Ad Hoc Networks 34 (2015) 184–195

Contents lists available at ScienceDirect

Ad Hoc Networks

journal homepage: www.elsevier.com/locate/adhoc

Modeling position uncertainty of networked autonomous underwater vehicles

Baozhi Chen, Dario Pompili *

Department of Electrical and Computer Engineering, Rutgers University, New Brunswick, NJ, United States

ARTICLE INFO

Article history:
Received 1 March 2014
Received in revised form 13 August 2014
Accepted 2 September 2014
Available online 10 September 2014

Keywords:
Underwater sensor networks
Position uncertainty
Autonomous underwater vehicles
Unscented Kalman Filter

ABSTRACT

Recently there has been increasing engineering activity in the deployment of Autonomous Underwater Vehicles (AUVs). Different types of AUVs are being used for applications ranging from ocean exploration to coastal tactical surveillance. These AUVs generally follow a predictable trajectory specified by the mission requirements. Inaccuracies in models for deriving position estimates and the drift caused by ocean currents, however, lead to uncertainty when estimating an AUV's position. In this article, two forms of position uncertainty – *internal* and *external* – are studied, which are the position uncertainty associated with a particular AUV *as seen by itself* and that *as seen by others*, respectively. Then, a statistical model to estimate the internal uncertainty for a general AUV is proposed. Based on this model, a novel mathematical framework using Unscented Kalman Filtering is developed to estimate the external uncertainty. Finally, the benefits of this framework for several location-sensitive applications are shown via emulations.

1. Introduction

Recently UnderWater Acoustic Sensor Networks (UW-ASNs) [1] have been deployed to carry out collaborative monitoring missions such as oceanographic data collection, disaster prevention, and navigation. To ensure coverage of the vast undersampled 3D aquatic environment, Autonomous Underwater Vehicles (AUVs) endowed with sensing and wireless communication capabilities become essential. These AUVs – which can be divided into two classes, *propeller-less/buoyancy-driven* (e.g., gliders) and *Propeller-Driven Vehicles* (PDVs) – rely on local intelligence with minimal onshore operator dependence. Due to propagation limitations of radio frequency and optical waves, i.e., high medium absorption and scattering, respectively, acoustic communication technology is employed to transfer vital information (data and control) multi-hopping between AUVs underwater and, ultimately, to a surface or onshore station where this information is collected and analyzed.

In terrestrial sensor networks, the position of a node can be characterized by a single point because localization error can be made small by using the Global Positioning System (GPS), which, however, does not work underwater. In contrast, underwater inaccuracies in localization models and the drift caused by ocean currents will significantly increase the position uncertainty of AUVs. Hence, using a deterministic point is not sufficient to pinpoint the position of underwater vehicles. Furthermore, in the water, such a deterministic approach may cause problems such as errors in inter-vehicle communications, vehicle collisions, loss of synchronization – all possibly leading to mission failures [2].

To address the problems caused by position uncertainty, we introduce a probability region to characterize stochastically a node's position. Depending on the view

* Corresponding author.
E-mail addresses: baozhi_chen@cac.rutgers.edu (B. Chen), pompili@ece.rutgers.edu (D. Pompili).

http://dx.doi.org/10.1016/j.adhoc.2014.09.003
1570-8705/

of the different nodes, we define two forms of position uncertainty, i.e., *internal uncertainty*, the position uncertainty associated with a particular entity/node (such as an AUV) *as seen by itself*; and *external uncertainty*, the uncertainty associated with a particular entity/node *as seen by others*. These two notions introduce a shift in AUV localization – *from a deterministic to a probabilistic view* – which can be leveraged to improve the performance of solutions for a variety of problems. For example, in *UW-ASNs*, by using the external-uncertainty notion, error failures in geographical routing protocols can be decreased, and the output power at the transmitting node can be optimized with the constraint to guarantee a certain Signal-to-Noise Ratio (SNR) at the receiver (taking into account not only channel impairments but also position uncertainty). This notion can also be used in *underwater robotics* to minimize the risk of vehicle collisions, in *underwater localization* to increase the position accuracy by selecting a subset of nodes characterized by a low external uncertainty to be used as "anchors" (i.e., reference nodes employed in "trilateration"), and in *task allocation*, i.e., the problem of selecting a subset of AUVs to accomplish a mission, to geocast the mission details to the AUVs within a certain region. Finally, this notion plays a major role in *data processing/visualization* to improve the quality of 3D data reconstruction as the AUV deviation from the original mission path can be estimated and factored in.

To enable these applications, each node needs to estimate the external uncertainty of other nodes. To do this, the nodes need to first estimate their internal uncertainty and then broadcast it to the neighbors. Due to the large *network latency* (including communication transmission and propagation delay) and *information loss*, this received uncertainty information is a delayed version of a node's internal uncertainty and is used as the base for the neighbors to estimate the sender's uncertainty (i.e., external uncertainty). As a result, these two forms of uncertainty are generally different. To estimate the external uncertainty, we first propose a statistical approach to model the internal uncertainty of AUVs following predictable trajectories. Based on this internal uncertainty, we then propose a solution using the Unscented Kalman Filter (UKF) algorithm to predict the external uncertainty associated with any localization technique and leverage this information for performance improvement. Note that in [3] we introduced and used the notion of external uncertainty, whose region for simplicity was considered to be equal to that characterizing the internal uncertainty (its lower bound). Here we remove that simplifying assumption and rigorously model the external uncertainty by incorporating network latency and packet loss, which brings great benefits to a variety of problems.

The remainder of this article is organized as follows: in Section 2, we present the notions of internal and external uncertainty and discuss the benefits of using these two notions. We then propose our solution for modeling these uncertainties in Sections 3 and 4, followed by a thorough performance evaluation in Section 5; conclusions are finally drawn in Section 6.

2. The external uncertainty and its benefits in UW-ASNs

We define here the two types of position uncertainty, discuss the relationship between them, and comment on the benefits of using the external uncertainty in a variety of research areas and problems.

2.1. Internal uncertainty

This represents the position uncertainty associated with a particular entity/node (such as an AUV) *as seen by itself*. Many approaches such as those using Kalman Filter (KF) [4,5] have been proposed to estimate this uncertainty assuming that the variables to be estimated have linear relationships among them, and that the noise is additive and Gaussian. While simple and robust, KF is not optimal when the linearity assumption among the variables does not hold. On the other hand, approaches using nonlinear filters such as the extended or unscented KF attempt to minimize the mean squared errors in estimates by jointly considering the navigation location and the sensed states such as underwater terrain features, which is non-trivial, especially in the unstructured underwater environment.

2.2. External uncertainty

This represents the position uncertainty associated with a particular entity/node *as seen by others*. Let us denote the internal uncertainty, a 3D region associated with any node $j \in \mathcal{N}$, the set of network nodes, as $\mathcal{U}_{jj}$; and the external uncertainties, 3D regions associated with j as seen by $i, k \in \mathcal{N}$, as $\mathcal{U}_{ij}$ and $\mathcal{U}_{kj}$, respectively ($i \neq j \neq k$). In general, $\mathcal{U}_{jj}, \mathcal{U}_{ij}$, and $\mathcal{U}_{kj}$ are different from each other; also, due to asymmetry, $\mathcal{U}_{ij}$ is in general different from $\mathcal{U}_{ji}$. External uncertainties may be derived from the broadcast/propagated internal-uncertainty estimates (e.g., using *one-hop or multi-hop neighbor discovery mechanisms*) and, hence, will be affected by the end-to-end (e2e) *network latency* and *information loss*. The estimation of the external-uncertainty region $\mathcal{U}_{ij}$ of a generic node j at node i (with $i \neq j$) involves the participation of both i and j. Fig. 1(a) illustrates the internal- and external-uncertainty regions and their difference; j's uncertainty regions seen by j itself ($\mathcal{U}_{jj}$, i.e., the internal uncertainty), by i (i.e., $\mathcal{U}_{ij}$) and by k (i.e., $\mathcal{U}_{kj}$) are all depicted to be different (general case). Note that, as shown in Fig. 1(b), in general, the longer an AUV remains underwater, the larger its external and internal uncertainties. Estimating $\mathcal{U}_{ij}$ involves estimating the change of $\mathcal{U}_{jj}$ with time; hence, in this work we propose a solution to predict $\mathcal{U}_{ij}$ based on the statistical estimation of $\mathcal{U}_{jj}$.

2.3. Benefits to underwater applications

We present here applications and research areas where the proposed notion of external uncertainty can be applied to improve performance.