A collaborative navigation approach in intelligent vehicles

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ABSTRACT

Proliferation of real time inter-vehicular communications provides new sources for exploitable positioning data. Vehicles can, under numerous situations, have GPS satellite shortages but there will always be vehicles in their vicinity, with a different set of satellites, to provide them with useful navigation information. In this paper, we propose a cooperative positioning technique making use of reliable positions of some vehicles to enhance positioning estimates of some others. We will exploit the useful inter-vehicle data flow to extract good position measurements from vehicles with good GPS satellite LOS (line of sight), in order to enhance low positioning accuracy of other vehicles, in the neighborhood. The integration of such information will be done using geometric data fusion approach.

INTRODUCTION

The envisioned intelligent vehicle systems (IVS) will be enabled to communicate, their navigation information, among other data, through Inter-vehicle communications (IVC). Such features will provide a doorway to much inter-vehicle collaboration. Indeed, IVS will be evolving in mobile Ad hoc networks called (MANET) that give access to valuable real time data, especially high precision positioning information.

However, in terms of global navigation systems (GNS), individual vehicles in a given MANET would not have access to the same constellation of satellites. And certainly vehicles with good lines of sight (LOS) have more precise positioning estimates than vehicles with a poor LOS. Moreover, some vehicles may possess high precision DGPS or beacon-based positioning information to share in the network.

In this paper we will investigate a collaborative positioning technique (CPT) that uses some of the above IVC features, along with additional range measurement capabilities, to ameliorate positioning estimates of neighboring vehicles in a MANET. Two vehicles at different locations can have different sets of visible satellites, and by collaboration the satellite information can be shared between the vehicles [1]. Many research activities are being conducted in IVS collaborations. For a more basic, yet good introduction to IVS research and development resources [4] is a good reference. For a little more technical, but quite outdated now, [5] would be worth reading. Research in the domain of Collaborative navigation has many forms, in [6] and [7] for instance Collaborative Driving Systems (CDS) are studied with applications in what is called car platoons. There are also ongoing projects for Collaborative Automated highways (CVHS) such as PATH in California or DRIVE in Europe. However these kinds of collaborations necessitate either costly vehicle-to-vehicle relative dependence or vehicle-to-infrastructure dependence, whereas our approach leads to a more inexpensive independent navigation.

We treat the case, although limited, of three vehicles yet important towards a more general case Fig. 1.

CONTEXT:

Designing a system solution for accurate estimation of relative positions of neighboring vehicles based on real-time exchange of individual GPS coordinates using vehicle-to-vehicle radio communications is a challenging task.[2]. In fact we will narrow down such difficulties by reducing the complexities according to certain paradigms that we will specify in the next section.
WORK CONDITIONS

Prior to performing any detailed analysis of our CPT we ought to define the scope of our work with conditions under which our technique could be applied. We thus suppose the following conditions to be valid:

- All vehicles in the MANET are equipped with necessary navigation items (GPS, DR, IVC sensors...etc.)
- All vehicles have range measurement radars, to provide precise inter-vehicle distance. Millimeter wave radars MMW for automotive, studied in [3], would be appropriate solution to our application for they have a high Doppler sensitivity and a 200 meters range with a good precision which is very suitable for our case.
- No vehicle dynamics were considered in the application, we instead used a simple motion model.
- Error covariance matrix on position, heading, and inter-vehicle distance contains the global errors of vehicle systems.
- No special vehicle frame is considered
- Coordinate reference system is geodetic altitude, latitude and azimuth.
- No altitude difference is considered, this corresponds to the case where all three vehicles are located on a relatively flat plane with a constant altitude.
- Inter-vehicle communications are real time and safe.

GEOMETRIC DATA FUSION

GEOMETRIC UNCERTAINTY MINIMIZATION

This method is based on the geometric analysis of the sensing uncertainty and is motivated by the geometric idea that the volume of the uncertainty ellipsoid should be minimized. The resultant fusing equation coincides with those obtained by Bayesian inference, by Kalman filter theory, and by weighted least-squares estimation [8].

The uncertainty ellipsoid encloses a region in space where the true value most likely exists. The center of the ellipsoid is the mean of the measurement and the ellipsoid boundary represents a distance of one standard deviation from the mean [9], Fig. 2.

Geometric data fusion has been used in many research applications; [9] and [10] are few examples; and had proven to be a powerful uncertainty management data fusion technique.

THEORY OVERVIEW

Here is a brief summary of geometric data fusion as developed by Nakamura [8].

We define, \( \theta^i \) as the output of sensor \( i \), and \( x^i \in \mathbb{R}^n, i = 1, ..., p \) as sensory information computed from \( \theta^i \) as follows:

\[
x^i = f^i(\theta^i)
\]

The disturbance or uncertainty included in the sensory data is assumed additive:

\[
\theta^i = \hat{\theta}^i + \delta \theta^i
\]

Where \( \hat{\theta}^i \in \mathbb{R}^m (i = 1, ..., p) \) is the undistributed data or the true values, and \( \delta \theta^i \in \mathbb{R}^m (i = 1, ..., p) \) is the disturbance. Now, assume a Gaussian distribution for \( \delta \theta^i \) and denote its covariance matrix by \( Q^i \).

If we assume \( \delta \theta^i \) is small enough, we can write the following:

\[
x^i = f^i(\hat{\theta}^i + \delta \theta^i) = f(\hat{\theta}^i) + J^i(\theta^i) \delta \theta^i
\]

Where:

\[
J^i(\theta^i) = \frac{\partial f^i}{\partial \theta^i} \in \mathbb{R}^{n \times m}, \text{ is the Jacobian matrix of } f^i \text{ with respect to } \theta^i.
\]

The mean and covariance matrix of \( x^i \) are as follows:
\[ E[x'] \cong \bar{x}' = f' (\theta') \]
\[ V[x'] = J'Q'J'^T \]

To get a good consensus \( x \) out of the multiple sensory information \( x' \) the following linear combination is used:

\[ x = \sum_{i=1}^{p} W^i x^i \]

Where the weighting matrix \( W^i \) is found to be:

\[ W^i = \left( \sum_{i=1}^{p} (J'Q'J^T)^{-1} \right)^{-1} \left( J'Q'J^T \right)^{-1} \]

And the covariance matrix of \( x \) is computed as follows:

\[ V[x] = \left\{ \sum_{i=1}^{p} (J'Q'J^T)^{-1} \right\}^{-1} \]

Where \( \theta^i, i = 1, ..., 3 \) is the sensory information, containing 2-D position (latitude, longitude), distance to the master vehicle and the heading angle, of the \( i \)th vehicle.

The following simple scheme is utilized for position uncertainty minimization:

\[ u^i = [u^i, v^i]^T = \begin{bmatrix} u^i &= x^i + d^i \cos(\alpha) \\ v^i &= y^i + d^i \sin(\alpha) \end{bmatrix} \]

The ‘+’ is a generic sign meaning both ‘+’ and ‘-’ depending on the position of the vehicle with respect to the master vehicle.

The scheme above gives the following generic Jacobian matrix:

\[ J^i = \begin{bmatrix} 1 & 0 & \cos(\alpha^i) & -d \sin(\alpha^i) \\ 0 & 1 & \sin(\alpha^i) & d \cos(\alpha^i) \end{bmatrix} \]

Here again certain signs differ depending on the position of the vehicle with respect to the master vehicle.

The covariance matrix used is the following:

\[ Q^i = \begin{bmatrix} \sigma_{x^i}^2 & 0 & 0 & 0 \\ 0 & \sigma_{y^i}^2 & 0 & 0 \\ 0 & 0 & \sigma_{d^i}^2 & 0 \\ 0 & 0 & 0 & \sigma_{\alpha^i}^2 \end{bmatrix} \]

Where diagonal elements represent variances of the four elements of \( \theta^i \).

**Figure 2**: Uncertainty ellipses reduction

**OUR ALGORITHM**

For convenience we treat the case of three vehicles on the same road with the same heading angle Fig. 1. Vehicle 2 is the master vehicle (the one concerned with position uncertainty management); the other two provide reliable position estimates. Vehicle data fusion device receives data in the following format:

\[ \theta^i = [x^i, y^i, d^i, \alpha^i] \]

**SIMULATION**

Simulation was performed on a Matlab-Simulink based application of vehicle and sensor models.

**VEHICLE MODEL**

The vehicle model is a point-like element model with a motion in geodetic reference system on a real road data. Acceleration is generated by the following Gauss-Markov transfer function

\[ \frac{2 \sigma^2 \beta}{S + \beta} \] that takes a white noise input. The velocity and distance are then just simple and double integration of the transfer function output.
During our simulations we tested the case where no position estimate of the master vehicle (vehicle 2) is given, and we could not determine a reliable position estimate. By taking it into account the results showed to be good.

SENSOR MODELS

A GPS, an INS, an inclinometer and a compass used in the simulation are all simulated sensors. They are all based on well known mathematical models. Different noise sources were emulated for every sensor; here are few of them: low time-varying bias, scale factor error, random noise source, GPS clock bias, etc.

PRELIMINARY SENSOR FUSION

To determine its position every vehicle performs, first, an independent data fusion of its different sensors outputs (GPS, INS, etc.). In our model this fusion was done locally by a centralized Kalman filter.

EXPERIMENTAL RESULTS

![Fig. 3 Positions obtained in red](image)

![Fig. 4 Position variance reduction](image)

DISCUSSION

Fig. 3 shows how collaboration contributed to decrease uncertainty on green positions. The red line represents positions obtained by the described collaboration technique using geometric uncertainty reduction algorithm. The green line represents initial master vehicle position estimates (computed by preliminary sensor fusion in low LOS conditions). The blue line is the reference data collected from a real vehicle traveling on a real road.

Tests were performed with different configurations, by changing inter-vehicle distance variance, position uncertainties, and vehicle velocity. However, only low speed tests were done, 14 km/h, 20km/h and 46 km/h, our simulation platform does not handle high speed effects such as, Doppler, wind chill effects etc.

The uncertainty on the master vehicle position is reduced from green values to red values Fig. 4. Substantial improvement in position precisions were noticed during our numerous simulations.

The geometric data fusion chosen for this application has proven to be very precise; when we tried to obtain the position of the master vehicle with only vehicle 1 and vehicle 2 positions we only got the middle point between the two vehicles, even with a high number of samples and distance change. This fits logically the triangulation computation requirement, which necessitates three estimates. And there are only two estimates then the optimum choice should be the middle point of the two.

CONCLUSION

A collaborative navigation technique was proposed. We proved, under certain assumptions, using a geometric data fusion technique that the proposed approach is a valid navigation tool for intelligent vehicles of the future. Indeed the uncertainty of the master vehicle was reduced significantly with respect to the uncertainty of the initial position estimate.

The achievement is, in fact, two-fold: we proposed a new navigation scheme on one hand and we proved that geometric data fusion algorithm is suitable for dynamic positioning, under low speed on the other hand.

REFERENCES


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