Collaborative Opportunistic Navigation

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INTRODUCTION

Despite the extraordinary advances in global navigation satellite systems (GNSS), the inherent limitation of the weakness of their space-based signals makes such signals easy to block intentionally or accidentally. This makes GNSS insufficient for reliable anytime, anywhere navigation, particularly in GNSS-challenged environments, such as indoors, deep urban canyons, and GNSS-denied environments experiencing intentional jamming [1]. Several approaches have been proposed to address this inherent limitation of GNSS-based navigation, most notably augmenting GNSS receivers with dead-reckoning systems. This approach typically fuses the outputs of a fixed number of well-modeled heterogeneous sensors, particularly, GNSS receivers, inertial navigation systems, and digital map databases, with specialized signal processing algorithms.

Motivated by the plenitude of ambient radio frequency signals in GNSS-challenged environments, a new paradigm to overcome the limitations of GNSS-based navigation is proposed. This paradigm, termed opportunistic navigation (OpNav), aims to extract positioning and timing information from ambient radio frequency signals of opportunity (SOPs). OpNav radio receivers continuously search for opportune signals from which to draw navigation and timing information, employing on-the-fly signal characterization as necessary [2]. In collaborative opportunistic navigation (COpNav), multiple OpNav receivers share information to construct and continuously refine a global signal landscape.

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BACKGROUND

In its most general form, OpNav treats all ambient radio signals as potential SOPs, from conventional GNSS signals to communications signals never intended for use as timing or positioning sources. Each signal's relative timing and frequency offsets, transmit location, and frequency stability, are estimated on-the-fly as necessary, with prior information about these quantities exploited when available. At this level of generality, the OpNav estimation problem is similar to the simultaneous localization and mapping (SLAM) problem in robotics [3]. Both imagine an actor which, starting with incomplete knowledge of its location and surroundings, simultaneously builds a map of its environment and locates itself within that map.

In traditional SLAM, the map that gets constructed as the actor (typically a robot) moves through the environment is composed of landmarks—walls, corners, posts, etc.—with associated positions. OpNav extends this concept to radio signals, with SOPs playing the role of landmarks. In contrast to a SLAM environmental map, the OpNav signal landscape is dynamic and more complex. For the simple case of pseudorange-only OpNav, where observables consist solely of signal time-of-arrival measurements, one must estimate, besides the position and velocity of each SOP transmitter's antenna phase center, each SOP's time offset from a reference time base, rate of change of time offset, and a set of parameters that characterize the SOP's reference oscillator stability. Even more SOP parameters are required for an OpNav framework in which both pseudorange and carrier phase measurements are ingested into the estimator [2]. Of course, in addition to the SOP parameters, the OpNav receiver's own position, velocity, time offset, and time offset rate must be estimated.

The Global Positioning System (GPS) control segment routinely solves an instance of the COpNav problem: the location and timing offsets of a dozen or more GPS ground stations are simultaneously estimated with the orbital and clock parameters of GPS satellite vehicles (SVs). Compared to the general COpNav problem, the GPS control segment's problem enjoys the constraints imposed by accurate prior estimates of site locations and SV orbits. Moreover, estimation of clock states is aided by the presence of highly-stable atomic clocks in the SVs and at each ground station. In contrast, a COpNav receiver entering a new signal landscape may have less prior information to exploit and cannot assume atomic frequency references, neither for itself nor for the SOPs.

Figure 1 illustrates a COpNav environment in which two receivers share their observations on the various SOPs through a signal characterization database (SCD) and a central estimator (CE). The SCD and CE maintain the latest state estimates of the signal landscape states by fusing the observations made by the COpNav receivers. Relevant estimates are communicated back to each COpNav receiver.

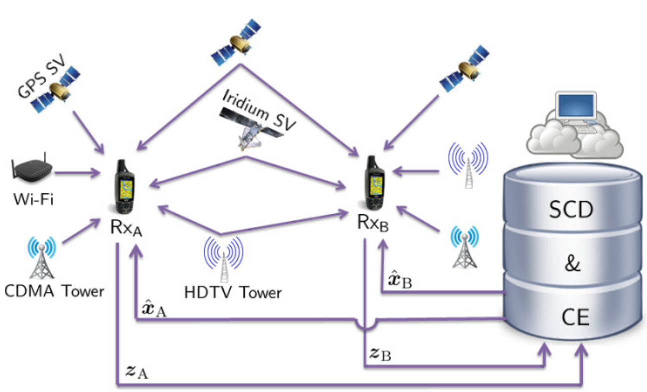

Fig. 1. COpNav Environment with SCD and CE

CONTRIBUTIONS

Research questions pertaining to COpNav can be categorized into two classes: (*i*) optimal signal extraction and (*ii*) fundamental estimation questions.

Optimal signal extraction focuses on grouping the SOPs according to their modulation schemes so that the signals can be modeled appropriately for optimal signal extraction of parameters of interest for navigation purposes. For example, GPS, Galileo, and Compass GNSS along with some cell phone carriers modulate their signals through code division multiple access (CDMA). The Iridium SVs communication system, global system for mobile communications (GSM), and high-definition television (HDTV) signals are modulated through time division multiple access (TDMA). In [2], it was demonstrated that the receiver's time offset can be estimated by exploiting CDMA signals from nearby cell phone towers. The obtained estimates were comparable to the estimates achieved by relying on GPS signals. To exploit TDMA signals for carrier-phase-based navigation, one must address their intermittent nature and phase ambiguities. In [4], a technique was developed for reconstructing a continuous phase time history from the non-continuous phase bursts of TDMA signals.

Two fundamental estimation questions of COpNav are concerned with observability and estimability. Conceptually, observability of a dynamic system is a question of solvability of the states from a set of observations that are linearly or nonlinearly related to the states, and where the states evolve according to a set of linear or nonlinear difference or differential equations. While observability is a Boolean property, i.e. it asserts whether a system is observable or not, estimability quantifies the degree of observability of the various states. In [5] and [6], the minimum conditions under which a COpNav environment is completely observable were derived and the states estimability was quantified. It was shown that a planar COpNav environment comprising multiple receivers with velocity random walk dynamics making pseudorange measurements on multiple terrestrial static SOPs is completely observable if and only if the initial states of at least: (*i*) one receiver is fully-known, (*ii*) one receiver is partially-known and one SOP is fully- known, or (*iii*) one SOP is partially-known and one SOP is fully-known. The receiver's state vector consisted of the receiver's position x_r and y_r, velocity $\dot{x}_r$ and $\dot{y}_r$, clock bias δt_r, and clock drift $\dot{\delta t}_r$, whereas the SOP's state vector consisted of the SOP's position x_s and y_s, clock bias δt_s, and clock drift $\dot{\delta t}_s$. Fully-known refers to the knowledge of all the initial states in the state vector, while partially-known refers to the knowledge of the initial position states in the state vector.

A COpNav simulator was developed, in which the receivers' noisy measurements were fused through an Extended Kalman Filter to estimate the various states in the environment. Figure 2 shows results for case (*i*), defined previously. As it is expected for an observable system, the estimation error trajectories of all the SOP states converged and were bounded by the estimation error variances σ^2. In Figure 2, c is the speed of light.

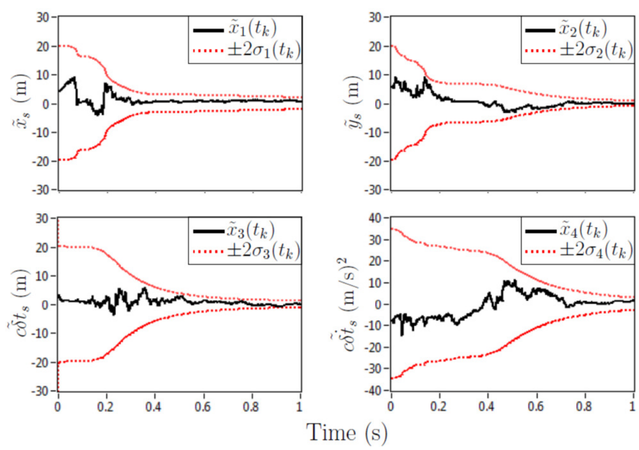

Fig. 2. Estimation Error Trajectories and Estimation Error Variances of the States of an Unknown SOP

Future work will focus on optimal signal extraction methods from other types of SOPs, and additional estimation architectural questions will be addressed, such as how to deal with dynamical and statistical environmental model uncertainties, and which estimation architecture is appropriate: decentralized, centralized, or hierarchical.

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