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Localization in vehicular ad hoc networks using data fusion and V2V communication

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ABSTRACT

In Vehicular ad-hoc networks (VANETs), one of the challenging tasks is to find an accurate localization information. In this paper, we have addressed this problem by introducing a novel approach based on the idea of cooperative localization. Our proposed scheme incorporates different techniques of localization along with data fusion as well as vehicle-to-vehicle communication, to integrate the available data and cooperatively improve the accuracy of the localization information of the vehicles. The simulation results show that sharing the localization information and deploying that of the neighboring vehicles, not only assures the vehicles in a vicinity to obtain more accurate localization information, but also find the results robust to sensor inaccuracies or even to failures. Moreover, further improvement has been achieved by estimating the vehicle prior (prior mean and covariance) using unscented transform (UT) together with sequential decentralized extended Kalman filtering.

1. Introduction

Vehicular ad-hoc networks (VANETs) are a specific type of ad-hoc networks, which are infrastructure-free as well as they have fixed and mobile nodes. In VANETs, the nodes are deemed vehicles with high dynamicity causing rapid changes in the network topology. VANET can be viewed as an intelligent component of Intelligent Transportation Systems (ITS) as the vehicles communicate with each other as well as with the roadside base stations/roadside units (RSUs) located at critical points of the road, such as intersections or construction sites. VANETs differ notably from other types of ad-hoc networks, such as wireless sensor networks (WSNs) or mobile ad-hoc networks (MANETs) in terms of node dynamics and heterogeneity. The comprehensive well-organized VANETs are responsible for extracting, managing and interpreting the information to achieve knowledge, and making it available for travelers. A comprehensive overview of the properties, features and applications of VANETs are presented in [1].

VANETs have various applications including safe and convenient driving, emergency and entertainment applications, intelligent navigation, etc [2]. The key features of the VANETs over the conventional ITS are their network-based structure and the capability of communication between vehicles, i.e. vehicle-to-vehicle (V2V), and vehicles to roadside units (V2R) or other available infrastructures (V2I), by utilizing the underlying communication platforms and standardized protocols [2,3]. In V2V, the vehicles communicate with each other to share the information needed by an application or so called "service". For example, vehicles can share velocity information while they are moving on the same lane, to provide information on safe speed under safety service. Vehicles can even communicate with the nearby roadside units (V2R) for further assistance, for instance a vehicle could inform about the surrounding traffic situation to an approaching distant vehicle by sharing the traffic information with its nearest roadside unit. Moreover, the vehicles have privilege to communicate with the already existing infrastructures and the ITS service providers, such as traffic agencies to get relevant information (e.g. traffic information for convenient driving). The information exchange over a wireless network between the vehicles, roadside units, and infrastructure usually consists of various context based attributes, such as vehicle's speed, location, and direction of travel [4,5]. With these information, an advanced driving system can decide whether a crash is likely to alert the driver to brake, or even a more advanced autonomous driving system can brake the vehicle if a driver is slow to respond. Besides V2V, the V2I communications are further deployed to develop assisted driving systems. Other services of V2V include transferring the emergency messages, enhancing GPS accuracy, etc. V2I, on the other hand, is applied in toll collection, transferring important localized message related to road-traffic situation as well as providing access for some ITS related services.

One of the crucial information attributes in VANETs is location and its accurate calculation is a challenging issue [6]. The commonly used sensors such as odometer and Global Positioning System (GPS) are

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often employed to calculate the location of a vehicle. The use of GPS is fairly simply and the cost is low. However, it sometimes gives inaccurate results because of satellite blockage particularly in the urban areas. Therefore, the localization problem in VANETs is still an open issue.

In this paper, we propose a new localization approach for localization of a vehicle using vehicle motion model (for modeling the dynamic motion model of a vehicle) along with V2V communication and a data fusion method. We measure the belief of each vehicle about its current location using Extended Kalman Filter (EKF) [7], and then improve it by communicating with the neighboring vehicles and incorporating their beliefs about that vehicle's location. This approach allows us the simultaneous and efficient use of all the available sources of information unlike inability of the existing systems. This would lead us to achieve a real-time autonomous framework in VANETs due to their recursive online location estimation and ability to recover from failure.

The remaining of the paper is organized as follows. The related works are reviewed in Section 2, while a brief background is given in Section 3. Section 4 describes our new localization approach. Section 5 presents the simulation results. Section 6 addresses some important issues associated with the proposed method. The conclusion is drawn in Section 7.

2. Related works

Different localization approaches in VANETs are categorized in [6] according to Global Positioning Systems, Map Matching, Dead Reckoning, Cellular Localization, Image/Video Processing, Localization Services, and Relative Distributed Ad-Hoc Localization. Although most of the methods have their own advantages over the basic methods, only few of them are combined approaches with new ideas. We introduce here some interesting relevant contributions as those are either under one of the categories mentioned above, or an integration of them.

In [8], the vehicle localization is based on directional information by measuring the inter-radio distances between each node to other nodes within their proximity. This directional/dual wireless radio localization (DWRL) algorithm consists of semi-localization and rigid-localization without requiring the GPS. The localization process initiates by one of the node designated/located as *sink* node, which selects a node within its wireless range under the semi-localization. Then other unknown nodes are located with respect to the known locations of the sink node and semi-localized node in the rigid localization (Algorithm 1).

Algorithm 1 Extended Kalman Filter (EKF).

Require: $\mathbf{x}_{t-1}, \mathbf{P}_{t-1}, \mathbf{u}_t, \mathbf{z}_t$

$\mathbf{Q}_t$: *control noise matrix*

$\mathbf{R}_t$: *measurement noise matrix*

$\mathbf{K}_t$: *Kalman gain matrix*

$\mathbf{G}_t$: *Jacobian matrix*

$\mathbf{I}$: *Identity matrix*

$\bar{\mathbf{x}}_t \leftarrow f(\mathbf{u}_t, \mathbf{x}_{t-1})$

$\bar{\mathbf{P}}_t \leftarrow \mathbf{G}_t \mathbf{P}_{t-1} \mathbf{G}_t' + \mathbf{Q}_t$

$\mathbf{K}_t \leftarrow \bar{\mathbf{P}}_t \mathbf{H}_t' (\mathbf{H}_t \bar{\mathbf{P}}_t \mathbf{H}_t' + \mathbf{R}_t)^{-1}$

$\mathbf{x}_t \leftarrow \bar{\mathbf{x}}_t + \mathbf{K}_t (\mathbf{z}_t - h(\bar{\mathbf{x}}_t))$

$\mathbf{P}_t \leftarrow (\mathbf{I} - \mathbf{K}_t \mathbf{H}_t) \bar{\mathbf{P}}_t$;

return $\mathbf{x}_t, \mathbf{P}_t$

The authors of [9] present the idea of using radio-range techniques by measuring the distance (radiolocation) between a sender and a receiver and discuss about various radio-ranging distance measurement methods based on the ways to estimate the distance. In [9], the distance between the sender and the receiver is estimated based on theoretic modeling of path loss attenuation of the radiolocation signal. The distance can also be estimated from Angle of Arrival (AOA) and Time of Arrival (TOA) information, where the angle of the incoming signal at the receiver and one-way propagation time between transmitter and receiver are measured, respectively. The distance can be further estimated by measuring the Time Difference Of Arrival (TDOA) between a pair of receivers.

In [10], Yao et al. propose a cooperative positioning (CP) method which fuses kinematics information obtained from GPS or other kinematic sensors, with the distance measurements calculated based on radio-ranging techniques such as TOA and TDOA. The vehicles positions accuracy within each vehicle cluster have been further improved by using a routing algorithm in [11]. The effect of exchanging large amount of information between vehicles on positioning accuracy is further studied. The efficiency of the CP system has been evaluated over the unassisted GPS positioning in terms of a proposed performance metric called as positioning accuracy gain (PAG). The accuracy bounds of CP in VANETs are found as the inverse of Fisher Information Matrix (FIM) [12]. As shown in [10], the positioning accuracy of the whole cluster can be increased to more than 40%, even in low traffic density, while the accuracy gain PAG exceeds 70% under heavy traffic density. However, the performance is significantly affected by the packet collisions under real-world communication constraints. Another CP based method is proposed recently in [13], where low-level GPS information (psuedoranges) is used to be shared among the participating vehicles. The relative position of each vehicle to its neighbors is then estimated by fusing the local GPS observations and those of the neighbors, which can be received through vehicular communication.

A grid-based vehicle localization scheme is proposed in [14], which controls the propagation of the location error and exploits different typical geometrical patterns between the vehicle and its neighbors. It is found in [14] that error propagates slowly and linearly in grid-based schemes which makes the proposed scheme efficient in calculating the vehicle location than the nongrid-based scheme, where the error rapidly increases with large variance.

The proposed localization scheme in [15] relies on Road-Side Units (RSUs) assuming that a pair of RSUs are deployed on either side of the road while communicating with the passing vehicles continuously. In this scheme, each vehicle communicates with each of RSUs through broadcasting beacon messages, and estimates its position by measuring the distance to each RSU using radio-ranging techniques such as TOA or TDOA. Then, two intersecting circles are found, and their intersections are calculated. Assuming that a vehicle knows in which direction it is traveling, the correct position of the vehicle is assessed after the second round of message broadcasting. The performance is evaluated in terms of root mean squared error (RMSE) of the corresponding localization results and found robust against traffic density as well as vehicle speed for both faulty and fault-free RSU conditions. It is shown that this RSU-based V2I method in the fault-free environment outperforms the common V2V-based localization methods [16–18].

In [19] and [20], cooperative vehicle localization (CoVel) is addressed for which the authors propose a comprehensive framework incorporating different types of localization methods as discussed in [6] to utilize different levels of available information. In their framework, final position is estimated by combining the outputs of Absolute Positioning, Relative Positioning, and Group Map Matching components. Various sources of data/information are used by these components obtained from a data access system EDAS (EGNOS Data Access System), odometer, GNSS (Global Navigation Satellite System) receiver, car-to-car communication, and a digital map. For the relative positioning component, each vehicle determines the relative vector to other vehicles, using location information provided by absolute positioning component, and uses this information to do the group map matching in digital map in order to refine the