Cooperative Vehicle Positioning via V2V Communications and Onboard Sensors

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Abstract— **This paper presents a vehicular positioning system in which multiple vehicles cooperatively calibrate their positions and recognize surrounding vehicles with their GPS receivers and ranging sensors. The proposed system operates in a distributed manner and works even if all vehicles nearby do not or cannot participate in the system. Each vehicle acquires various pieces of positioning information with different degrees of accuracies depending on the sources and recency of information, and compiles them based on likelihood derived from estimated accuracies to minimize estimation errors. A simulation based performance evaluation given in the paper shows that the proposed system improves the estimation accuracy by 85% on average with respect to the standalone GPS receiver, and recognizes about 70% surrounding vehicles with an error of 1m.**

ITS; Vehicle positioning; Situation awareness; Cooperative distributed algorithm; V2V communications;

I. INTRODUCTION

Improvement of driving safety is one of the most important aspects in the Intelligent Transportation System (ITS), as evidenced by activities of various industry and government agencies. They have studied a variety of safety applications and assumed that vehicles running those applications alarm the drivers for possible or potential dangers of hitting other vehicles or pedestrians by measuring their current positions, braking status, and/or their surrounding obstacles, and share such information by wireless communication devices. It is highly important to note that these safety applications rely heavily on vehicle positions. In [1], Vehicle Safety Communications Consortium (VSCC) of Vehicle Infrastructure Integration (VII) suggests that vehicle safety applications need to obtain realtime positions with errors of a few meters to avoid critical accidents. Also, it mentions that each vehicle needs to transmit the information including its position every 100 ms.

One critical issue for the proper functioning of these applications is the accuracy of position information brought by GPS commonly-used as positioning technology. For instance, positioning errors introduced by GPS receivers can be several times larger than that in urban areas with many obstacles to GPS receivers [2]. Some methods assume additional hardware such as Differential GPS, gyroscopes and acceleration sensors, and fuse the information to improve the position accuracy [3-5]. Some other methods estimate relative positions of vehicles originating from position of a vehicle using information shared among vehicles via V2V communication [6-8]. In addition, some methods have been proposed to estimate driving lanes of vehicles by using onboard sensors and V2V communication [9-10]. These existing methods can achieve sufficient accuracy to some ITS applications such as car navigation systems. However, it is difficult to satisfy more severe requirements in vehicle safety applications. Moreover, we should also consider not all vehicles have DSRC/WAVE communication devices and GPS receivers. Recently, some automotive companies commercialize safety systems such as Volvo's Collision Warning with Auto Brake and Toyota's Pre-Collision System based on situation awareness. They utilize distances from surrounding obstacles obtained by ranging sensors such as millimeter wave radar and laser sensors. Some researches have also been proposed to improve situation awareness of vehicles using ranging sensors and V2V communications [11]. However, they do not consider how to share the information among vehicles to improve the recognition and position accuracy. In sensor networks, there are some methods to track mobile objects using static sensors [12], but the assumption of these methods is very different from ours.

This paper proposes a cooperative distributed system which provides ITS safety applications with positions of surrounding vehicles. We assume that some vehicles hold GPS receivers and ranging sensors such as millimeter wave radar sensors and DSRC/WAVE communication devices. Each vehicle shares measurements from GPS and ranging sensors with surrounding vehicles, and updates positions using the measurements by different vehicles at different times. In order to mitigate the impact of the measurement with large error caused by decay with time, a vehicle estimates the "accuracy" for each measurement, and estimates the positions by reference to it. Also, a vehicle estimates the "accuracy" of estimated positions based on the Central Limit Theorem to share the most accurate positions with surrounding vehicles. From performance evaluation, we confirm that our system could reduce position error of vehicles by 85% on average from that of the standalone GPS receiver, and recognize about 70% of all surrounding vehicles with an error of 1m.

II. Proposed System Overview

A. Preliminaries

We assume that some vehicles are equipped with DSRC/WAVE communication devices. They are called *equipped vehicles*, and vehicles without those devices are called *non-equipped vehicles*. Each equipped vehicle has a unique 48-bit MAC address according to the IEEE 802.11p standard. We call the vehicles which exist in the wireless range of vehicle *i nearby vehicles* of vehicle *i*. Since many safety applications require every vehicle to advertise its current position every 100ms, our proposed system assumes 100ms as a time unit (i.e. time slot interval), and equipped vehicles update positions of nearby vehicles every time slot.

The followings are assumed for each equipped vehicle. Firstly, it broadcasts a Basic Safety Message every T_s time slots. We follow the SAE J2735 standard to define the message format. Secondly, it measures its own position by GPS every T_g time slots. The measured position is called *GPS position*. Thirdly, it measures its own velocity by an accelerometer every T_z time slots. Fourthly, it has a ranging sensor (such as a millimeter wave radar sensor), and measures relative angles and distances to other vehicles which exist in the immediate sight every T_z time slots. Thus the relative positions of those vehicles from the equipped vehicle can be calculated. Additionally, each equipped vehicle can estimate their velocities using the sequences of two or more relative positions. The vehicles detected by the ranging sensor are called *detected vehicles*. We assume that the maximum sensing range is about 100m considering modern products.

We conducted experiments to evaluate the spatial locality of GPS error using multiple GPS receivers and determine error distribution of GPS. From the results, errors from multiple GPS receivers which were close were uncorrelated. Thus, we assume that the errors of GPS positions follow normal distributions with a mean zero and variance σ_g^2. Also, we assume that the errors of relative positions and velocities follow normal distributions with a mean zero and with variances σ_r^2 and σ_v^2, respectively. Note that σ_g^2 is usually much larger than σ_r^2 and σ_v^2. This is because GPS positioning often incurs large errors by multipath and signal blocks, while ranging sensors and accelerometers are hardly susceptible to such factors. We consider that the default values of T_g and T_z are 10 and 1 time slots, respectively. They are based on the features of modern products, but our method is independent of those specific values.

B. Cooperative positioning: principle and examples

Each equipped vehicle holds positions of nearby vehicles, and updates them every time slot. In order to update the positions, each vehicle detects its surrounding vehicles as well as its own GPS position and velocity. This information is transmitted via a Basic Safety Message to its nearby vehicles. On receiving each other's GPS positions and relative positions, each equipped vehicle estimates the current positions of its own nearby vehicles.

It is worth noting that the goal of our method is to allow equipped vehicles (i) to recognize the presence of non-equipped vehicles, and (ii) to estimate the positions of equipped vehicles more accurately than GPS and those of non-equipped vehicles. To achieve the second goal, each equipped vehicle uses multilateral range measurements from different vehicles (i.e. relative position information brought by ranging sensors). This enables to use GPS positions of nearby vehicles as "anchors", and multilateration mitigates the GPS errors that those "anchors" originally contain. In addition, such multilateration can be explored to detect non-equipped vehicles to accomplish the first goal. However, due to asynchronous and distributed execution of position estimation, the "vehicle map" recognized by each equipped vehicle may be different from others.

Fig. 1 exemplifies our system's behavior where equipped vehicle *A* updates the positions of its nearby vehicles. Vehicle *A* can measure its GPS position, and the relative positions of equipped vehicles *B*, *D* and non-equipped vehicle *E* (similar measurements are done by equipped vehicles *B* and *D*). Thus, vehicle *A* can explore the multilateral range measurements to estimate the positions of vehicles *A*, *B*, *D* and *E*.

(i) *A*'s GPS position, and *A*'s relative positions from both *B* and *D*'s GPS positions are used to estimate the position of *A*.

(ii) *B*'s GPS position, and *B*'s relative positions from both *A* and *D*'s GPS positions are used to estimate the position of *B*.

(iii) *D*'s GPS position, and *D*'s relative positions from both *A* and *B*'s GPS positions are used to estimate the position of *D*.

(iv) *E*'s relative positions from *A*, *B* and *D*'s GPS positions are used to estimate the position of *E*.

We note that vehicle *C* is first recognized by vehicle *B* (by ranging sensor) and afterward by vehicles *A* and *D* via a message from vehicle *B*. Also, we mention measurement-target association problem later.

As explained, equipped vehicles can provide relative positions originating from their GPS positions. Composition of a relative position and its origin generates a position measurement, which we call *position candidate* hereafter. We employ the following approach toward better accuracy of V2V positioning and reasonable design of protocol and algorithm.

- Based on the principle of multilateration, more position candidates can achieve higher position accuracy. Therefore, position candidates originating from

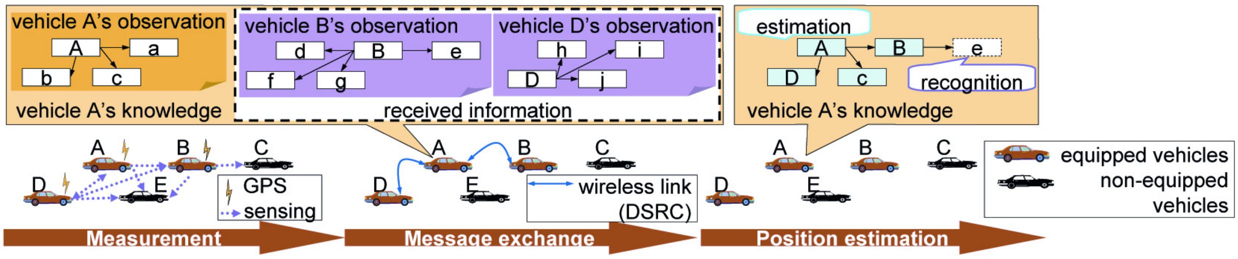


Figure 1. System overview.

time-different GPS positions of a single vehicle may be used. We can easily imagine that position candidates generated from those past measurements may have larger errors than recent ones due to information decay. Hence, each position candidate is weighted by the freshness of its information source in estimating position by multilateration.

- Vehicles also share range measurements with each other. However, since ranging sensors only detect "objects" and tell their relative positions, it is necessary to identify whether two relative positions indicate the same vehicle or not. For this identification, each vehicle compares the relative positions that compose the position candidates to see the degree of conformance.

- Since a vehicle's position may be calculated by different vehicles independently, these vehicles may have different estimation results with different accuracy. In order to choose the "most accurate" one from those sent by different vehicles, vehicles expect the "likelihood" of each estimated position by the Central Limit Theorem.

III. Design Details

The positioning consists of the following three steps: (1) obtaining observations (GPS and range measurement), (2) updating estimation from observations and (3) exchanging messages. These steps are explained in the followings.

A. *Obtaining observation (GPS and range measurement)*

As we mentioned in Section II-A, each equipped vehicle i measures its own GPS position and velocity, and the relative positions and velocities of its nearby vehicles periodically. For position estimation, each vehicle sends these measurements via Basic Safety Messages every T_s time slots, and holds the GPS positions and velocities of other equipped vehicles and the relative positions and velocities of their nearby vehicles. We let $O_i(a)$ denote the information about vehicle "a", which is a detected vehicle by equipped vehicle i. This information is called *observation* of the vehicle with ID "a" measured (i.e. observed) by vehicle i, and consists of the tuple ($\mathbf{g}$, $\mathbf{r}$, $\mathbf{v}$) where $\mathbf{g}$ is a GPS position of vehicle "a", $\mathbf{r}$ is a relative position of vehicle "a" measured by vehicle i (it is a zero vector in case of $a = i$) and $\mathbf{v}$ is a velocity of vehicle "a" measured by vehicle i. Since $O_i(a)$ is generated every time slot, we distinguish $O_i(a)$ by their generated time slots.

B. *Updating estimation from observations*

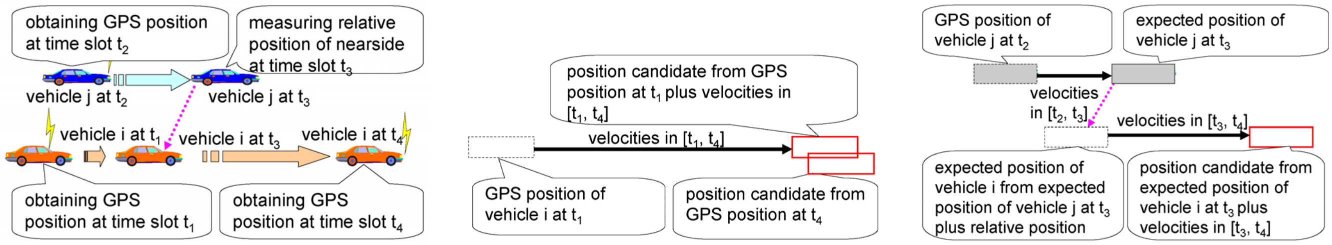
Each equipped vehicle i holds "estimation" of nearby vehicles that includes estimated positions and the confidence on estimation accuracy. This information is simply called *estimation*. Estimation of vehicle "a" is denoted by $E(a)$, where "a" is a vehicle ID. We note that estimation is defined for every vehicle and vehicle i assigns a temporal ID for a non-equipped vehicle. $E(a)$ consists of the tuple ($\mathbf{p}$, l, $\mathbf{v}$, $\mathbf{r}$) where $\mathbf{p}$ is an estimated position, l is "likelihood" (i.e. confidence of estimation) of $\mathbf{p}$, $\mathbf{v}$ is a velocity vector, and $\mathbf{r}$ is a relative position of vehicle a originating from vehicle i. Likelihood l is defined as inverse of estimated standard deviation of $\mathbf{p}$. We note that $\mathbf{r}$ is included for vehicle identification purpose explained later.

Each estimation $E(a)$ is updated every time slot using observations that observe vehicle "a". In order to solve such association problem, we need to identify such observations. These are called *corresponding observations*. Vehicle i finds corresponding observations generated by another vehicle j for each estimation $E(a)$ by topological comparison of detected vehicles in receiving Basic Safety Messages as will be mentioned in Section III-C. A velocity $\mathbf{v}$ and a relative position $\mathbf{r}$ of the current estimation $E(a)$ are updated by assigning those of corresponding observations $O_j(b)$. Also, if vehicle i does not measure a GPS position in the current time slot, estimated position $\mathbf{p}$ is updated from the last estimated position $\mathbf{p'}$ by linear prediction. In this case, likelihood l is updated from the last likelihood l' by (1), where a smaller variance of velocity or a larger likelihood yields a larger likelihood.

$$l = \frac{1}{\sqrt{1/l'^2 + \sigma_v^2}} \tag{1}$$

If vehicle i measures a GPS position, $\mathbf{p}$ is updated by the weighted average of position candidates generated from GPS positions and relative positions of corresponding observations $E(a)$. In this case, vehicle i generates position candidates $\mathbf{q_1}$, …, $\mathbf{q_n}$ from GPS positions and relative positions included in the corresponding observations generated in the current time slot. Then it calculates likelihood l_x for each position candidate $\mathbf{q_x}$. In case of a GPS position of vehicle a which is measured k time slots before, vehicle i generates a position candidate using k velocities of vehicle a measured every time slot in $[t - k, t]$ where t is the current time slot. In this case, it calculates likelihood of the position candidate by (2) to consider the accumulated errors of velocities in k time slots plus GPS error.

$$l_x = \frac{1}{\sqrt{\sigma_g^2 + k\sigma_v^2}} \tag{2}$$



(a) Situation (b) Generation of position candidates from GPS positions (c) Generation of a position candidate from a relative position

Figure 2. Generation of position candidates.

We show an example to generate position candidates in Fig. 2. For the situation illustrated in Fig. 2(a), Fig. 2(b) shows two position candidates of vehicle i at time slot t_4. One is generated from the direct measurement of GPS position at t_4, but the other is calculated by the GPS position of vehicle i at t_1 plus linear prediction of movement between t_1 and t_4. Fig. 2(c) shows another case. This position candidate is generated in a more complex way where the GPS position of vehicle j at t_2 is the origin, and the expected position of vehicle j at t_3 is calculated by linear movement prediction, and using the range measurement from vehicle j to vehicle i at t_3, the expected position of vehicle i at t_3 is derived. Finally, we again conduct linear movement prediction to obtain the candidate at t_4.

We note that the likelihood of a position candidate originating from a GPS position with a relative position and k-slot movement prediction is calculated as follows, where those errors are accumulated.

$$l_x = \frac{1}{\sqrt{\sigma_g^2 + \sigma_r^2 + k\sigma_v^2}} \tag{3}$$

Then, vehicle i calculates new position $\mathbf{p}$ as the weighted average of position candidates $\mathbf{q}_x$ giving likelihood of position candidates l_x as the weights ($x = 1,\ldots, n$) as defined by (4). Also, it calculates likelihood of $\mathbf{p}$ defined as follows based on the Central Limit Theorem as defined by (5).

$$\mathbf{p} = \frac{\sum_{x=1}^{n} \mathbf{q}_x l_x}{\sum_{x=1}^{n} l_x} \tag{4}$$

$$l = \frac{1}{\sqrt{n/(\sum_{x=1}^{n} l_x)^2}} \tag{5}$$

C. Message exchange

Every T_s time slots, equipped vehicle i sends a Basic Safety Message. Equipped vehicle i generates message contents using the estimation of vehicle i itself and some detected vehicles. For each detected vehicle (including vehicle i itself) recognized by vehicle i as vehicle "a", $S(a)$ denotes the information that vehicle i sends in the message. $S(a)$ consists of the tuple $(E(a),O_i(b))$ where $O_i(b)$ denotes the corresponding observation. When vehicle i receives a Basic Safety Message from vehicle j, it creates observation $O_j(d)$ from message structure $S(c)$ = $(E(c),O_j(d))$. Then, vehicle i compares relative positions of all received observations with those in estimation it holds, and determines corresponding estimation for each received observation $O_j(d)$. In the case of Fig.1, vehicle A determines that $O_B(B)$, $O_B(d)$, $O_B(f)$ and $O_B(g)$ are related with $E(a)$, $E(A)$, $E(b)$ and $E(c)$, respectively, when it receives a Basic Safety Message from vehicle B. If vehicle i cannot find corresponding estimation, it creates new estimation $E(e)$ based on $E(c)$ in $S(c)$. Also, vehicle i updates estimation $E(a)$ which corresponds to $O_j(d)$ using $E(c)$ when likelihood of estimation $E(c)$ is larger than that of estimation $E(a)$.

IV. Performance Evaluation

A. Simulation settings

As a simulation map, we used an intersection with lane width 5m and length 1km shown in Fig. 3. We generated vehicle mobility using the traffic simulator VISSIM [13]. The average speeds of vehicles was 60km/h. Vehicle density of major road and minor road were 1,800 vehicles and 1,200 vehicles per hour, respectively. The time slot was 100ms. We set the standard deviation of GPS position errors σ_g to 5m, the standard deviation of relative position errors σ_r to 0.25m, and the standard deviation of velocity errors σ_v to 0.08m/ms. Also, we set the maximum sensing range to 100m, the interval of GPS measurement T_g to 10 time slots, and the interval of sensor measurement T_z to 1 time slot. Moreover, the default value of the sending interval of Basic Safety Messages T_s is 1 time slot. We used the two-ray ground reflection model as a radio propagation model, and set the transmission power to 23 dBm. Also, the communication protocol is DSRC/WAVE with data transmission rate 6Mbps. In the above settings, we conducted simulations using the network simulator Scenargie [14].

B. Simulation results

First, we evaluated how much equipped vehicles can improve the accuracy of their GPS positions. In general, applications such as navigation systems use GPS positions corrected by estimation from past measurement and map information. We compared the proposed method with "GPS with self calibration", which estimates positions by multilateration of accumulated GPS positions. The ratio of equipped vehicles was 100%.We show the average position error in estimation $E(i)$ for all equipped vehicles i in the whole

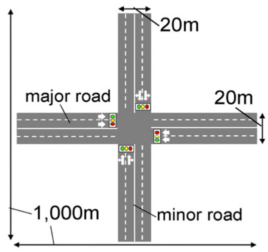


Figure 3. Simulation map.

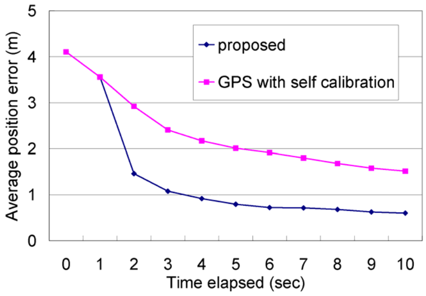


Figure 4. Average position errors of equipped vehicles.

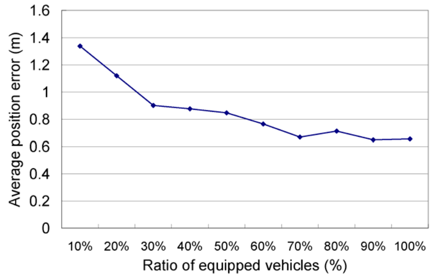
target area. The position error is defined as Euclidean distance to the true position. The result shows that the average error of positions at 10sec after the system started was 0.6m. Hence, our proposed system can achieve sufficient accuracy in short time for vehicle safety applications, which need realtime positions with errors of a few meters. The position error was improved about 85% to native GPS positions, and about 60% to GPS with self calibration. The results mean that our system improves the accuracy of positions by using the information generated by different vehicles at different time.

Second, we evaluated the impact of the ratio of equipped vehicles on performance. Fig. 5(a) shows the average position errors of positions in estimation *E(i)* of each equipped vehicle *i* after 10sec when the ratio of equipped vehicles varies from 10% to 100%. From the result, the lower ratio makes the position accuracy because the position candidates decrease. However, in case of the low ratio of equipped vehicles, the average position error was less than a half of error of GPS positions.

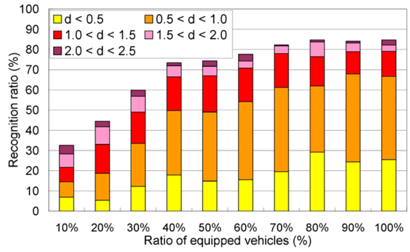
Third, we evaluated the impact of the ratio of equipped vehicles on recognition ratio. The recognition ratio *R(d)* is defined as the average ratio of the vehicles whose positions are estimated uniquely within *d*m error to all vehicles in the whole target area for all equipped vehicles. Fig. 5(b) shows the average recognition ratio of all equipped vehicles after 10sec when the ratio of equipped vehicles varies from 10% to 100%. From the result, the higher ratio makes the recognition ratio better. Especially, in the case of 100%, the proposed system could recognize about 70% of all nearby vehicles with an error of 1m. Though all vehicles equipped with DSRC/WAVE communication devices and GPS receivers, *R(2.5)* could not reach 100%. This is because some vehicles in the edge of target area started estimation just before 10sec and could not be estimated accurately enough. On the other hand, even in the case of 40%, about 50% of all nearby vehicles could be estimated with an error of 1m.

V. CONCLUSION

This paper has proposed a cooperative vehicle positioning system which provides accurate positions for ITS applications in real-time under the situation where some vehicles have GPS receivers and ranging sensors such as millimeter wave radar sensors and DSRC/WAVE communication devices. From performance evaluation, we confirmed that our system could reduce position errors of vehicles for average 85% and recognize 70% of all nearby vehicles with an error of less 1m. As our future work, we are planning to evaluate the performance of our system by using realistic scenarios.



(a) Average position errors.



(b) Recognition ratio

Figure 5. Impact of the ratio of equipped vehicles.

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