherent defects of rank deficiency, the solution cannot be accurately derived in this case.

REFERENCES

Bryson, M. and Sukkarieh, S. (2009). Architectures for cooperative airborne simultaneous localisation and mapping. *Journal of Intelligent and Robotic Systems*, 55(4-5), 267–297.

Gao, G., Sgammini, M., Lu, M., and Kubo, N. (2016). Protecting GNSS receivers from jamming and interference. *Proceedings of the IEEE*, 104(6), 1327–1338. doi: https://doi.org/10.1109/JPROC.2016.2525938.

Grejner-Brzezinska, D., Toth, C., Li, L., Park, J., Wang, X., Sun, H., Gupta, I., Huggins, K., and Zheng, Y. (2009). Positioning in GPS-challenged environments: dynamic sensor network with distributed gps aperture and internodal ranging signals. In *Proceedings of the 22nd International Technical Meeting of The Institute of Navigation*, 111–123.

Humphreys, T. (2017). Interference. In P. Teunissen and O. Montenbruch (eds.), *Springer Handbook of Global Navigation Satellite Systems*, chapter 16, 469–504. Springer.

Jekeli, C. (2001). *Inertial Navigation Systems with Geodetic Applications*. Walter de Gruyter, Berlin, New York.

Maaref, M., Khalife, J., and Kassas, Z. (2018). Integrity monitoring of LTE signals of opportunity-based navigation for autonomous ground vehicles. In *Proceedings of the 31st International Technical Meeting of the Satellite Division of The Institute of Navigation*, 2456–2466. doi: https://doi.org/10.33012/2018.16093.

MacGougan, G., O'Keefe, K., and Klukas, R. (2009). Ultra-wideband ranging precision and accuracy. *Measurement Science and Technology*, 20(9), 095105.

Moore, S. (2017). Super-accurate GPS coming to smartphones in 2018. *IEEE Spectrum*, 54(11), 10–11. doi: https://doi.org/10.1109/MSPEC.2017.8093787.

Retscher, G., Kealy, A., Gabela, J., Li, Y., Goel, S., Toth, C., Masiero, A., Blaszczak-Bak, W., Gikas, V., Perakis, H., Koppanyi, Z., and Grejner-Brzezinska, D. (2020). A benchmarking measurement campaign in gnss-denied/challenged indoor/outdoor and transitional environments. *Journal of Applied Geodesy*, 14(2), 215–229. doi:https://doi.org/10.1515/jag-2019-0031.

Rome, H. and Stambaugh, J. (1977). Evaluation of the accuracy of community relative navigation organization concepts. *Navigation*, 24(2), 168–180.

Roumeliotis, S. and Beke, G. (2002). Distributed multi-robot localization. *IEEE Transactions on Robotics and Automation*, 18(5), 781–795. doi:https://doi.org/10.1109/TRA.2002.803461.

Rustamov, A., Gogoi, N., Minetto, A., and Dovis, F. (2020). Assessment of the vulnerability to spoofing attacks of GNSS receivers integrated in consumer devices. In *2020 International Conference on Localization and GNSS (ICL-GNSS)*. doi:https://doi.org/10.1109/ICL-GNSS49876.2020.9115489.

Schaffrin, B. and Snow, K. (2017). Advanced adjustment notes. URL https://earthsciences.osu.edu/sites/earthsciences.osu.edu/files/AdvancedAdjustmentNotes_2017-09-06_0.pdf. Visited on 2022-06-15.

Schneider, A. (1985). Observability of relative navigation using range-only measurements. *IEEE Transactions on Aerospace and Electronic Systems*, AES-21(4), 569–581. doi:https://doi.org/10.1109/TAES.1985.310645.

Vydhyanathan, A., Luinge, H., Tanigawa, M., Dijkstra, F., Braasch, M., and de Haag, M.U. (2009). Augmenting low-cost GPS/INS with ultra-wideband transceivers for multi-platform relative navigation. In *Proceedings of the 22nd International Technical Meeting of The Satellite Division of the Institute of Navigation*, 547–554.

Widnall, W. and Gobbini, G. (1982). Community relative navigation based on measurement sharing. In *Proceedings of the IEEE Position, Location, and Navigation Symposium (PLANS 82)*.

Xiong, J., Cheong, J., Xiong, Z., Dempster, A., Tian, S., and Wang, R. (2021). Integrity for multi-sensor cooperative positioning. *IEEE Transactions on Intelligent Transportation Systems*, 22(2), 792–807. doi:https://doi.org/10.1109/TITS.2019.2956936.

Zhu, N., Betaille, D., Marais, J., and Berbineau, M. (2020). GNSS integrity monitoring schemes for terrestrial applications in harsh signal environments. *IEEE Intelligent Transportation Systems Magazine*, 12(3), 81–91. doi: https://doi.org/10.1109/MITS.2020.2994076.