Improving vehicle localization with two low-cost GPS receivers

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Abstract. A primary concern of intelligent traffic management systems (ITMS) is to collect necessary traffic data. Vehicle position is one of the most important data types to manage traffic effectively. Most current approaches to localize modern vehicles (MVs) fall into three categories. The first category uses standalone reference stations, such as the wide-area augmentation system (WAAS), which are expensive modules. The second category uses multiple expensive localization sensors such as the global positioning system (GPS), global navigation satellite system (GNSS), and inertial measurement unit (IMU). However, such expensive solutions may not be applicable in all vehicles, impacting generalizability. The third category is a software-based approach. As opposed to the abovementioned approaches using expensive hardware, the third category uses software, such as map-matching techniques, to augment noisy localization sensors. In this study, we investigated map-matching software in some case studies and found that it cannot locate the vehicle effectively if the positional data are collected by a low-cost and too noisy GPS receiver. Therefore, this paper analyzes and highlights the impact of GPS receiver's noise in applying self-localization. It also proposes a new methodology by integrating cross-GPS validation, interpolation/best fit, and map-matching techniques to localize a vehicle in the presence of GPS signal noise and investigate it in real traffic data from a metropolitan area. Our proposed methodology is able to identify the more accurate GPS receiver dynamically, by considering the fixed distance between the two GPS receivers. Our evaluations indicate that the proposed methodology can significantly improve vehicle self-localization performance.

Keywords: Vehicle Self-Localization, Accurate GPS Receiver, Map-Matching.

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1 Introduction

Over the past several years, population growth has led to an increase in vehicle numbers. Combined with global urbanization trends, this has resulted in increased traffic congestion in many cities. Therefore, traffic management systems should be implemented or improved in order to mitigate traffic congestion. As a result, ITMS is introduced to manage traffic based on traffic data and make smart decisions. Such data could originate from stationary sensors such as inductive loop detectors, or from vehicle-mounted sensors, such as GPS, camera radar, and LiDAR.

One of the most important kinds of traffic data is the vehicle location. A GPS receiver is a common solution to estimate the vehicle location in a GPS coordinate system, as most MVs are equipped with it. However, the accuracy of data collected via a GPS receiver depends on several parameters, such as hardware accuracy, satellite geometry, signal blockage, and atmospheric conditions [6].

To satisfy vehicle localization requirements and mitigate the estimated location error, three major categories of approaches are proposed in the literature [3], [5]. One category of approaches uses a standalone reference station, such as WAAS (e.g., [17]), to align the computed GPS data. The second one is the hardware-based approach, which utilizes various sensors (e.g., IMU [8]). Using technologically advanced sensors to determine vehicle location would boost estimation accuracy. However, equipping the vehicle with such sensors will increase the vehicle cost. Thus, many vehicle manufacturers may choose to use low-cost GPS receivers for localization purposes, which are likely to be noisy. The third category uses software, such as map-matching techniques, to augment noisy localization sensors [18]. Map-matching is a technique that integrates map information and recorded geolocation data from the vehicle in order to increase the accuracy of the vehicle location [19]. Although map-matching techniques are applied widely to minimize vehicles' localization error, in this study, we found that map-matching techniques (e.g., QGIS offline map-matching [13], [12]) do not work well if the GPS data collected via a low-cost GPS receiver are too noisy.

Therefore, a much-debated question is how to keep the hardware/sensors' cost low as well as localization accuracy high. This paper analyzes and highlights the importance of the accuracy of the low-cost GPS receiver in the performance of vehicle self-localization (i.e., a vehicle determining its position on the map) and proposes a new methodology by integrating cross-GPS validation, interpolation/best fit, and map-matching techniques to localize a vehicle in the presence of GPS signal noise. Our proposed methodology is able to identify the more accurate GPS receiver dynamically, by considering the fixed distance between the two GPS receivers. We implemented and evaluated our approach using real traffic data from a metropolitan area in Chengdu, China. The results show that our proposed approach is able to enhance vehicle localization performance.

The paper is organized as follows. Section 2 gives a brief overview of related work. Section 3 explains our proposed research design. Section 4 presents our proposed research approach. Section 5 describes our proposed research approach.

The discussion is presented in section 6. The last section concludes and proposes future works.

2 Related Work

Vehicle localization based on GPS receivers is a key component in managing traffic safely and effectively. However it can be imprecise, causing operational difficulties. Many approaches have been proposed to process imprecise data from GPS receivers to acquire accurate vehicle localization [3], [5]. For instance, Islam et al. [5] enhanced GPS accuracy by considering the vehicle movement direction, velocity averaging, and distance between waypoints using coordinate data. Their experiment used a vehicle-mounted Garmin GPS 19xHVS receiver. In order to study the accuracy, they plotted data on Google Maps. The proposed approach achieved a GPS position accuracy of 4–10 meters [5]. Acosta et al. [11] proposed an approach based on Kalman filter, fuzzy logic, and information selection. In the experiment step, they used three Garmin 18X USB GPS receivers that were connected to two notebook computers. The proposed approach in [11] smoothened the measurement error, and mitigated the error that fluctuates in time. In 95% of the measurements, the error fluctuates with ± 1 meter, and in some cases in ± 0.2 meters [11]. Tang et al., in [15], proposed an adaptive map-matching algorithm based on the hierarchical fuzzy system. In this approach [15], a historical trajectory, adaptive learning scheme, and hierarchical fuzzy inference structure were used. The experimental results showed that the proposed algorithm in [15] was able to increase the matching accuracy, outperformed the topological and geometric methods. Recent research has focused on AI (Artificial Intelligence) to address the vehicle localization problem. For instance, Lecce et al. [1] used generalized regression neural networks to increase GPS position accuracy by correcting the receiver's position. The idea was to use the analytical description of the time series to improve the position accuracy. The authors used a two-layer neural network. They proposed an approach based on removing the GPS positioning error by training a neural network to mitigate the periodic components of GPS positioning error. In the experiment step, they used only one GPS receiver BU-353. The mean improvement in the accuracy of the GPS position of the proposed approach is 25%. However, the output of this approach strongly depended on the training data set [1].

3 Research Design

In our recent studies [9], [10], data were collected with a vehicle equipped with a monocular camera with a built-in GPS receiver. The purposes of those studies were to use the ego-vehicle as a mobile sensor, estimating traffic data for surrounding vehicles, in order to share them with ITMS. This approach would enable ITMS to generate a model (e.g., digital twin) of a traffic status and make accurate and smart decisions. Through our studies [9], [10] we found that the image-based target vehicle localization accuracy is tightly connected to the localization accuracy of the ego-vehicle itself.

In the current study, to collect data, we used three vehicles to follow various trajectories. Each vehicle was equipped with two monocular cameras. One camera was mounted on the front windshield, and another camera was mounted on the rear window of the vehicle. These two cameras were located at a known distance from each other on each vehicle and helped us to validate the GPS receiver accuracy, as well as collecting footage from both sides of the vehicle, which were needed for further image processing-based studies in the future. All cameras used were of the type GoPro Hero 7. The monocular camera is a low-cost sensor with great potential to be mounted on most MVs, making our approach generalizable. Moreover, existing advanced vehicles are already equipped with monocular forward-facing cameras for safety and insurance reliability purposes. Therefore, an approach based on a monocular camera will be compatible with both existing advanced vehicles and future ego-vehicles. Furthermore, monocular cameras are one of the most used sensor types in previous research. In addition to collecting video footage, the chosen camera enabled GPS data collection, as it included a built-in GPS receiver.

To begin this research, first, we analyzed the accuracy of the collected GPS data via the GPS receiver mounted on the front window glass by plotting them on a map (the data collection process is described in detail in section 5.1). Fig. 1 shows one example of the studied scenarios where the ego-vehicle turns right at an intersection. In Fig. 1-A, the blue arrow shows the vehicle's movement scenario. The polyline, which is a combination of green and red colors, represents the vehicle location based on the front GPS receivers mounted in the vehicle. The color of the polyline represents vehicle speed. This polyline and its colors are plotted automatically by using Telemetry Extractor for GoPro [16].

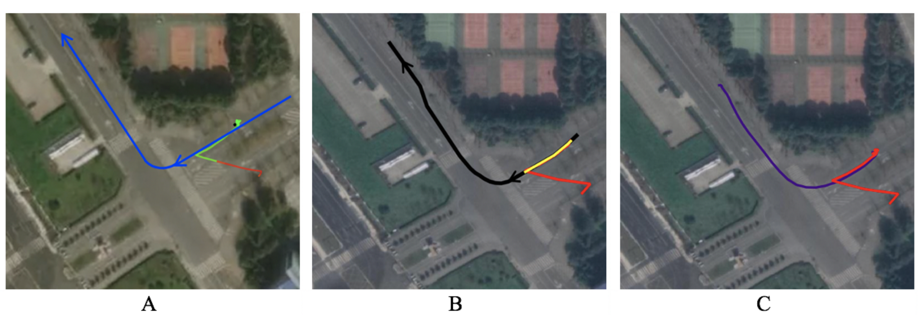

Fig. 1. Problem formulation. A) Vehicle locations collected via a front-mounted GPS receiver in the vehicle (green-red polyline), compared with the vehicle's movement scenario (blue polyline). B) Map-matching output (yellow polyline) related to the noisy front GPS receiver (red polyline) by considering the true vehicle trajectory (black polyline). C) Vehicle locations via two GPS receivers on the same vehicle (front GPS receiver: red polyline, rear GPS receiver: purple polyline.)

Our first attempt was to use map-matching software to address the GPS receiver noise issue to get the precise vehicle location. We used QGIS offline map-matching software [12], [13], which is one of the widely used approaches to minimize the GPS error. Fig. 1-B presents our finding after applying map-matching to the same studied scenario. In this figure, the black polyline is the true vehicle trajectory on the road. The red polyline represents the positions collected via the front GPS mounted on the vehicle (part of this red polyline is covered by the yellow polyline), and the yellow polyline represents the map-matched positions of the noisy GPS receiver. It is clear from this figure that QGIS offline map-matching software [13], [12] is not able to identify and map-match the entire trajectory accurately if the vehicle localization error is too high.

Then, we analyzed data from another GPS receiver on the same vehicle in the studied scenario. We found varying degrees of positional error between the two GPS receivers. Fig. 1-C shows the results. In Fig. 1-C, the red polyline is the vehicle position based on the GPS receiver mounted on the front window glass. The purple polyline shows the vehicle position based on the GPS receiver mounted on the rear window glass on the same vehicle. As this figure shows, the localization error of the front-mounted GPS receiver is much higher than that of the rear-mounted GPS receiver in this scenario.

4 Research Approach

Fig. 2 illustrates our proposed approach, which comprises data collection, data pre-processing, and methodology.

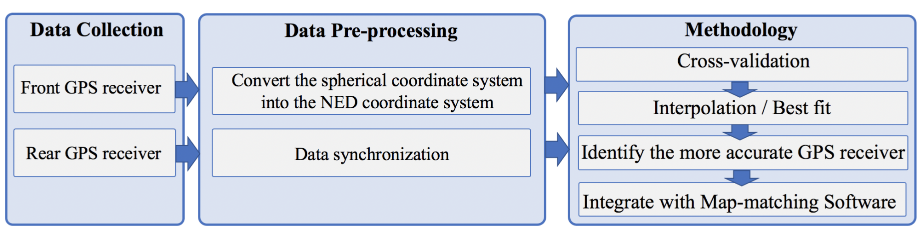

Fig. 2. Our proposed approach.

4.1 Data Pre-Processing

As previously stated, positional data were collected using two GPS receivers mounted on ego-vehicles. Before applying our methodology, the data were pre-processed. In this step, first, we need to convert a spherical coordinate system [14] into a north, east, down (NED) coordinate system [7] on the earth's surface. The conversion is both practical and justified, since we are studying a small, demarcated area on the earth's surface. Secondly, since the two mounted GPS receivers in the vehicle are independent and the data collection was not started concurrently, we need to synchronize them in the time domain in order to facilitate analysis.

4.2 Methodology

In this step, first, we need to analyze the accuracy of the two mounted GPS receivers in the same vehicle. To detect whether the GPS signals are accurate, we calculated the vector distance of the estimated positions via the two GPSs at equal timestamps, as the two GPS receivers were mounted a known distance from each other in the same vehicle. If it is found that the vector distances are different from this fixed distance, we can conclude that at least one of the GPS receivers is inaccurate, which means we need to identify the accurate GPS receiver.

To identify the more accurate GPS receiver, we developed a new algorithm based on cross-validation, interpolation/best fit techniques. Cross-validation aims to find the positions in the trajectory where both GPS receivers are almost in agreement (with a threshold $\pm e$) with regard to vehicle position. It does so based on the Euclidean distance between the front and rear GPS receivers. As the number of validated positions that both GPS receivers agreed on is limited, we generated extra points based on the validated positions by applying interpolation techniques [4]. In addition, for the straight vehicle movements, which are determined based on the vehicle movement slope, the best fit technique [2] is used to generate more points in the whole trajectory based on the validated and interpolated points. Then, to identify the more accurate GPS receiver, we used the average Euclidean distance between the validated/generated (i.e., interpolation/best fit) positions and the positions collected by each GPS receiver. The GPS receiver with the smallest average distance is identified as the more accurate one. Although we can identify that one GPS is more accurate than the other, it is possible that the more accurate one is also noisy. This step inserts the data from the identified more accurate GPS receiver into a map-matching algorithm, using it to further amend the noisy GPS signal. We investigated the effectiveness of several existing map-matching software applications and identified the one which was most compatible with our data. We found QGIS offline map-matching software [13], [12] was a suitable and effective tool to apply map-matching in our research context.

5 Evaluation

5.1 Data Collection

To evaluate our proposed approach, experiments were run in several case studies from real traffic. The three equipped vehicles described in section 3 were driven in the metropolitan region of Chengdu, China. In order to provide acceptable data coverage and generalizability, eight different scenarios were defined, comprising both straight streets and intersection movements. In total, 24 trajectories were considered. As Fig. 3 shows, there are many tall buildings surround the studied area, which may interfere with GPS signal accuracy and cause GPS information inaccuracies, which is a regular occurrence in a metropolitan environment.

Fig. 3. One example of traffic status in a studied scenario from a metropolitan area.

As the ground-truths related to vehicle movements in this study were not available, we extracted them manually by visually observing forward-facing video footage and identified the ground-truth vehicle movement using Google Earth Pro.

5.2 Evaluation Results

As we experimented, if the GPS signal was too noisy, QGIS offline map-matching [13], [12] was able to minimize the localization inaccuracy of only a segment of the trajectory, which reduced the performance. The performance of self-localization may improve by widening that segment, which is addressed in this article. Therefore, we used the Cartesian length of the trajectory to evaluate our proposed self-localization approach. Table 1 summarizes our findings. This table included 8 scenarios (S1-S8) by considering three equipped vehicles (V1-V3). The second column, named **Data**, shows input data features: I) the Cartesian length of the vehicle movement via GPS receivers (Cartesian length measurement error is in the range of $\pm 2m$). II) the average distance between the vehicle positions collected via each GPS receiver and the ground-truth vehicle trajectory. If the Cartesian length of the vehicle via both GPSs varies, we can conclude one of the GPS receivers is noisy. To identify the amount of noise related to each GPS on the same vehicle, we calculated the average distance between the vehicle positions collected via each GPS receiver and the ground-truth vehicle trajectories _that were estimated by visually observing the video footage and the GPS information acquired from Google Earth Pro_ based on distance to nearest hub (points). The last column, named **Output**, summarizes our findings related to both using pure

QGIS offline map-matching [13], [12] and our proposed approach, which relies on identifying the more accurate GPS receiver.

Table 1. Case study evaluation.

Scenario	Vehicle	Data				Output			
		Cartesian Length (m)		Avg. Dis. (m)		map-matching-based Cartesian Length (m)		Our proposed approach	
		Front GPS	Rear GPS	Front GPS	Rear GPS	Front GPS	Rear GPS	Accurate GPS	Cartesian Length (m)
S1	**V1**	491	535	12.009	4.935	490	532	Rear	532
	V2	513	517	2.044	10.746	513	514	Front	513
	V3	441	437	2.324	4.415	441	437	Front	441
S2	**V1**	180	176	1.457	6.058	179	178	Rear	178
	V2	191	180	4.358	3.385	191	177	Front	191
	V3	148	145	1.669	2.19	147	145	Front	174
S3	**V1**	193	153	1.955	1.774	191	155	Rear	155
	V2	190	183	1.552	4.612	189	184	Front	189
	V3	160	153	3.608	13.860	159	150	Front	159
S4	**V1**	157	159	4.241	0.665	156	159	Rear	159
	V2	163	163	6.044	1.84	163	162	Front	163
	V3	188	188	1.388	2.264	188	188	Front	188
S5	**V1**	179	157	5.170	1.798	174	162	Rear	162
	V2	188	188	3.126	4.900	188	188	Front	188
	V3	116	116	1.450	2.385	118	118	Front	188
S6	**V1**	123	116	3.752	6.913	124	117	Rear	177
	V2	186	192	1.333	7.131	186	194	Front	186
	V3	–	–	–	–	–	–	–	–
S7	**V1**	114	111	1.834	4.460	106	106	Rear	106
	V2	141	143	7.660	4.803	141	142	Front	141
	V3	–	–	–	–	–	–	–	
S8	**V1**	**27**	**103**	**3.515**	**1.402**	**27**	**109**	**Rear**	**109**
	V2	100	96	1.493	2.983	103	107	Front	103
	V3	150	148	1.627	2.939	150	148	Front	150

To describe the information presented in 1 in detail, consider scenario S8, vehicle V3 as an example. In this row, the Cartesian length of the map-matched positions via both GPS receivers are almost similar (front GPS:=150 m, rear GPS:=148 m). This shows that applying map-matching software would be enough to correct such small errors satisfactorily. However, this table shows that when the GPS error is high, applying only QGIS offline map-matching [13], [12] may not be effective. For instance, consider scenario S8, vehicle V1. In this case, in the **Data** column, the Cartesian length related to the front GPS receiver equals 27 m, while it is equal to 103 m for the rear GPS receiver. As the difference in estimated movement length across the two receivers is high, it can be concluded that one of the receivers is very noisy and unable to estimate the vehicle trajectory correctly. In the **Output** column, we can see that applying only map-matching matched 27 m of the whole trajectory and was not able to improve the measurement error caused by the front GPS effectively, which means that identifying the more accurate GPS is vital. Therefore, by applying our proposed approach, the accurate GPS receiver is identified and presented in the **Output**–Accurate GPS column. So, in this case, the rear GPS is labeled as the accurate one, and the applied map-matching used that GPS receivers and improved the accuracy of 109 m of the trajectory. By applying further analysis, it was found that our proposed approach increased the localization performance in 53.86% of the studied scenarios. In this table, for vehicle 3 in scenarios S6 and S7, the more accurate GPS receiver was unidentified, as the rear-end GPS receiver did not record during the whole scenario. The reason for this could be that the battery died, or the memory card became full.

6 Discussion

Prior studies have noted the importance of identifying and mitigating the measurement error of GPS receivers. This paper developed a new algorithm to identify the more accurate GPS receiver if there are multiple possibly noisy GPS receivers installed on the same vehicle, based on cross-validation and interpolation/best fit techniques.

Compared to the approach relying on expensive GPS receivers or multiple sensors, our approach provides a low-cost solution to identify a vehicle's location precisely. Compared to the approach that solely relies on map-matching, our strategy of detecting GPS inaccuracy and prioritizing using the data from the more accurate GPS helped enhance the performance of the map-matching software.

The most important limitation in this study lies in the fact that the cross-validation step relies on finding overlapping positions collected by both GPS receivers on the same vehicle. If the localization error of one GPS receiver is too high and there are no overlapping points with the other receiver, cross-validation is simply not feasible. This might be the case if one GPS receiver has estimated the vehicle position totally wrong. Also, this method is based on post-processing and is not instantaneous.

7 Conclusion and Future Work

In this study, our focused context is defined as mounting two low-cost and possibly imprecise GPS receivers on the same vehicle with a fixed and known distance from each other to accurately identify the position of the vehicle based on cross-validation, interpolation/best fit while the vehicle is moving. We developed a new algorithm to identify the more accurate GPS receiver in the presence of noise and fed the GPS information from the identified more accurate GPS receiver to map-matching software. The proposed approach minimized the measurement error of the low-cost GPS receiver and was able to enhance the vehicle localization performance, specially when the GPS signal was too noisy. Since the study was limited to vehicle movements through intersections and along straight streets, more studies are needed to be able to generalize our approach by considering various vehicle movements, driving speeds, and weather conditions. Also, further research should be undertaken to evaluate the accuracy of our proposed approach by considering different types of scenarios with longer trajectories.

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