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Improving positioning accuracy for VANET in real city environments

Ming-Fong Tsai · Po-Ching Wang · Ce-Kuen Shieh · Wen-Shyang Hwang · Naveen Chilamkurti · Seungmin Rho · Yang Sun Lee

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Abstract With advances in technology and the economy, people are more inclined to buy cars. However, as a result, people forfeit their lives and property through accidents due to traffic congestion and traffic chaos. To ensure safe driving, anti-collision warning applications have been widely discussed. Most vehicular safety applications

M.-F. Tsai
ICT Design and Validation for Vehicles Department, Division for Telematics and Vehicular Control System, Information and Communications Research Laboratories, Industrial Technology Research Institute, Hsinchu, Taiwan
e-mail: mingfongtsai@gmail.com

P.-C. Wang · C.-K. Shieh
Department of Electrical Engineering, National Cheng Kung University, Tainan, Taiwan
e-mail: willydog029@gmail.com

C.-K. Shieh
e-mail: shieh@ee.ncku.edu.tw

W.-S. Hwang
Department of Electrical Engineering, National Kaohsiung University of Applied Sciences, Kaohsiung, Taiwan
e-mail: wshwang@mail.ee.kuas.edu.tw

N. Chilamkurti (✉)
Department of Computer Science and Engineering, La Trobe University, Melbourne, Australia
e-mail: n.chilamkurti@latrobe.edu.au

S. Rho
Department of Multimedia, Sungkyul University, Anyang-si, South Korea
e-mail: smrho@sungkyul.edu

Y. S. Lee
Division of Convergence Computer & Media, Mokwon University, Daejeon, Korea
e-mail: yslee@mokwon.ac.kr

use vehicular positioning and vehicular communication technologies to avoid car accidents. With Vehicular Ad Hoc Networks, it is common to use the global positioning system (GPS) as the vehicular positioning tool owing to its comprehensive development in vehicular navigation. However, there are factors that affect GPS positioning accuracy (e.g., multipath effect, atmospheric effect, etc.). To improve GPS vehicular positioning accuracy, we propose a cooperative positioning algorithm that can improve localization accuracy. We also demonstrate that our algorithm can work well in a real city environment.

Keywords Cooperative positioning · Vehicular positioning and real city environments

1 Introduction

More and more people are more inclined to buy cars because of advances and improvements in technology and the economy. However, the more people that buy cars, the greater the chance that they must endure a hazardous driving environment and the greater the risk that they might forfeit their lives and property through accidents due to traffic congestion and traffic chaos. In light of this, intelligent transport systems [1–5] have been proposed to provide various services to improve the vehicular environment, of which driving safety is the most important element. To ensure driving safety, anti-collision warning applications have been widely discussed. It is believed that if drivers can be made aware of the locations of other nearby vehicles in advance, they can avoid the occurrence of dangerous accidents and prevent injuries to life and property.

The basic solution is that every vehicle informs its neighbours of its position by broadcasting continually via vehicular wireless technology, such as the wireless access in vehicular environment/dedicated short range communications (WAVE/DSRC) system whose communication protocol is IEEE 802.11p (IEEE 1609) standard. The fundamental component is a vehicular positioning technology, which may affect the reliability of vehicular safety applications, such as emergency electronic brake light and intersection collision warning. Therefore, vehicular positioning accuracy depends significantly on the global positioning system (GPS) device. The GPS is a space-based satellite navigation system that has been exploited for the development of vehicular navigation. Unfortunately, GPS devices still suffer from some factors that influence the positioning accuracy [6]. For example, the GPS signal may be blocked by buildings or affected by atmospheric influences from the troposphere and ionosphere. In general, regular GPS can provide accuracy to within 5–30 m in a dense urban city environment. Clearly, that level of accuracy in the GPS positioning is insufficient for use in vehicular safety applications. Therefore, a great deal of work has been undertaken by various scholars and professionals to address the vehicular positioning problem.

The cooperative positioning (CP) concept has been widely discussed in recent years as a means by which the positioning error bias can be reduced. Since the invention of WAVE/DSRC, vehicles have been able to communicate with each other to share their information. Moreover, the CP concept combines DSRC and GPS to improve the overall accuracy. There has been much research published in the literature regarding CP methods, which can be classified into two categories: vehicle-to-roadside (V2R) unit CP methods [7–9] and vehicle-to-vehicle (V2V) CP methods [10–16]. The former uses some referenced roadside units to inform the vehicle of road conditions in advance. The most well-known method is differential GPS. It uses ground-based reference stations to compare the absolute position and the GPS position of a vehicle and to share its differential GPS error with its neighbours. But the cost of roadside unit stations restricts its comprehensive development. On the other hand, the latter, V2V CP methods, can involve multiple vehicles sharing their driving information to improve awareness of their mutual locations. By collecting the information, a vehicle can improve its positioning accuracy, and then broadcast the new data to its neighbours to update their information synchronously.

This paper proposes a CP method which integrates the camera sensor that can improve the localization error, even for just two vehicles in the Vehicular Ad hoc NETwork (VANET). In addition, this paper proposes a method that does not require any extra information in advance, such as a city digital map. We take the Industrial Technology Research Institute (ITRI) WAVE/DSRC Communication Unit (IWCU) device [17] as the GPS receiver and DSRC communication functions and use a D-Link DCS-930L webcam as our measurement sensor in the experiments. The experimentation results show that the proposed method can improve the positioning error in real city environments. The remainder of this thesis is organized as follows. In Sect. 2, relevant background information is discussed in greater detail. We describe in depth the proposed CP method and the system architecture in Sect. 3. In Sect. 4, experiments and performance results are discussed, and conclusions and thoughts on future work are summarized in Sect. 5.

2 Related work

2.1 Map matching

A geographic information system (GIS) is a system that integrates all geographical data and GISs have undergone rapid development in recent years. Information and communications technology is often applied to GIS technology to create digital maps of cities for vehicular navigation. Some work has investigated implementing GIS to improve the positioning accuracy of GPS. The simple concept is based on using a digital map to limit the estimated position of a vehicle in relation to roads. Yang et al. [7] identified three different types of related map-matching technology: point-to-curve, distance of curve-to-curve and angle of curve-to-curve. The point-to-curve method matches a GPS point to the nearest road and the distance of curve-to-curve method matches a vehicle to the road according to the sum of two end GPS points. The angle of curve-to-curve method matches a vehicle to the smallest angle from its two end GPS points and the road. However, map-matching technology requires additional hardware cost and time to save GIS information in advance.

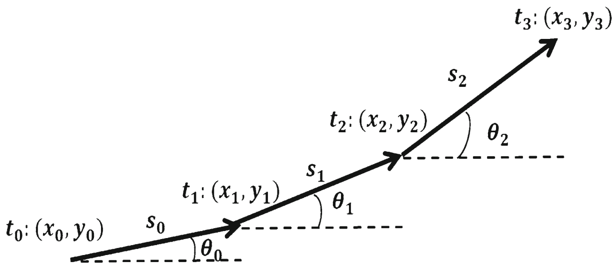


Fig. 1 Dead reckoning

2.2 Dead reckoning

Dead reckoning (DR) is a method that enables a vehicle to maintain an estimate of its current position with a bad GPS signal. With this technology, DR measurements use the vehicle's driving data (e.g., speed and direction) obtained from an inertial navigation system and a reference location to calculate its position of next time. Figure 1 illustrates a two-dimensional planar space for vehicular travel. The equation of the vehicle's position at (x_k, y_k) at time t_k can be expressed by

$$x_k = x_0 + \sum_{i=0}^{k-1} s_i \cos\theta_i \tag{1}$$

$$y_k = y_0 + \sum_{i=0}^{k-1} s_i \sin\theta_i, \tag{2}$$

where (x_0, y_0) is the initial location of the vehicle at time t_0 and s_i and θ_i are the vehicle's distance of travel during time interval Δt and the angle of the displacement vector from the vehicle's position (x_i, y_i) at time t_i to (x_{i+1}, y_{i+1}) at time t_{i+1}, respectively.

2.3 Cooperative positioning

In recent years, the rapid development of wireless communication technology in vehicular networks, such as the WAVE/DSRC system, has enabled many aspects of vehicular applications to be more powerful through shared information. The communication protocol of the WAVE/DSRC system is the IEEE 802.11p (IEEE 1609) standard. So some academics want to introduce this technology to solve the vehicle positioning problem. The CP concept is one methodology that can exploit wireless communication technology to improve vehicular positioning accuracy. In general, the CP concept can be separated easily into two different methods: V2R and V2V, as shown in Figs. 2 and 3. The former uses referenced roadside units to inform the vehicle of road conditions in advance. The latter uses multiple vehicles sharing their driving information to improve awareness of their mutual locations. Conventional CP methods are presented in [18]. The CP methods localization process typically consists of three phases.

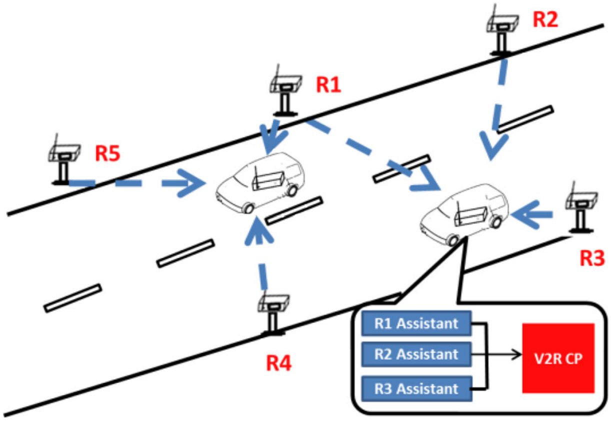


Fig. 2 Vehicle-to-roadside (V2R) CP

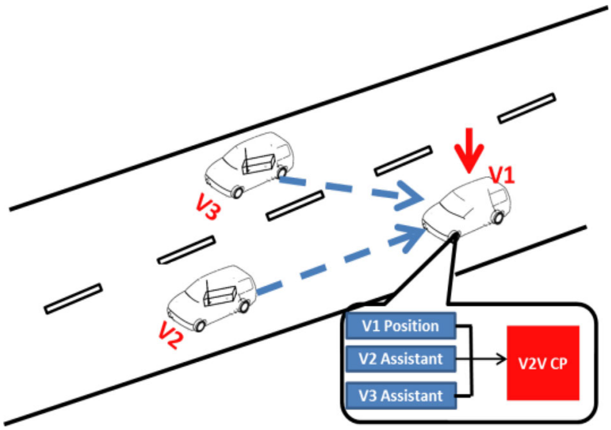


Fig. 3 Vehicle-to-vehicle (V2V) CP

The first phase is called the detection or measurement phase. The detection phase is usually designed for roadside units or on-board units (OBUs) to estimate the condition of relative objects (i.e., relative distance and object ID). The second phase is the data-sharing phase, during which vehicles communicate their driving information or information regarding what has happened on the road to their neighbours. The third phase is the location-update phase via data fusion. This final phase uses a mathematical model to update the vehicle's state and some common methods for this are presented in [18].

Research on the V2R CP method is presented in [9–11]. The best-known method is differential GPS (DGPS) [9]. The DGPS uses ground-based reference stations to determine the differential GPS error, by comparing the known fixed position and GPS position and broadcasting this error to help nearby vehicles fix their location. Another method [10] uses roadside units to provide an accurate position for the vehicles as they pass them. This can provide the initial DR position more accurately to help overcome the DR error accumulation problem. Therefore, the V2R CP method usually requires additional hardware cost to improve positional accuracy. In fact, the distribution of the reference stations has a hugely significant influence on the V2R CP method, in terms of both cost and making sure that any vehicle must be within the range of coverage of one reference station in VANET. On the other hand, the V2V CP method can overcome this problem easily. Many vehicles have the ability to measure relative V2V distances via the OBU devices such as radar and video sensors. In the literature, there are many researches [12–14] on the use of radio-based technologies, such as time of arrival (TOA), time difference of arrival (TDOA) and received signal strength (RSS), to measure relative distances without the cost of OBUs. All the above articles exploit the characteristics of wireless radio to measure vehicular relative distances; however, radio-based ranging measurements suffer from inadequate ranging accuracy due to environmental effects such as noise and multipath interference [15]. Some research has considered technologies other than radio-based measurement, such as radar scanners, video sensors, or even the Doppler effect, to measure relative distance accuracy.

The authors in [16] proposed the idea of using the DSRC communication between two vehicles travelling in opposite directions to measure the relative speed based on the Doppler shift. The vehicles receive driving information from neighbouring vehicles and use the Doppler shift to calculate the distance via DSRC communication. All this information is fed into an extended Kalman filter, which is widely used in vehicular positioning estimation, to update a vehicle's position. However, if the relative velocity of the two vehicles is small, the Doppler effect may not be obvious. Moreover, the analysis of Doppler shift offset requires extra hardware for frequency analysis in physical layers. In addition, the authors in [19] make use of vehicular video loggers and lane-level digital maps to help overcome GPS positioning errors. When vehicles receive a GPS position, they match their position to the digital map to identify a lane index, called the GPS lane. Owing to GPS error, their GPS lane may also contain an error. Therefore, they use the video image to determine the absolute lane index on the road, which they call the video lane. Each vehicle compares its GPS lane and video lane to validate the accuracy of the GPS position. Finally, each vehicle can update its own position using the validating values of its neighbours and the positions that the other vehicles predict. However, there are no detailed lane-level digital maps in most cities and the GPS error vector drifts in the vertical of the road direction. The authors in [20] use only the raw GPS of each vehicle to compute relative distances, assuming that the GPS error follows a Gaussian distribution. They want to maximize the Gaussian distribution possibility density function and consider that the difference between the tentative estimated vehicular locations and vehicular GPS positions is most likely the height possibility. They use the distributed location estimate algorithm to improve localization accuracy. However, if the number of vehicles is small (i.e., only two vehicles), the performance may decrease. On the other hand, every road in a real city environment has different multipath effects due to the different surroundings of buildings and obstacles. Thus, we cannot derive a universal mathematical model based on GPS errors in real city environments. Above all, these CP methods have some difficulty in real traffic environments.

3 Cooperative positioning via dead-reckoning

The detail of this paper's proposed positioning process is given in this section. We propose the system architecture called cooperative positioning via dead reckoning (CPDR) to improve GPS position error in VANET. Actually, the DR method can filter some unreasonable GPS positions by referencing travel history records. Taking into consideration some shortcomings of DR, we also propose the improving positioning in real city environments (IPC) algorithm to overcome it. The IPC algorithm can integrate the driving information from just two vehicles to correct the positioning error quickly and even decrease the GPS error range in real city environments. The remainder of this section is organized as follows. In Sect. 3.1, we introduce our system devices and give a system overview. Section 3.2 gives the basic concept of the IPC system. The algorithm designs are discussed in Sect. 3.3. In Sect. 3.4, we give a simple flow chart to implement our system. In Sect. 3.5, we provide a simple example to help everybody understand our proposed algorithm. Finally, in Sect. 3.6, we use the DR concept to correct positioning in advance.

3.1 System architecture

In this section, we introduce the implementation of the proposed system in a real environment. Figure 4 shows a block diagram of our system architecture working with a V2V CP system in the target vehicle. First, this vehicle must have its basic GPS position, for which the protocol of the GPS is the National Marine Electronics Association, and it waits for its neighbouring vehicles to broadcast information through WAVE/DSRC communication. The communication protocol of WAVE/DSRC is IEEE 802.119 (IEEE 1609) standard [21] in this paper. When the target vehicle has received the driving data of the neighbouring vehicles, it can measure their relative distances using a measurement sensor, such as radar or webcam sensors. Since the GPS system

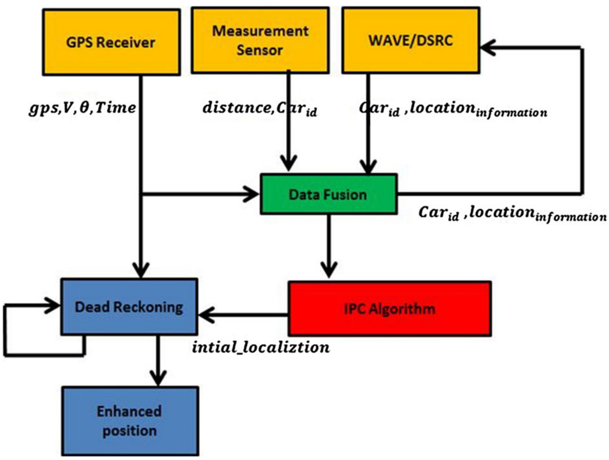


Fig. 4 System architecture

may be jumping and the error is about 5–30 m, our system architecture uses the DR algorithm to calibrate any jumping GPS signals via reference to the old travel records. In this way, the CP method can filter extra unreasonable positions. However, the DR algorithm has some shortcomings, such as error accumulation and the fact that the first reference point must be correct. So we propose the IPC algorithm to provide greater accuracy than the raw GPS to the DR algorithm to overcome these shortcomings. When the IPC algorithm cannot work normally due to environmental factors such as bad weather conditions, which will impact negatively on the webcam image recognition function, we also use the DR algorithm to fix it. Thus, these two mechanisms compensate each other. We consider that combining the IPC algorithm and the DR algorithm can make our system more comprehensive in a real driving environment. The three yellow blocks in the diagram of the system architecture are the external hardware used to collect outside information. The system tries to run the IPC algorithm via data fusion to correct the position well. The DR worked every time and referenced the IPC output.

In the following experiment, we take a webcam as our measurement sensor. Image recognition technology is the solution to measure the other vehicle information on the road. In our system architecture, the measurement sensor has the ability to measure relative distance and recognize the Car ID. We use image processing to find the licence plate location and create the number sample database to recognize the Car ID. And we use the car's scale in the image to compare the data record to predict the relative distance. To reduce the image complexity time, the image splits into different segments. As a simple example, if the original image pixel is 640×480, we can split it into three small segments, which are 300×480. Then, we can use the difference between two vehicle headings to choose the best corresponding segment via DSRC communication. Using DSRC technology, each vehicle can share its Car ID number to help the image processing time. In this way, image recognition technology does not waste time recognizing all car number numbers. It only needs to recognize some information and then compare the list of other vehicle broadcasting Car IDs. For example, if a vehicle knew the number plate of a nearby vehicle, such as 4567-AB, the image recognition would only need to recognize a few numbers, such as 4567, and then it could judge directly. So we can deduce the image data to enable the image processing time to be quicker. For the image processing time issue, the proposed method is using plate comparison, not conventional plate recognition. Hence, the image processing time of the proposed method is faster (below 500 ms) than conventional plate recognition. Moreover, for the privacy issue, the plate number does not need the whole number in the proposed method. For example, English symbols are not compulsory in the broadcast message because the proposed method can use Arabic numbers to identify the car. The proposed system is using the camera sensor to obtain the snapshot of the moving vehicle. Hence, the impact of the Manhattan and Random Waypoint model [22] will not affect the improving position accuracy.

3.2 Basic concept of IPC algorithm

A prerequisite to enable the IPC algorithm to operate is that there are at least two vehicles on the road and that they can communicate. Each vehicle V_i retrieves its

GPS information, including its latitude, longitude, speed and heading, and then begins to measure the relative distance between itself and its neighbours. Finally, by sharing their GPS and measurement information with their neighbours via WAVE/DSRC communication, each vehicle V_i will continue to select one candidate vehicle (such as front vehicle, right front vehicle or left front vehicle) at random to estimate the location using the IPC algorithm until all its neighbours are correct. The basic concept of the IPC algorithm is to use only GPS maximum error P_G and real distance d_v between two vehicles to limit the range of their possible locations. The correction steps are given in the following. First, as shown in Fig. 5a, assuming the maximum GPS error in this region is P_G, two vehicles V_1 and V_2 obtain their respective GPS locations, G_1 and G_2. We consider that the true location of V_i must be within range of the circle with its centre at its GPS location with a radius equal to P_G. For this reason, as shown in Fig. 5b, using the distance d_v decreases the true location range. Using the right movement of vector d_v, we determine that the maximum amount of movement is limited by V_1 and P_G. Thus, the true position of vehicle V_2 is restricted to within the red circle in Fig. 5b. Similarly, in Fig. 5c, we restrict the true position of V_1 by moving d_v left. Then, as shown in Fig. 5d, the modified positions of the two vehicles are found within the red circles. The steps of the IPC algorithm can be organized simply as follows:

Step 1: Receiving the GPS location of the vehicles and measuring their relative distance and angle

Step 2: Finding the new circle radius, which depends on the relative distance of the two vehicles

Step 3: Correcting the new position.

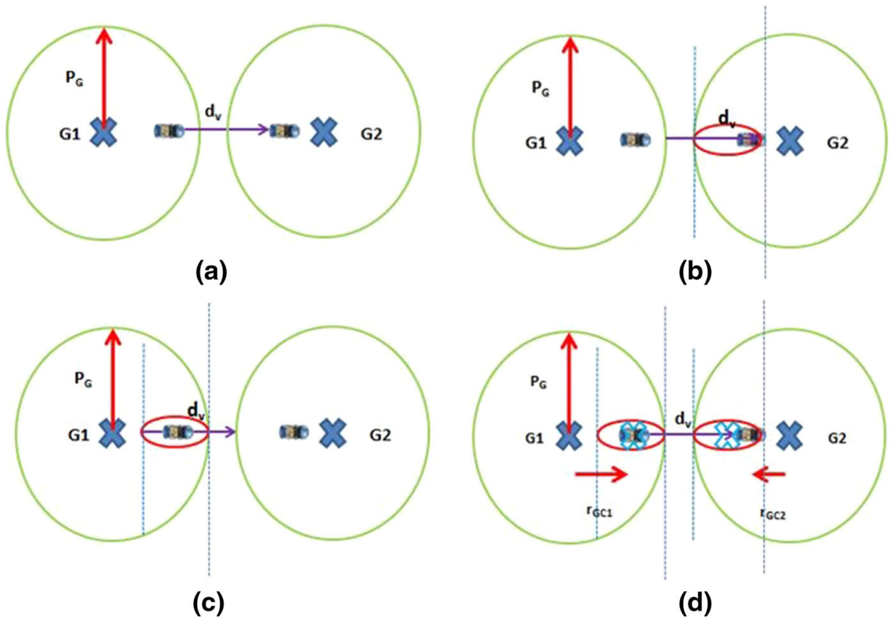


Fig. 5 IPC algorithm procedures

3.3 Estimate the final location

The true positions of the two vehicles are defined as: $C_1 : (C_x^{v1}, C_y^{v1})$ and $C_2 : (C_x^{v2}, C_y^{v2})$. Because of the GPS error effect, the locations of $V_1$and V_2drift to and $G_2 : (G_x^{v2}, G_y^{v2})$, as determined by the GPS receiver. Given that the relative distance is d_v and that the angle between the two vehicles is θ_v, the IPC algorithm is compartmentalized into a parallel correction and a vertical correction along the longitude (East) and latitude (North) axes, respectively. First, in the parallel correction step, G_1^x and G_2^x are the projections of G_1 and G_2 onto the East-axis and d_v^x is also the projection of d_v.

$$d_v^x = d_v \times \cos\theta_v \tag{3}$$

The GPS distance d_G between two GPS locations can be computed by comparing the difference between their latitude and longitude. The projection of d_G onto the East-axis is $\hat{d}^x$, which is directly calculated by the distance between G_1^x and G_2^x. And we use these data for the direction of the horizontal correction vector, as shown in Table 1. Actually, the IPC algorithm calculated the correction value, and it must also decide the correction direction. Table 1 describes in detail four cases about the different relations between the true positions and the GPS positions. The standard for classification of these four cases is according to two vehicular GPS locations and P_G parameters. Then, deciding the correction direction is achieved using the restriction condition. More detailed procedures are discussed as follows. And the P_G value is according to the vehicle positioning ability. For example, when the positioning technology used is GPS, the P_G value is assumed as 20–30 m. If the GPS positioning technology is converted to the wide area augmentation system or differential GPS, the P_G value could change the value to 7 or 10 m. So the IPC could also work well in the other positioning technology. Because of the GPS error effect, the true location must be within P_G. Therefore, we can consider:

$$C_x^{v1} \in [G_1^x - P_G, G_1^x + P_G] \tag{4}$$

$$C_x^{v2} \in [G_2^x - P_G, G_2^x + P_G] \tag{5}$$

However, the correction value is different for the two cases. For case 1, C_x^{v1} and C_x^{v2} are within range of G_1^x and G_2^x. For case 2, C_x^{v1} and C_x^{v2} are beyond the range of G_1^x and G_2^x. In case 1, the GPS error range can be reduced by our algorithm as follows:

$$C_x^{v1} \in [G_2^x - P_G - \hat{d}^x, G_1^x + P_G] \tag{6}$$

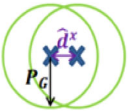
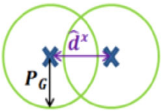
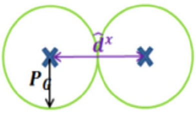
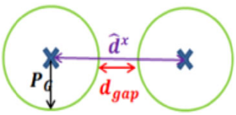
$$C_x^{v2} \in [G_1^x - P_G, G_2^x + P_G + \hat{d}^x] \tag{7}$$

In case 2, the GPS error range can be reduced by our algorithm as follows:

$$C_x^{v1} \in [G_1^x - P_G, G_2^x + P_G - \hat{d}^x] \tag{8}$$

$$C_x^{v2} \in [G_1^x - P_G + \hat{d}^x, G_2^x + P_G] \tag{9}$$

Table 1 Direction of correction vector

Possible cases	Restrictions condition	Correction direction
	$d_v^x > 3P_G - \hat{d}^x$	C_x^{v1} and C_x^{v2} are in range of G_1^x and G_2^x C_x^{v1} and C_x^{v2} are in out of G_1^x and G_2^x
	$d_v^x < P_G - \hat{d}^x$ $d_v^x > 3P_G - \hat{d}^x$	C_x^{v1} and C_x^{v2} are in range of G_1^x and G_2^x C_x^{v1} and C_x^{v2} are in out of G_1^x and G_2^x
	$d_v^x < P_G$ $d_v^x > 3P_G$	C_x^{v1} and C_x^{v2} are in range of G_1^x and G_2^x C_x^{v1} and C_x^{v2} are in out of G_1^x and G_2^x
	$d_{gap} < d_v^x < P_G + d_{gap}$ $d_v^x > 3P_G + d_{gap}$	C_x^{v1} and C_x^{v2} are in range of G_1^x and G_2^x C_x^{v1} and C_x^{v2} are in out of G_1^x and G_2^x

The modified location is the middle point of their new range. In addition, we can reduce P_G in the x-axis. P_G can be reduced to the new value $((X_1 - X_2) + 2P_G + d_R)/2$ in case 1 and it can be reduced to the new value$((X_2 - X_1) + 2P_G - d_R)/2$ in case 2. Similarly, we also performed the vertical correction for the y-axis and tried to deduce the vertical GPS error vector of two vehicles. Finally, we combined both the vertical correction and parallel correction results to reach the improved GPS position.

3.4 Flow chart

Figure 6 illustrates the flow chart of the proposed algorithm, which uses the restrictions condition shown in Table 1. First, every vehicle calculates its GPS information and prepares to broadcast for its neighbours. When the target vehicle receives its neighbour information via DSRC communication, it uses the webcam sensor to catch the view in front of itself. And it uses this image to recognize the other vehicle ID and relative distance between them. If it is successful in finding out this information, it will go to the second step. In the second step, when the target vehicle has both their GPS information and relative distance, the IPC algorithm is compartmentalized into vertical adjustment and horizontal adjustment according to the latitude and longitude. Then, we use Table 1 as our restrictions condition to predict their distribution to decide the correction direction. After the correction direction is decided, the IPC algorithm can use these data to calculate the correction vector for improving the positioning error. We use the new reduced circle radius r to compare the P_G to avoid the correction error. Finally, the IPC algorithm combines the vertical and horizontal adjustments as the new location. In fact, the IPC algorithm not only improves the GPS positioning

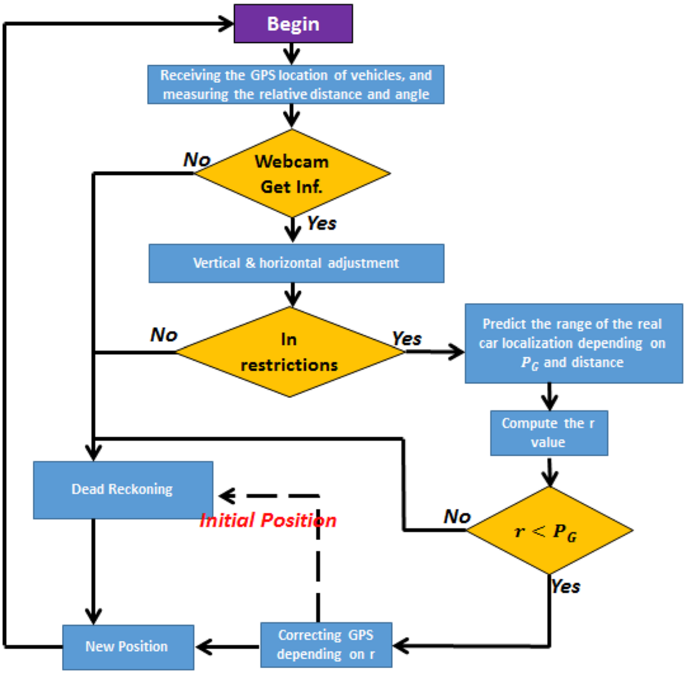


Fig. 6 Flow chart

but also provides the most accurate initial location for the DR algorithm. And the DR algorithm can prevent GPS jitter and can predict a reasonable location referenced from old travel records. So if something exceptional happens, the proposal is that the DR algorithm can be used to adjust this error.

3.5 An example

We illustrate the computing details with the following example. As shown in Fig. 7, the yellow vehicle is V_1 and the grey vehicle is V_2. They retrieve their 2-D GPS locations (having considered the ellipsoidal effects), which are GPS1 and GPS2. The relative distance and angle between V_1 and V_2 are 15 m and 65 °. We assume that the GPS maximum error P_G is 3 m.

First, we use parallel correction for this example. Figure 8 shows that the projection of GPS2 is GPS2^x. From Eq. 2, we assume that the GPS distance between GPS1 and GPS2^X is 19 m. The projection of relative distance can be computed as follows:

$$15 \times \sin 65^\circ = 14.49$$

Then, we compute the red circle radius:

$$[14.49 - (19 - 3\times 2)]/2 = 0.745$$

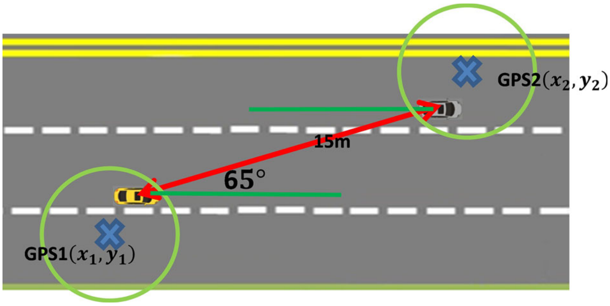


Fig. 7 Example (a)

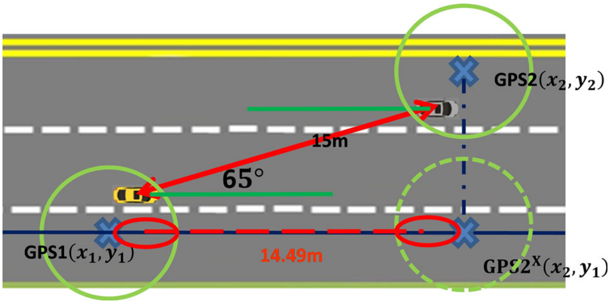


Fig. 8 Example (b)

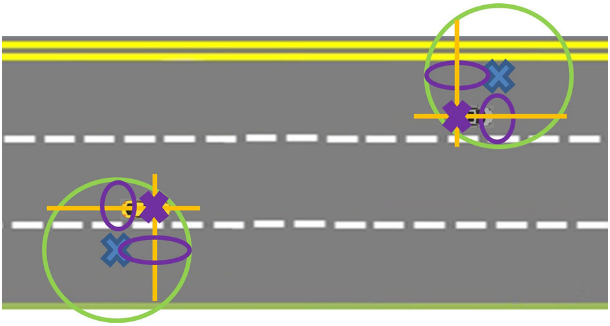


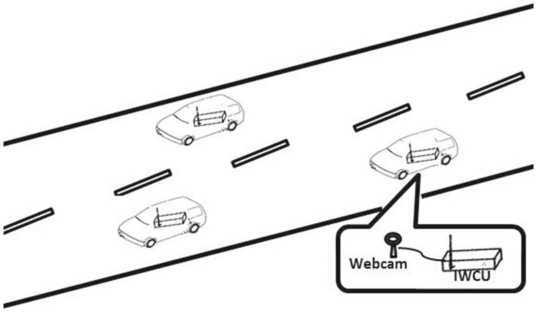
Fig. 9 Example (c)

The centre of the red circle is the new modified location. Therefore, the correction value is computed as:

$$3 - 0.745 = 2.25$$

Therefore, GPS1 will be moved to the right by 2.25 m and GPS1 will be moved to the left by 2.25 m. The vertical correction step is the same. The final location modified by the IPC algorithm is shown in Fig. 9. We can see the result of combining vertical and parallel correction in this example.

Fig. 10 Vehicle devices



3.6 IPC correction

This paper's proposed system must provide a mechanism to improve the positioning accuracy if the IPC algorithm does not work, such as without any vehicle in front. The introduction of the concept of the DR method and driver habit is our solution. In general, the driver does not drive at high speed when he wants to change vehicle direction. And the next position must be located in the range of the last time travel information. According to the old travel record, the proposed system could have the ability to help the driver improve his location on his own in advance.

4 Experimental results

4.1 Setup and environments

To achieve the basic operation of our proposed system architecture in terms of improving vehicular position in real environments, this paper takes the IWCU as the vehicle device. The IWCU can calculate its position continuously by coordinating at least four different GPS satellites and it has the capacity to communicate with other IWCU devices based on the WAVE/DSRC communication protocol. It also has the basic computing ability to function with our proposed algorithm. This paper uses a D-Link DCS-930L webcam as the measurement sensor, which can calculate the distance to the vehicle ahead and recognize the number plate via our imaging program. Figure 10 illustrates a scenario of our system implementation with VANET. Each vehicle is equipped with an IWCU and video webcam sensor and broadcasts its driving information, such as GPS, heading and timestamp, etc. The proposed system fuses these data and uses the webcam to determine the relative mobility of the neighbouring vehicles to facilitate its operation. In the experiments, two scenarios are considered to verify that our proposed algorithm has the capability to improve GPS accuracy in real environments. The IWCU obtains GPS information (such as latitude, longitude, heading and speed) every 100 ms. In Scenario I, two IWCU devices work within six different roads, which have many surrounding buildings and objects. For each road, we select six different distance pairs between the two IWCU devices: 5, 10, 15, 20, 25 and 30 m. For each pair, we receive 1200 items of GPS information. We use Scenario I to show how the IPC algorithm compares with the absolute true position. In Scenario

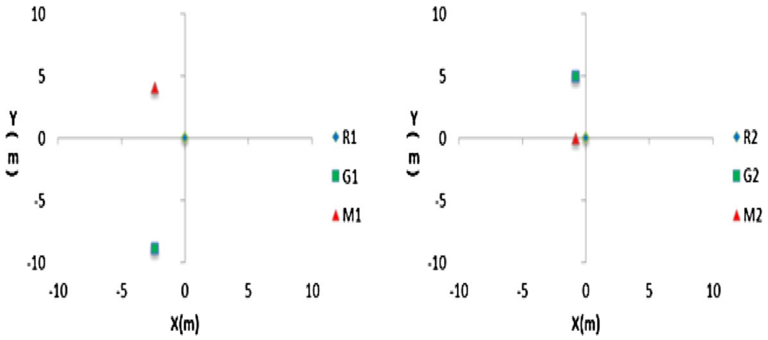


Fig. 11 Correction effect (pair 1)

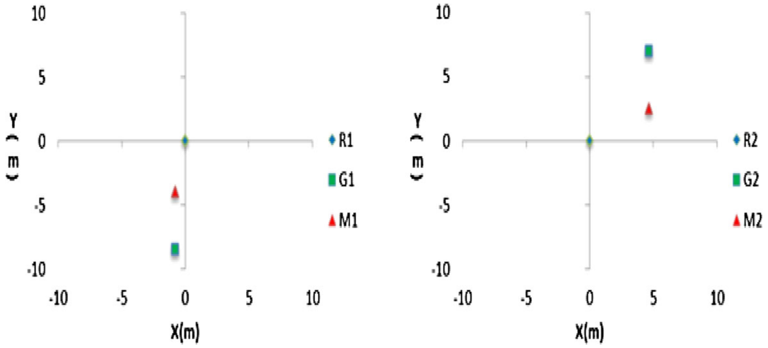


Fig. 12 Correction effect (pair 2)

II, we mount both the IWCU device and D-Link 930L in the two vehicles. The D-Link 930L is the measurement sensor used to recognize the relative distance in front of it. The IWCU also obtains GPS information and broadcasts every 100 ms. We drive the two vehicles in Hsinchu, Taiwan. This paper's proposed system can improve the position error, even for just two vehicles. This means that the proposed system will choose one of the neighbouring vehicles to improve the position error. When there are more vehicles in the neighbourhood, we can obtain more accurate position results. Hence, this paper uses two vehicles to show the experimental results.

4.2 Scenario I

In this scenario, we select six roads in Tainan, Taiwan: Linsen Rd. (22.988592, 120.225447), Zhuangjing Rd. (22.995741, 120.232959), Qianfeng Rd. (22.990704, 120.212775), Shengli Rd. (23.005775, 120.218856), Nanyuan St. (23.007987, 120.225387) and Kaiyuan Rd. (23.004861 120.217476). In these roads, we choose sections that have many buildings and objects to verify the IPC algorithm. In the experiments, we use the absolute GPS position in Google Maps as the true position. First, we display only two of these road data to show the error improvement. Figures 11 and 12 show the reduction of GPS error using the IPC algorithm for two distance pairs between the two IWCUs and they also show the results in the x-axis and

Table 2 IPC compared with GPS

	GPS error (m)		IPC error (m)
Figure 13	Vehicle 1	9.22	3.62
	Vehicle 2	4.94	1.74
Figure 14	Vehicle 1	8.53	3.07
	Vehicle 2	8.43	4.92

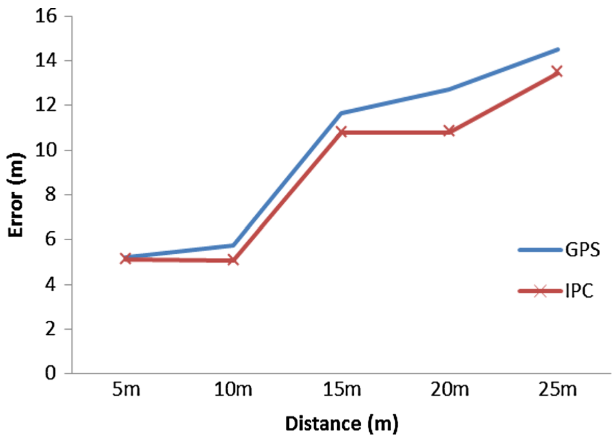


Fig. 13 Nanyuan St. position error

y-axis respectively. The true position of the vehicle is at the origin of the coordinates, where the x-axis and y-axis represent longitude and latitude. In Figs. 11 and 12, R_i is the true position of vehicle V_i, G_i represents the raw GPS position of vehicle V_i and M_i shows its position modified by our proposed algorithm. We show the results in Table 2.

We choose randomly the two roads in these data to discuss whether the IPC can reduce the GPS error. Figures 13 and 14 are positioning errors for two different roads. The x-axis is the distance between two vehicles, and the y-axis is the position error. Figure 15 illustrates the street view of Figs. 16 and 17. We saw that the street was full of high-rise buildings nearby, and the GPS signal was disturbed by the multipath and other environmental vectors. Figures 16 and 17 show the accuracy performance (A.P.) for two different roads:

$$A.P. = (E_{\text{GPS}} - E_{\text{IPC}})/(E_{\text{GPS}}), \tag{10}$$

where E_{GPS} is the GPS positioning error and E_{IPC} is the IPC positioning error. The reason why the two vehicles have low performance at a distance of 30 m in Fig. 16 and at a distance of 15 m in Fig. 17 is either that the GPS distance is more approximate to the real distance or that there are open areas in this section and thus this area has relatively low GPS error. Table 3 presents the mean of the positioning errors for the six different roads without any GIS information. The results show that the average performance of six roads is improved by 15 % ref-

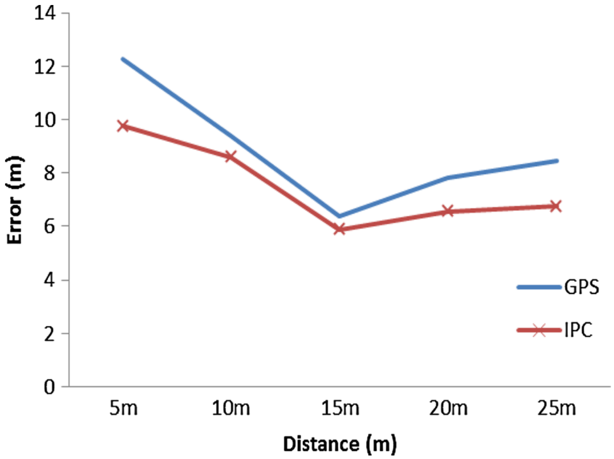


Fig. 14 Linsen Rd. position error

Fig. 15 Street views of Figs. 16 and 17

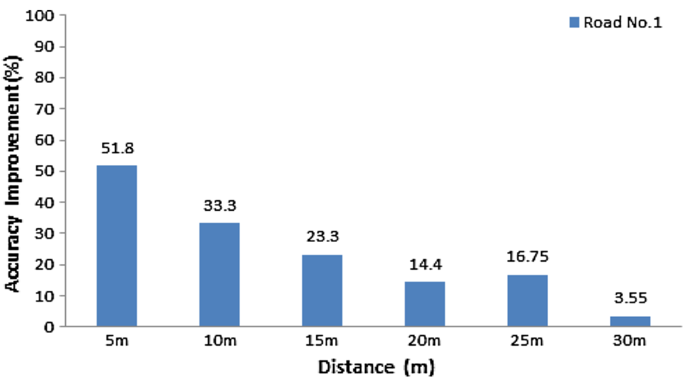


Fig. 16 Zhuangjing Rd. accuracy performance

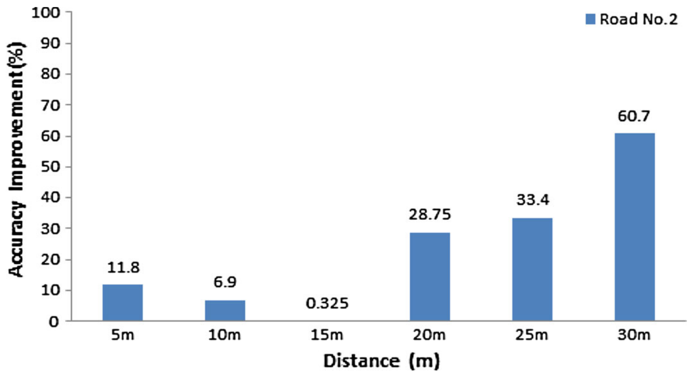


Fig. 17 Qianfeng Rd. accuracy performance

Table 3 IPC compared with GPS and DLEA

	5 m	10 m	15 m	20 m	25 m	30 m
GPS error (m)	10.87	12.46	9.60	9.64	8.36	9.25
IPC error (m)	08.83	11.18	8.84	7.70	6.90	7.67
DLEA error (m)	09.85	11.23	12.87	12.14	11.41	12.32

Average positioning error statistics of data on the six roads

erenced from the raw GPS. The results also show that the DLEA [20] algorithm has a poor performance when the two vehicles have a distance greater than 15 m. This is because the DLEA algorithm requires many vehicles to define its correct direction.

4.3 Scenario II

In Scenario II, we also tested our system with two prototype vehicles. We set up the IWCU and D-Link 930L as our devices so that the former could get a GPS signal and communicate based on WAVE/DSRC and the latter was our measurement sensor. The experimental area was in Hsinchu, Taiwan (24.777286, 121.042793). The vehicles' speeds are about 20–40 km/h, which come from the GPS receiver. We use the Google Map to locate the positions to compare with raw GPS and our proposed system. First, two vehicles run the IPC algorithm to get a more accurate initial position. Then, they use our proposed system as they travel. And we record one vehicle path and show the results. Figure 18a, b shows the results of our proposal compared with raw GPS. We can see that the proposed system path is smoother than the raw GPS path. Figure 19a, b also shows the results of our proposal compared with raw GPS in the other travel path. We can see the same effect in the proposed system.

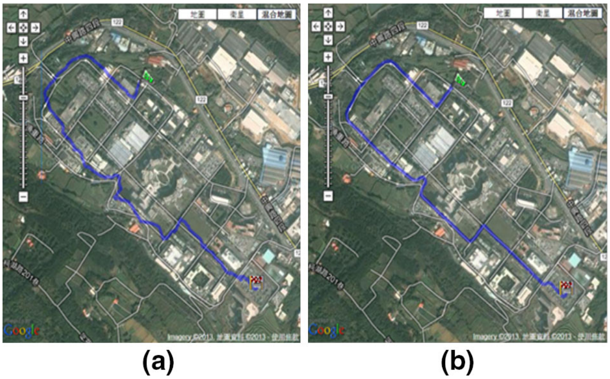


Fig. 18 **a** Raw GPS, **b** our proposal

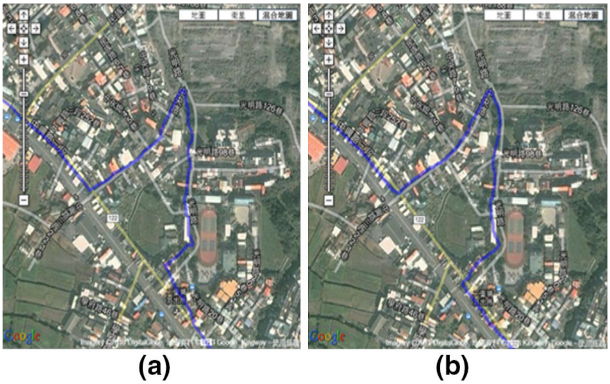


Fig. 19 **a** Raw GPS, **b** our proposal

5 Conclusions and future works

The conventional technology for improving GPS positioning has a low accuracy positioning ability in vehicular safety applications, such as vehicle-to-roadside and vehicle-to-vehicle methods. In this work, motivated by the urban requirements of vehicular positioning from a safety perspective, this paper proposes the vehicular improving positioning algorithm, IPC, to work in real city environments. This proposed IPC algorithm can reduce the localization error, even for just two vehicles in the VANET. In addition, the proposed IPC algorithm does not require any extra information in advance, such as a city digital map. In the experiment of Scenario I, we used the absolute relative distance to work by the IPC algorithm. The results show that the IPC algorithm can reduce GPS positioning errors and the average accuracy performance is improved by 15 % on the six different roads in the real city environment. Scenario II shows the driving path on the Google Map. We know that the IPC algorithm is useful for promoting vehicle positions in real environments. In future work, more accurate vehicle number plate recognition will be developed in the embedded system, or we can use other devices such as radar sensors to overcome the video shortcomings such as image quality, which is affected by real environment factors. Instead of the raw GPS technology, which has more positioning error, we can also introduce other positioning technology in our system, such as differential GPS or the wide area augmentation system. In this way, we can further improve the positioning ability and provide greater accuracy. After all, more accurate positioning ability in the application of vehicular safety can protect us by avoiding unexpected accidents.

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