Collaborative GNSS Positioning with the Aids of 3D City Models

Guohao Zhang, Weisong Wen, Li-Ta Hsu
Interdisciplinary Division of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University

BIOGRAPHY (IES)

Mr. Guohao Zhang received the bachelor degree in Mechanical Engineering and Automation from University of Science and Technology Beijing, China, in 2015. He received the master degree in Mechanical Engineering and currently is a research assistant in the Hong Kong Polytechnic University. His research interests including GNSS urban localization, vehicle-to-vehicle cooperative localization and multi-sensor integrated navigation.

Mr. Weisong Wen received the bachelor degree in Mechanical Engineering and Automation from Beijing Information science and Technology University, China, in 2015 and the master's degree in Mechanical and electronics in China Agricultural University, China, in 2017. He is currently a PhD. student at the Department of Mechanical Engineering, The Hong Kong Polytechnic University, Hong Kong. His research interests include localization with multi-sensors (GNSS/INS/LiDAR/HD Map) and deep learning-based objection detection.

Dr. Li-Ta Hsu received the B.S. and Ph.D. degrees in aeronautics and astronautics from National Cheng Kung University, Taiwan, in 2007 and 2013, respectively. He is currently an assistant professor with Interdisciplinary Division of Aeronautical and Aviation Engineering, Hong Kong Polytechnic University, before he served as post-doctoral researcher in Institute of Industrial Science at University of Tokyo, Japan. In 2012 and 2013, he was a visiting scholar in University College London, U.K and Tokyo University of Marine Science and Technology, Japan, respectively. His research interests include GNSS positioning in challenging environments and localization for autonomous driving vehicle and unmanned aerial vehicle.

ABSTRACT

GNSS collaborative positioning receives great attention because of the rapid development of vehicle-to-vehicle (V2V) communication. Its current bottleneck is in urban areas. During the calculation of double difference of GNSS measurements between two receivers to obtain their relative positions, the notorious multipath effects and NLOS reception in the pseudorange measurement cannot be eliminated. Even worse, these effects become more severe due to the multipath effects of two receivers are aggregated. Recently, the studies explored the use of 3D city models to aid GNSS positioning are increasing. It is widely believed the3D map aided (3DMA) GNSS is a solution to mitigate or even correct the multipath and NLOS effects. This paper therefore investigates the potential to aid GNSS collaborative positioning using 3D city models. The 3D models are used in two phases. The first phase is in single receiver level. The models is used to exclude NLOS measurements based on GNSS shadow matching (SDM) positioning result. The second phase is in multi-receiver level. The 3D building model is used together with broadcast ephemeris data to generate the predicted GNSS positioning error map. Based on the error map, each receiver will be labelled as, *good*, *medium* and *bad*, conditions. The receiver labelled as *bad* condition will be improved by the receiver labelled as *good* condition. Five low-cost GNSS receivers are used to conduct a static experiment. According to the result, the positioning accuracy of the receiver located at deep urban canyon will be improved from 26.6 to 17.9 meters, where its SDM result is 19.3 meters.

1. INTRODUCTION

Intelligent transportation system (ITS) receives greater attention, aiming to improve transportation safety and efficient. However, one of the bottlenecks of ITS is the vehicle localization accuracy. The localization accuracy of vehicles is essential for navigation and traffic management, the localization error may cause incorrect driving route, or even traffic accidents. The common approaches for vehicular localization are based on the global navigation satellite system (GNSS), the inertial navigation system (INS), the light detection and ranging system (LiDAR) and vision sensors. In between, the GNSS is the only system providing the absolute positioning solution, making GNSS indispensable for ITS. With the significant development of communication technology, the vehicle-to-vehicle (V2V) communication becomes possible in the near future. The V2V collaborative positioning

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has becoming one of the popular researches. By making use of the numerous surrounding vehicular measurements, the positioning accuracy of the target vehicle can be optimized and highly improved. The V2V collaborative positioning can be categorized into two categories, the transponder-based and the GNSS-based positioning [1]. The transponder-based approach employs the radio frequency to measure the relative position between target vehicle and surrounding vehicles, such as time of arrival (TOA), time difference of arrival (TDOA) and angle of arrival (AOA). However, these methods still suffer from the non-light-of-sight (NLOS) reception. The transporting signal between vehicles may be blocked by obstacles, buildings or in-between vehicle, resulting the loss of measurement between vehicles. On the other hand, the GNSS-based method conducts collaborative positioning by exchanging the GNSS raw measurements between vehicles. The shared measurements are further applied with the double difference (DD) technique, which is widely used in real-time kinematic (RTK) to obtain the relative position. The DD technique is able to eliminate the systematic errors, including ionospheric, tropospheric and satellite clock/orbits bias [2]. Therefore, the GNSS-based collaborative positioning method can achieve better accuracy, even though the vehicles are under the NLOS situation. However, this GNSS based collaborative positioning is still highly affected by the GNSS multipath effects and NLOS reception, meaning its performance in urban areas can be significantly degraded [3].

In the urban area, the signal transmission from satellites to receiver may be blocked or reflected by the buildings. The receiver may receive both direct and reflected signal as multipath effect, or even worse, only the reflected signal, the NLOS. The reflected signal introduces an extra traveling distance, resulting in enormous GNSS positioning error [4]. By conducting differential technique, the multipath and NLOS error can even be doubled. Hence, the multipath and NLOS effects should be greatly mitigated before applying the GNSS raw measurement in collaborative positioning. Due to the nature that multipath and NLOS effects are produced because of buildings, the 3D building model can be employed to evaluate and mitigate such effects. Since the 3D building model of cities have been well constructed and easy to access, different methods are developed recently to aid the GNSS urban positioning [5]. The shadow matching is a widely used 3D map aided GNSS positioning method [6]. It matches the satellite visibility of receiver with the predicted satellite visibility in different locations to determine the position of the receiver. While in some deep urban situation, the severe NLOS signal reception may cause incorrect matching to degrade the performance of shadow matching [7].

This paper aims to combine the advantage of shadow matching in GNSS based collaborative positioning. First, due to the error distribution of GNSS shadow matching, its positioning solution is still able to combine with the 3D building model and ephemeris to classify and exclude the NLOS satellites. The survived raw GNSS measurements of each vehicle can be further applied with consistency check based fault detection and exclusion (FDE) [8]. After the 3D building model based and consistency check based FDE, the survived measurements can be considered as clean measurements to conduct DD technique, obtaining accurate relative positioning solutions between the vehicles. During the collaborative positioning, the estimated relative positions and absolute positions are cooperated to optimize the final position of the target vehicles. Among numerous measurements, the inaccurate measurements may lead to large error in the optimization. Therefore, it is important to classify whether the measurement is reliable or untrustworthy. Due to the multipath and NLOS effects, it is hard to evaluate the positioning performance by measurements or other factors, such as dilution of precision (DOP) and carrier to noise ratio (C/N_0) [9]. The newly proposed GNSS ray-tracing algorithm is able to use the broadcast ephemeris and 3D building model to predict the positioning error for a specific location, especially in urban areas [10]. Based on the predicted GNSS positioning error, the reliability of each measurement is able to be classified. The reliable measurements can be picked out and further applying the collaborative positioning, obtaining the accurate positioning solution for the target vehicle. Finally, an average collaboration positioning is implemented to calculate the final positioning result.

2. THE 3D MAP AIDED GNSS COLLABORATIVE POSITIONING ALGORITHM

The collaborative positioning algorithm is commonly based on the optimization of the absolute position of single vehicle and the relative positions between vehicles. The advantage of collaborative positioning is to make use of the measurements from surrounding vehicles, obtaining a better positioning result. For the vehicle in deep urban, the GNSS positioning error is about 50 meters or worse due to the multipath and NLOS effects. By employing the collaborative positioning algorithm, the surrounding vehicle under a good positioning environment can share its measurement to the vehicle in deep urban. The shared healthy measurements can contributes the positioning performance of vehicle in deep urban canyon, resulting a more accurate positioning solution even with severe multipath and NLOS effect.

In this study, the flowchart of the proposed V2V collaborative positioning algorithm is shown as Fig.1. For each vehicle, the received GNSS raw measurement will be applied with the GNSS shadow matching (SDM) positioning based on the 3D building models. By using the SDM, an accurate initial positioning solution for each vehicle can be obtained. The detail algorithm can be found in [11]. Based on the initial positioning solution, the satellite visibility can be calculated from the *skymask* (skyplot with building information) and further identify which satellite signal could be blocked by buildings, namely NLOS signals. Then, the reminding GNSS measurements (after excluding those NLOS measurement) will be conducted with consistency check based FDE [12]. After the two exclusions, the survived measurements are considered as clean GNSS measurements. The survived measurements of each vehicle will be cooperated and applied with double difference to obtain the relative positions in between vehicles. Meanwhile, the consistency check will be employed again during the DD calculation, ensuring the consistency of measurements [8].

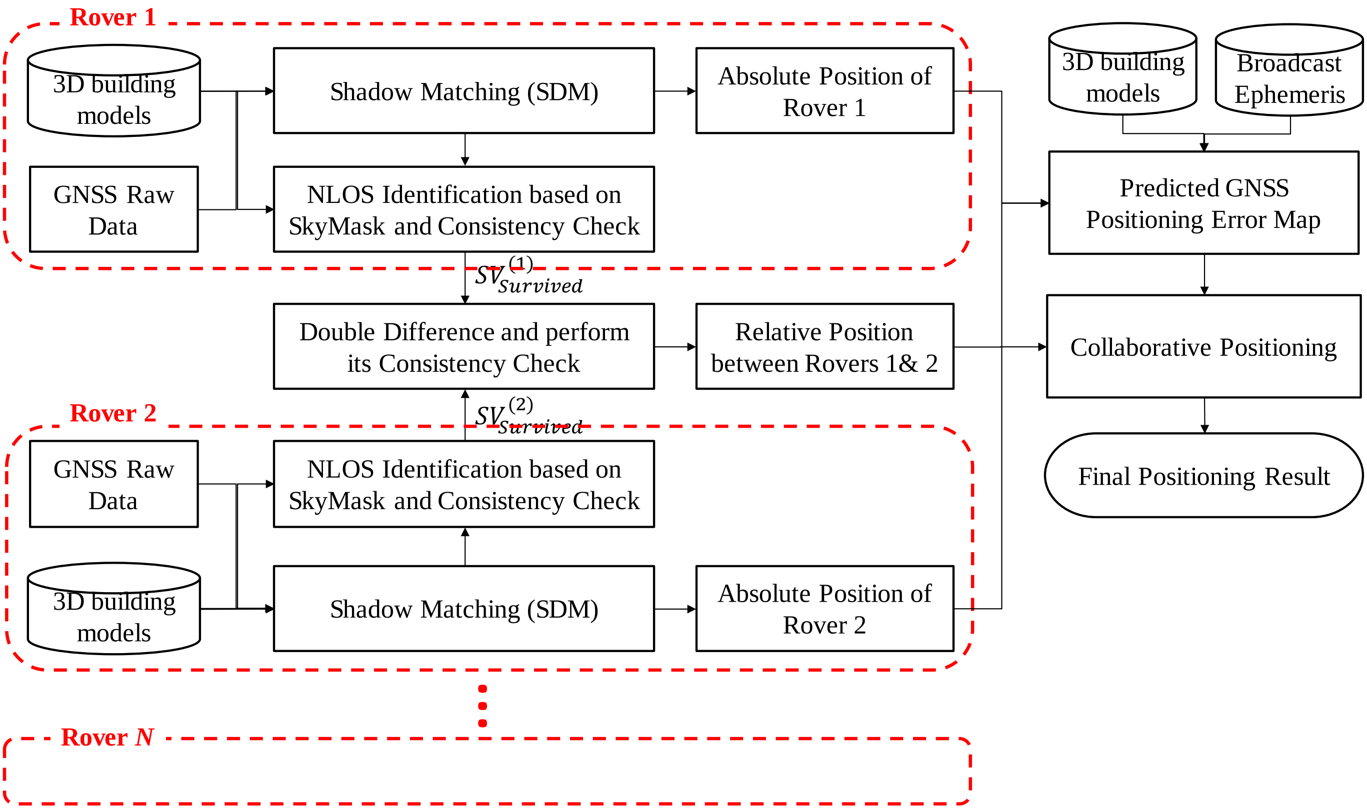

Fig.1 The flowchart of the proposed 3D map aided V2V collaborative positioning algorithm.

Based on the 3D building model in the operating area and the broadcast ephemeris, the GNSS range measurement that consisted of multipath and NLOS delay can be predicted using ray-tracing algorithm [13]. After processing the simulated measurement, the positioning error of each location can be obtained comparing the true location. The positioning error of each location can be constructed into a positioning error map, indicating the predicted positioning error for each location as Fig.2 [10].

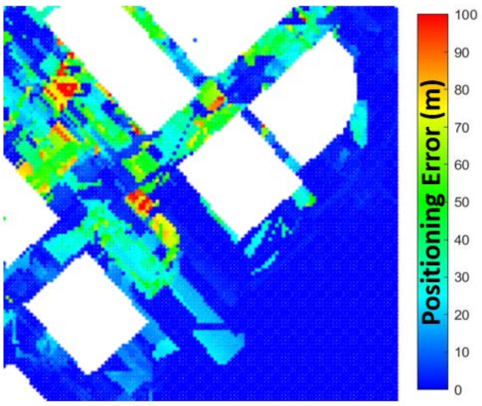

Fig.2 The predicted positioning error map. The color bar denotes the positioning error (m).

Using the positioning error map, we are able to predict each vehicle's positioning error based on the SDM estimated absolute position, and then categorize into different class. The positioning performance status of the vehicle is determined by the predicted positioning error with the Table.1.

Table.1 Classification based on the predicted GNSS positioning error

Predicted Positioning Error (m)	Classification Result
< 5	Good
5 - 15	Medium
> 15	Bad

For the bad positioning performance vehicle, the positioning solution of LS or SDM may still includes large error, due to the large multipath/NLOS delay and the high NLOS/LOS ratio. Since the good vehicle receivers enough healthy measurements, both the absolute and relative positioning solutions achieve better accuracy comparing with that of bad vehicles. Therefore, it is suggested to use the measurements and positioning solutions of good vehicles to determine the position of bad vehicles. Based on the SDM of good vehicles (absolute position) and the DD with double layer consistency check FDE between good and bad vehicle (relative positions), the final estimated position of the bad vehicle can be derived as following:

$$\mathbf{r}_{bad} = \mathbf{r}_{SDM,good} + \Delta\vec{\mathbf{r}}_{DD,good-bad} \tag{1}$$

where $\mathbf{r}$ denotes the position of vehicle, the subscript SDM denotes the positioning solution from SDM. $\Delta\vec{\mathbf{r}}_{DD,good-bad}$ denotes the relative positioning vector between good vehicle and bad vehicle obtained using the double difference technique with double layer consistency check. By using the good vehicle as reference to determine the bad vehicle's positioning, the positioning accuracy of bad vehicle can be improved.

3. EXPERIMENT SETUP AND RESULT

Experiment setup

To verify the proposed 3DMA GNSS based collaborative positioning algorithm, an experiment is design as Fig.3 (a). Five different location is selected representing 5 different vehicles under different environment: Vehicle 1) 22.298332°N, 114.179559°E with open sky; Vehicle 2) 22.297950°N, 114.179175°E with open sky; Vehicle 3) 22.298299°N, 114.178953°E with one-side building; Vehicle 4) 22.298739°N, 114.179484°E with one-side building; Vehicle 5) 22.298650°N, 114.178760°E in dense urban. For each vehicle's location, the u-blox M8T receiver as Fig.3 (b) is used to collect the raw GNSS measurements with GPS and GLONASS constellation. All receivers are simultaneously collecting 10 minutes data statically. The recorded measurements are further applied with the proposed algorithm by post-processing.

(a) (b)

Fig.3 (a) The vehicle locations for the proposed 3DMA collaborative positioning experiment; (b) The u-blox M8T receiver used during the experiment.

Classification of the positioning performance of single vehicle

Using the broadcast ephemeris data and the 3D building models, the predicted GNSS positioning error map is generated. Based on the SDM, the predicted positioning error of a receiver can be obtained from the generated GNSS positioning error map. The distribution of the predicted positioning error from the generated positioning error map and the least square are shown in Fig.4, The corresponding mean errors and classification results are shown in Table 2.

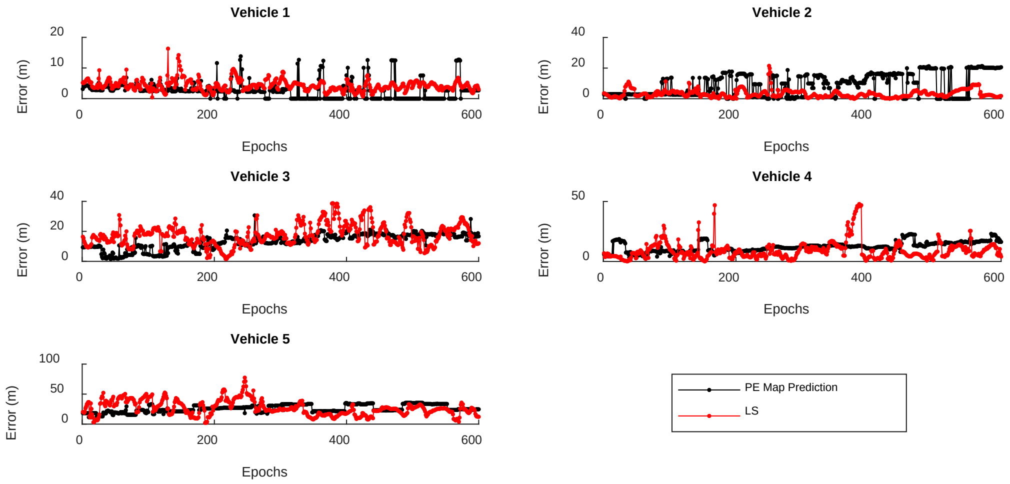

Fig.4 The predicted positioning error from the generated positioning error map and least square estimation.

Table.2 The mean positioning error (m) and class from predicted positioning error map and LS for each vehicle

Vehicle	1	2	3	4	5
LS (m)	4.3	3.3	17.4	9.0	26.6
PEM (m)	2.6	9.1	13.2	12.2	25.8
Class	Good	Normal	Normal	Normal	Bad

Comparing the positioning error between the error map (black line in Fig.4) and LS (read line in Fig.4), although the deviation of the true positioning error is larger than value given in the error map, the predicted error of each vehicle is similar to the real positioning error that estimated by LS. Therefore, the result verifies that the positioning error map is able to predict the positioning error of each vehicle. For vehicle 1, the predicted error is less than 5 meters, which will be classified as good performance vehicle for collaborative positioning. For vehicle 2, 3 and 4, the predicted positioning error is between 5 and 15 meters as normal vehicle, will not have contribution during collaborative positioning. For the vehicle 5, the positioning error is predicted as 25.8 meters, the vehicle may have severe positioning error, requiring other good vehicle to aid during collaborative positioning.

Collaborative positioning

The performance of the proposed collaborative positioning algorithm will be compared with the following four approaches:

1) LS: Least square positioning algorithm, regarding as a conventional positioning result.
2) SDM: Shadow matching technique, regarding as an innovative 3D map aided positioning for a single user. [14]
3) CP-DD2CC: Collaborative positioning based on double layers consistency check [8].
4) CP-3DMA: The proposed 3D map aided GNSS collaborative positioning algorithm.

The positioning solutions of LS, SDM, CP-DD2CC and CP-3DMA with regard to the true receiver location (Ground Truth) are shown as Fig.5. The positioning error distributions of different the approaches are shown as Fig.6. The mean and standard deviation of the positioning error of LS, SDM, CP-DD2CC and CP-3DMA are shown in Table.3.

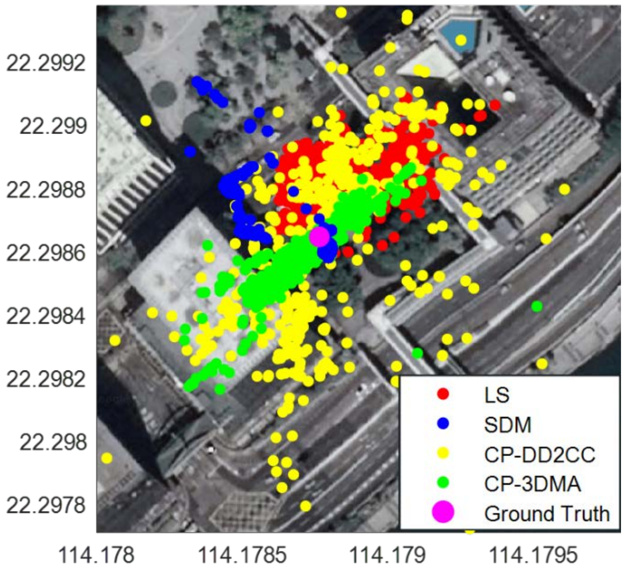

Fig.5 The positioning solution of least square (LS), shadow matching (SDM), collaborative positioning with double layers of consistency check (CP-DD2CC) and the proposed 3D map aided GNSS collaborative positioning (CP-3DMA) with regarding to the true receiver location (Ground Truth).

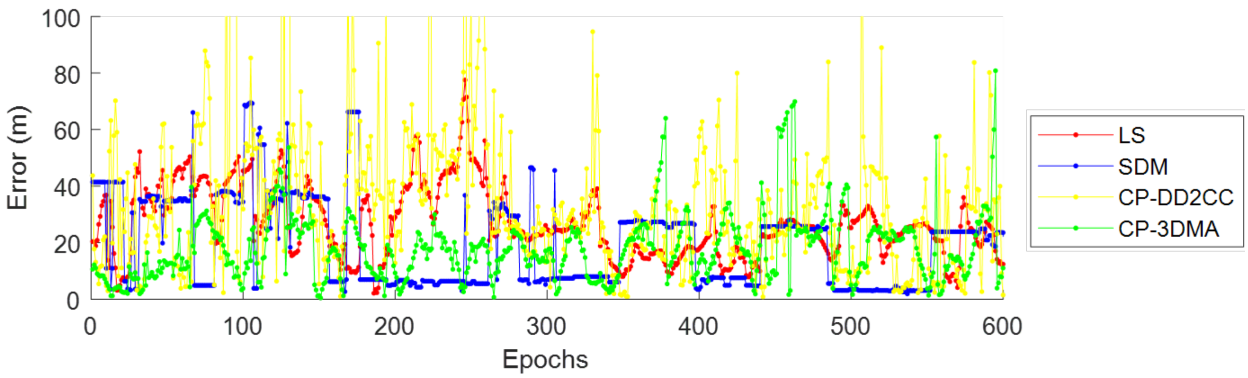

Fig.6 The positioning error of LS, SDM, CP-DD2CC and CP-3DMA.

Table.3 The mean positioning error and standard deviation of LS, SDM, CP-DD2CC and CP-3DMA

Method	LS	SDM	CP-DD2CC	CP-3DMA
Mean (m)	26.6	19.3	36.3	17.9
STD (m)	12.4	15.7	41.2	12.1

The estimated positions of the conventional LS are largely drifted from the true location because of the multipath effort and NLOS reception, resulting 26.6m as mean error. Since the multipath effects and NLOS receptions are severe, the consistency check algorithm may occur fake consistent issue. The healthy measurements may be wrongly excluded, making the positioning accuracy degraded to 36.3 meters. GNSS shadow matching is able to avoid using the multipath/NLOS delayed pseudorange measurements, improving the accuracy to 19.3m in mean and 15.7m in STD. However, the large NLOS/LOS ratio makes the receiver's satellite visibility incorrect. As a result, the positioning error is still large. The proposed 3D map aided GNSS collaborative positioning method is able to firstly exclude the obvious NLOS measurements by shadow matching based satellite visibility. Then, the healthy vehicles are selected with the predicted GNSS positioning error map and collaborated with bad vehicle's measurement using double difference. The double layer consistency check can further exclude the inconsistent measurements. Finally, the proposed CP-3DMA method achieves 17.9 meters positioning error with 12.1 meters STD for the bad vehicle, improving its positioning performance in dense urban areas.

4. CONCLUSIONS

In this study, a 3D map aided GNSS collaborative positioning algorithm is developed to improve the positioning accuracy in dense urban areas. The GNSS shadow matching can obtain an accurate initial absolute position of all the participating vehicles. This absolute position is further used with 3D building model to exclude the obvious NLOS measurements. During deriving the estimation of relative positions between two vehicles via double difference, a double layers of consistency check method is used to exclude inconsistent GNSS range measurements. After the exclusions, the multipath and NLOS error can be mitigated. Based on the classification from the predicted GNSS positioning error map, the measurements of the vehicles with good performance are cooperated with the measurements from vehicles with bad performance, aiding the bad vehicles achieving a more accurate positioning solution in a dense urban area. The experiment results verify the proposed 3DMA GNSS collaborative positioning algorithm obtains a more accurate positioning performance comparing to the conventional LS method.

However, the predicted positioning error may have large difference with the real positioning error in some epochs, since the random noise may not be the same as the real operation. Moreover, the collaborative positioning solution is typically distributed along one direction. Due to the geometry of the distribution visible satellites with regarding to the receiver, the positioning solution may deviate a lot on from one direction. The future work is to improve the accuracy of the predicted positioning error map to ensure the correctness of vehicle status classification. Also, the positioning error distribution due to the DOP distortion of the proposed 3DMA GNSS collaborative positioning method is worth to be investigated.

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