Network Localization and Navigation via Cooperation

Moe Z. Win, Massachusetts Institute of Technology
Andrea Conti, University of Ferrara
Santiago Mazuelas and Yuan Shen, Massachusetts Institute of Technology
Wesley M. Gifford, IBM Thomas J. Watson Research Center
Davide Dardari and Marco Chiani, University of Bologna

ABSTRACT

Network localization and navigation give rise to a new paradigm for communications and contextual data collection, enabling a variety of new applications that rely on position information of mobile nodes (agents). The performance of such networks can be significantly improved via the use of cooperation. Therefore, a deep understanding of information exchange and cooperation in the network is crucial for the design of location-aware networks. This article presents an exploration of cooperative network localization and navigation from a theoretical foundation to applications, covering technologies and spatiotemporal cooperative algorithms.

PRELIMINARIES AND APPLICATIONS

The availability of real-time high-accuracy location-awareness is essential for current and future wireless applications. Reliable localization and navigation is a critical component for a diverse set of applications including logistics, security tracking, medical services, search and rescue operations, control of home appliances, automotive safety, and military systems, as well as a large set of emerging wireless sensor network (WSN) applications. Other applications that exploit position information include networking protocols (geo-routing) and interference avoidance techniques in future cognitive radios. New market opportunities in real-time location system (RTLS) technology have an expected value of $6 billion in 2017.[1]

Network localization and navigation represent a new paradigm where wireless networks support data communication, contextual information collection, and navigation. The purpose of such networks is to determine the unknown positions of agents based on intra- and inter-node measurements. In conventional approaches such as the Global Positioning System (GPS), each agent infers its position using only measurements made with respect to anchors (nodes in the infrastructure with a priori position knowledge). Such systems usually fail in harsh environments where network coverage is limited and measurement behavior is highly complex.

Cooperation among peer nodes at the physical layer improves the performance and extends the coverage of wireless networks, where nodes form a virtual array through distributed transmission and signal processing [1]. Recently, cooperative techniques have been introduced for localization and navigation to improve the accuracy and reliability of position information. Network localization and navigation circumvent the need for high-power transmitters and high-density infrastructure, and offer additional coverage and improved localization accuracy by enabling the agents to estimate their positions via cooperation [2–5]. The main components of cooperative location-aware networks involved in RTLS design are shown in Fig. 1.

The localization and navigation process typically consists of two phases: (i) a measurement phase, during which agents make intra- and inter-node measurements using different sensors; and (ii) a location update phase, during which agents infer their own positions using an algorithm that incorporates both prior knowledge of their positions and new measurements. For instance, an agent can update its position estimate based on inertial measurements using an inertial measurement unit (IMU) and distance measurements with respect to some fixed anchors using a range measurement unit (RMU). Localization accuracy strongly depends on the quality of the measurements, which are affected by impairments such as network topology, multipath propagation, environmental conditions, interference, noise, and clock drift. In addition to the underlying technologies used in the measurement phase, localization performance is also dependent on the specific processing or data fusion algorithm used in the location-update phase. Hence, a deep understanding of information evolution in different phases of the localization process is necessary for the design and

[1] *According to R. Das and P. Harrop "RFID Forecast, Players and Opportunities 2007-2017," http://www.idtechex.com, 2007.*

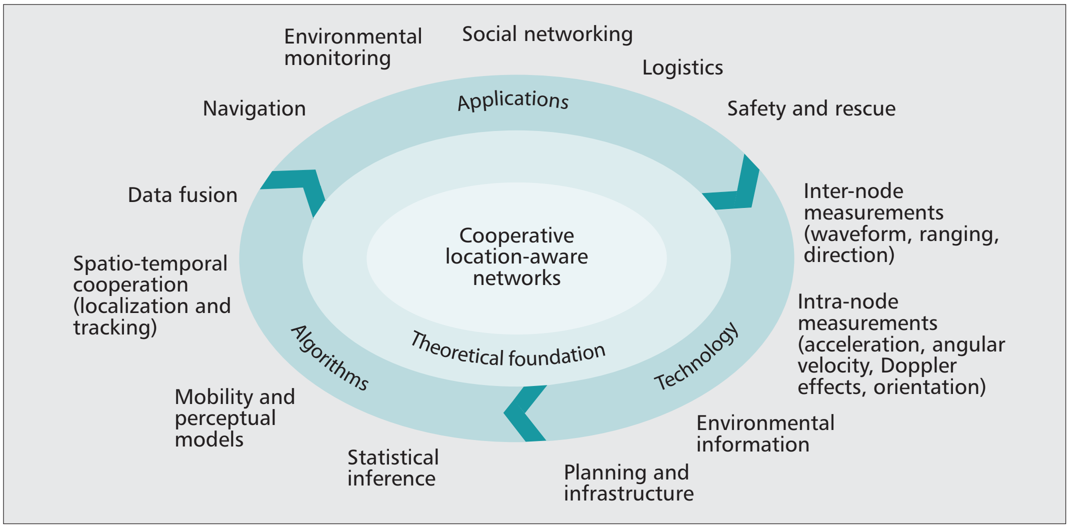

Figure 1. *The cycle of cooperative location-aware networks: theoretical foundation and aspects to be considered for technology, algorithms, and applications.*

Understanding the fundamentals of network localization and navigation via cooperation is important not only to provide a performance benchmark, but also to guide algorithm development and network design.

analysis of localization systems. A theoretical foundation that addresses these issues is described later.

The requirements of location-aware networks are driven by applications. A local performance metric is the root mean squared error (RMSE) of position estimates. In particular, the position estimation error is given by the Euclidean distance between the estimated position $\hat{\mathbf{x}}$ and the true position $\mathbf{x}$ as $e(\mathbf{x}) = \|\hat{\mathbf{x}} - \mathbf{x}\|$. A global performance metric evaluated over the entire localization area and time is the localization error outage (LEO) defined by $P_{\text{out}} = \mathbb{P}\{e(\mathbf{x}) > e_{\text{th}}\}$, where e_{th} is the target (i.e., maximum allowable) position estimation error, and the probability is evaluated over the ensemble of all possible spatial positions and time instants. Other requirements include localization update rate (i.e., the number of position estimates computed per second) and coverage area of the localization system. In particular, localization update rate is important for navigation (navigation of pedestrians and vehicles typically requires different localization update rates), which drives algorithm complexity and node cost.

In this article, we provide a snapshot of the current status of cooperative localization and navigation technologies, starting from a theoretical foundation to technological and algorithmic aspects, respectively. We then conclude this article with our remarks.

Theoretical Foundation

The concept of cooperation has been applied to WSNs, where distributed sensors work together to draw a consensus about the environment or to estimate a spatio-temporal process based on their local measurements [6]. Analogously, network localization and navigation allow agents to help each other in estimating their positions, offering additional benefits such as improved localization accuracy, resilience to system failure, increase in coverage, and reduction of cost per node [2–4]. Understanding the fundamentals of network localization and navigation via cooperation is important not only to provide a performance benchmark, but also to guide algorithm development and network design.

Consider a network with anchors and agents, where each of the N_{a} agents is equipped with multiple sensors that can provide intra- and inter-node measurements (e.g., using IMU and RMU, respectively) for the purpose of localization and navigation. Using these intra- and inter-node measurements, represented by $\mathbf{z} = [\mathbf{z}_{\text{self}}\ \mathbf{z}_{\text{rel}}]$, the agents aim to infer their positions $\mathbf{x} = [\mathbf{x}_1\ \mathbf{x}_2 \cdots \mathbf{x}_{N_{\text{a}}}]$. The accuracy of location estimates is inherently limited due to random phenomena affecting $\mathbf{z}$, and fundamental limits of such accuracy have been derived using the information inequality [4].

Spatial Cooperation

For a static network, or a dynamic network at a given time instant, only spatial cooperation among agents can be exploited. By using the notion of the equivalent Fisher information matrix (EFIM) [4], the squared position error for agent k is bounded by

$$\mathbb{E}\left\{\|\mathbf{x}_k - \hat{\mathbf{x}}_k\|^2\right\} \geq \text{tr}\left\{\left[\mathbf{J}_{\text{e}}(\mathbf{x})^{-1}\right]_{\mathbf{x}_k}\right\}, \tag{1}$$

where $\mathbf{J}_{\text{e}}(\mathbf{x})$ is the $2\,N_{\text{a}} \times 2\,N_{\text{a}}$ EFIM for $\mathbf{x}$ [as depicted in Fig. 2b], $\mathbb{E}\{\cdot\}$ and $\text{tr}\{\cdot\}$ are the expectation and trace operators, respectively, and $[\cdot]_{\mathbf{x}_k}$ denotes the square submatrix on the diagonal corresponding to $\mathbf{x}_k$. The right side of Eq. 1 is referred to as the squared position error bound (SPEB). It can be shown that the EFIM $\mathbf{J}_{\text{e}}(\mathbf{x})$ is a sum of two parts, the localization information from anchors (shown as the block-diagonal matrices consisting of $\mathbf{K}$s in Fig. 2) and that from agents' spatial cooperation (shown as the structured matrix consisting of $\mathbf{C}$s in Fig. 2).

The basic building blocks of the EFIM $\mathbf{J}_{\text{e}}(\mathbf{x})$ represent the localization information between pairs of nodes in the form $\lambda \mathbf{u}_\phi \mathbf{u}_\phi^{\text{T}}$, where $\mathbf{u}_\phi$ is the unit vector with direction given by ϕ denoting the angle from one node to the other, and λ is a positive scalar that characterizes the ranging information intensity (RII) [4]. The value of λ

The total EFIM consists of two major components: cooperation in space as well as in time. The former characterizes the inter-node measurements in the entire network at each time instant, and the latter characterizes the information from intra-node measurements and mobility models at each individual agent.

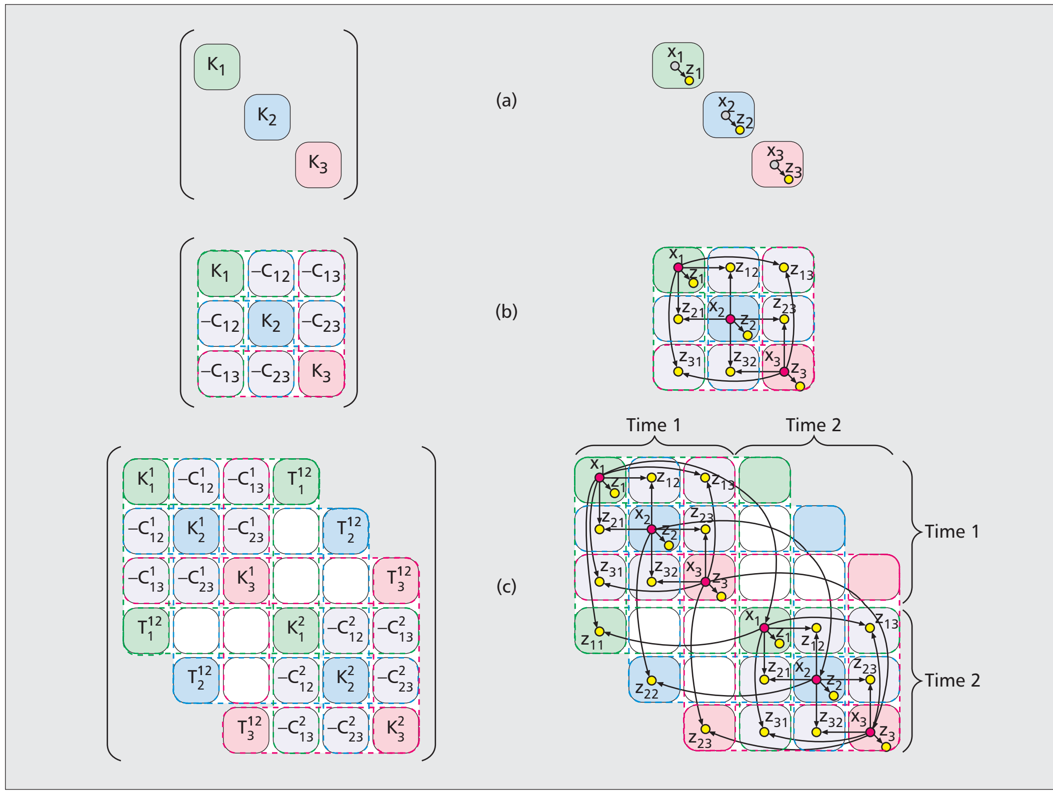

Figure 2. *EFIM structures and corresponding Bayesian networks for three agents: a) noncooperative localization; b) spatial cooperation; c) spatio-temporal cooperation for two time steps.*

depends on the ranging technique as well as the power and bandwidth of the received waveform, multipath propagation, and prior statistical channel knowledge. In particular, the RII is proportional to the square of the effective bandwidth [4]. Moreover, the localization information from anchors can be expressed in a canonical form as a weighted sum of "one-dimensional" information from individual anchors; while cooperation always improves the localization accuracy since it adds a positive semi-definite matrix to the EFIM corresponding to noncooperative localization. It was shown in [4] that the accuracy of localization is affected by two factors: the quality of point-to-point measurements, reflected by the expression of RII, and the network topology, reflected by the block structure of the matrix $\mathbf{J}_e(\mathbf{x})$.

In the absence of cooperation, every $\mathbf{C}_{i,j}$ corresponding to cooperation between nodes i and j becomes 0, resulting in a total EFIM $\mathbf{J}_e(\mathbf{x})$ with block-diagonal structure, as depicted in Fig. 2a. In such cases, localization information for different agents are uncorrelated, and the SPEB can be calculated using only local information at the agents.

Spatio-Temporal Cooperation

Building on the understanding of cooperative localization, we now discuss the case of cooperative navigation where agents in a dynamic network cooperate in both the space and time domains. For each time instant, the contribution of cooperation in space is similar to what we have seen in cooperative localization. In addition, another layer of cooperation in time, exploiting intranode measurements and mobility (dynamic) models, yields new information for navigation. Such information is characterized by $\mathbf{T}$ matrices in the total EFIM $\mathbf{J}_e(\mathbf{x}^{(1:t)})$ as depicted in Fig. 2c, where $\mathbf{x}^{(1:t)}$ consists of the positions of all agents from time 1 to t. Consequently, the SPEB for each agent at a given time instant can be obtained by a formula similar to Eq. 1.

Some observations can be drawn from the structure of the EFIM for cooperative navigation in Fig. 2c. First, the total EFIM consists of two major components: cooperation in space as well as in time. The former characterizes the localization information from inter-node measurements in the entire network at each time instant (shown as the diagonal $2N_a \times 2N_a$ block matrices), and the latter characterizes the information from intra-node measurements and mobility models at each individual agent (shown as components $\mathbf{T}$ outside the main block-diagonal). Second, since intra-node measurements and the mobility models for different agents are independent, the corresponding $\mathbf{T}$ matrices form a block diagonal matrix in the upper-right and lower-left quarter of the total EFIM. Third, the $\mathbf{T}$ components can be viewed as the temporal link that connects localization information from spatial cooperation of the previous time instant to the current one. If the temporal link is not available (i.e., $\mathbf{T}$ components are zero), the total EFIM is block diagonal, implying that position inference is independent from time to time. The structure of the EFIM for cooperative navigation allows a recursive method to calculate the EFIM at each time instant. This view also provides insights into the information evolution of spatio-temporal cooperation in cooperative navigation.

Technological Aspects

This section describes enabling technologies for network localization and navigation including network infrastructure, common signal metrics, and error mitigation techniques.

Network Infrastructure

GPS is currently the most important and widely used technology to provide location awareness around the globe. Through a constellation of GPS satellites, it provides positioning accuracy on the order of meters in open outdoor areas, but fails in harsh operating environments such as in buildings and urban canyons. In these GPS-challenged or even GPS-denied environments, terrestrial localization systems are increasingly more important. Such systems are currently based on cellular networks, wireless local area networks (WLANs), WSNs, and radio frequency identification (RFID) networks. Each of them exhibits different performance and has unique infrastructure requirements. As a case of interest, in harsh indoor environments, WLANs typically suffer impairments from surrounding objects such as furniture and people, whereas narrowband sensors and RFIDs typically require high node density to achieve the desired accuracy and coverage. Ultra wideband (UWB) technology offers high ranging accuracy in harsh environments due to its ability to resolve multipath and penetrate obstacles [7, 8]. It is expected that UWB-based localization will play an important role in future high-definition situation-aware and RFID networks. In particular, the IEEE 802.15.4a standard is the first to contemplate both communication and localization with high levels of availability and sub-meter accuracy.

Network navigation is based on intra- and inter-node measurements. The specific types of measurements available depend on the technology employed. Examples of intra-node measurements are acceleration, angular velocity, Doppler shift, and orientation, while inter-node measurements are waveforms, ranges, and directions. For instance, an IMU gives the distance traveled and direction for each time interval, while an agent with wireless transceivers can infer the distance with respect to its neighbors based on signal metrics extracted from exchanged radio frequency (RF) waveforms.

Signal Metrics for Inter-Node Measurements

Network localization can be classified as range-based, direction-based, and proximity-based depending on the type of inter-node measurement. Among them, range-based techniques (i.e., based on distance estimates) are more suitable when both localization accuracy and complexity are under consideration. The two most widely used ranging techniques are received signal strength (RSS)-based and time-based systems.

In RSS-based systems, the receiving node converts the measured RSS into a distance estimate using theoretical and/or empirical path loss models. The choice of the model strongly affects the ranging accuracy. A widely used model is given by $P_r(d) = P_0 - 10\,\gamma \log_{10} d + S$, where $P_r(d)$ (dBm) is the received power, P_0 is the received power (dBm) at 1 m, d (meters) is the receiver's distance from the transmitter, γ is the path loss exponent, and S (dB) is the large-scale fading (shadowing) commonly modeled as a Gaussian random variable with zero mean and standard deviation σ_S. RSS-based ranging suffers from mismatch between distance and signal attenuation leading to inaccurate distance estimates, especially in cluttered environments.

In time-based ranging, the distance between a pair of nodes is estimated by measuring the signal propagation delay, or time-of-flight (TOF) $\tau_f = d/c$, where d is the distance between the nodes, and c is the speed of electromagnetic waves ($c \simeq 3 \times 10^8$ m/s). This can be accomplished using one-way time of arrival (TOA), two-way TOA, or time difference of arrival (TDOA). Time-based ranging techniques are mainly affected by noise, multipath propagation, obstacles, interference, and clock drift. In particular, in dense multipath channels the first path is often not the strongest, making TOA estimation challenging. The maximum likelihood (ML) TOA estimator is known to be asymptotically efficient since it achieves the Cramér-Rao bound (CRB) in the high SNR region. The implementation of ML estimators usually requires sampling at the Nyquist sampling rate or higher, which is impractical for wideband and UWB signals. Thus, TOA estimation techniques relying on the energy collected at sub-Nyquist rates are receiving significant attention.

Various TOA estimators based on energy detection and the effects of impairments are analyzed in [8]. While the CRB is typically used as a performance benchmark for many estimation problems, it is not accurate at low and moderate SNRs for TOA estimation. Like all nonlinear estimators, the performance of the TOA estimator is characterized by the presence of a threshold effect with distinct SNR regions (low, medium, and high SNRs) corresponding to different modes of operation. At low SNRs (*a priori region*), measurements do not provide significant additional information, and the mean square error (MSE) of the estimator is close to that obtained solely from the a priori information about the TOA. At high SNRs (*asymptotic region*), the MSE of the estimator is accurately described by the CRB. Between these two extremes, there may be an additional region (also known as the *transition* or *ambiguity* region) where the performance is subject to ambiguities that are not accounted for by the CRB. Therefore, other bounds, which are more complicated but tighter than the CRB, have been proposed in the literature. The Ziv-Zakai bound (ZZB) [8, 9] can be applied to a wider range of SNRs, and accounts for both ambiguity effects and a priori information of the parameter to be estimated.

Ranging Error Mitigation

The performance of location-aware networks depends mainly on two factors: (i) the geometric configuration of the system (i.e., the deployment of the anchors relative to the agents), and (ii) the quality of the waveform and range measurements. The design of such networks requires a clear understanding of these phenomena through careful characterization of involved inter-node measure-

The performance of network localization and navigation depends mainly on two factors: (1) the geometric configuration of the system, and (ii) the quality of the waveform and range measurements.

The characterization of each possible link, by means of ranging and waveform measurements, enables the system designer to understand how to harness environmental knowledge, identify LOS and NLOS conditions, take advantage of cooperation, and choose cooperating nodes.

ments. These measurements are corrupted by propagation conditions caused by the environment; for example, partial or complete line-of-sight (LOS) blockage leads to positively biased range estimates for time-based ranging techniques. The localization performance can be improved by discarding or refining unreliable range measurements based on environmental information. In particular, regardless of the specific range-based localization algorithm used, the following three-step procedure can be adopted: (i) calculate the preliminary position estimate $\hat{\mathbf{x}}^{(1)}$ from initial range estimates based on measurements; (ii) correct range estimates based on $\hat{\mathbf{x}}^{(1)}$ by removing biases according to bias models; and (iii) estimate a refined position $\hat{\mathbf{x}}^{(2)}$ with the corrected range values.

In the absence of environmental information, ranging refinement can be made based on other information, such as non-LOS (NLOS) condition, extracted from the received waveforms. A variety of techniques have been proposed in the literature to identify NLOS conditions. The identification of signal obstruction is mainly accomplished by performing a likelihood ratio test (LRT) on binary (LOS or NLOS) hypotheses. This requires the extraction of features that are significantly affected by the propagation conditions from the received waveform. For example, the NLOS identification technique in [10] is based on signal features such as root mean square (RMS) delay-spread, Kurtosis, and mean excess delay. Other approaches include regression with support vector machines and Gaussian processes. The characterization of each possible link, by means of ranging and waveform measurements, enables the system designer to understand how to harness environmental knowledge, identify LOS and NLOS conditions, take advantage of cooperation, and choose cooperating nodes.

Localization and Navigation Algorithms

The task of network localization and navigation algorithms is to determine positions from measurements (observations) and prior knowledge. From a Bayesian perspective, this task amounts to determining the posterior distribution $p(\mathbf{x}|\mathbf{z})$, also referred to as the positional belief. Once this belief is obtained, point estimates can be computed by determining the mean or mode, leading to minimum mean square error (MMSE) or maximum *a posteriori* (MAP) estimates, respectively. The primary tools for obtaining such posterior distributions from measurements and prior knowledge are Bayes' rule and marginalization. Bayes' rule serves to update beliefs based on new observations, while marginalization reduces the dimension of the inference problem.

In noncooperative localization, each agent individually determines its position by using the measurements obtained only from anchors (see the top-right corner in Fig. 2). Each agent can then independently update its own belief by using the above mentioned Bayes' rule and the likelihood of its position based on new measurements. The belief update as well as the MMSE or MAP position estimators are easy to determine when the likelihood can be accurately modeled by a tractable statistical distribution, for example a Gaussian distribution. Under the Gaussian assumption the MMSE and MAP estimators for an agent's position x coincide and are the solution of a weighted least squares (WLS) problem, that is,

$$\hat{\mathbf{x}}_{\text{MMSE}} = \hat{\mathbf{x}}_{\text{MAP}} = \arg\min_{\mathbf{x}} \sum_{j \in \mathcal{N}_{\text{b}}} \frac{1}{\sigma^2_{\mathbf{z}_j}} \left\| \mathbf{z}_j - h(\mathbf{x}, \mathbf{x}_j) \right\|^2,$$

where $\mathcal{N}_{\text{b}}$ is the set of anchor nodes, $\sigma^2_{\mathbf{z}_j}$ is the variance of the noise in each measurement, and $h(\mathbf{x}, \mathbf{x}_j)$ is a functional of: the distance $\|\mathbf{x} - \mathbf{x}_j\|$ in range-based methods, or the angle $\angle\overrightarrow{\mathbf{x}\mathbf{x}_j}$ in direction-based methods, or both in hybrid schemes. When the likelihood has a non-Gaussian distribution, the optimization process required for MMSE and MAP can be complex, in which case the WLS solution can be used as a tractable suboptimal solution.

While each agent determines its belief based on information obtained from its local measurements in the noncooperative scenario, the localization performance can be improved if agents incorporate the beliefs of neighbors (spatial cooperation) and the beliefs obtained in the past (temporal cooperation).

Spatial Cooperation

In this setting, a centralized processor can update the joint belief of all agents by using all the measurements as well as the prior joint belief. However, the process of belief updates and inference is highly complex and inefficient for the following reasons:

- The joint positional belief of all agents is a high dimensional distribution.
- The overhead needed to transmit all measurements to a central processor and to communicate estimated positions back to agents require an unacceptable usage of resources.

Furthermore, the centralized solution is not robust against failure. For these reasons, distributed algorithms for cooperative localization are attractive. In a cooperative setting, inferred node positions are correlated; this fact is evident from the non-diagonal structure of the EFIM and the presence of cycles in the Bayesian network (Fig. 2b). Thus, distributed algorithms for cooperative localization cannot achieve the CRB.

A common method to implement distributed algorithms for cooperative localization is by means of loopy belief propagation (LBP) [2]. These algorithms assume the positional beliefs are independent and propagate the beliefs of each agent through the cooperative network in an iterative fashion based on the sum-product algorithm. In the algorithm, the sums (integrals) and products perform marginalizations and Bayes' rule updates, respectively.

An example of two agents in cooperation for localization is shown in Fig. 3, describing the position errors before and after cooperation. The red and blue ellipses in Figs. 3a and 3c represent the agents' localization information and errors, respectively; and the contours in Figs. 3b and 3d represent the agents' positional beliefs. As the

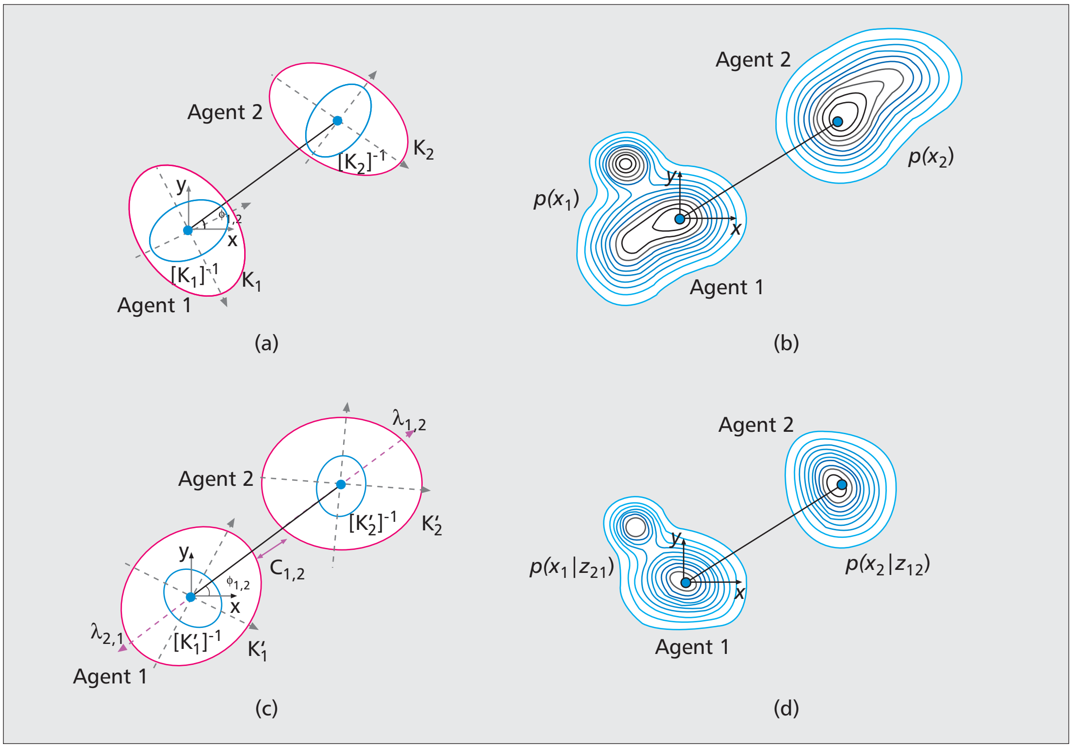

Figure 3. *Localization information provided by spatial cooperation. The red and blue ellipses respectively represent the localization information and error in (a) and (c); contours represent the positional beliefs in (b) and (d).*

two agents cooperate, the information ellipses increase and the error ellipses decrease, as predicted by the theoretical results. Correspondingly, the positional beliefs of the two agents become more concentrated after cooperation.

Spatio-Temporal Cooperation

In spatio-temporal cooperation, the agents' positional beliefs obtained through spatial cooperation are refined by information related to temporal evolution through intra-node measurements and mobility models, as depicted in Fig. 2c. The addition of this temporal cooperation can further increase network performance.

The positional evolution is stored in the state vector $\mathbf{y}^{(t)}$, consisting of positions, orientations, and several of their derivatives at time instant t. Temporal cooperation is accomplished using mobility and intra-node measurement (likelihood) models. The former statistically describe the evolution in time of the positional states, $p(\mathbf{y}^{(t)}|\,\mathbf{y}^{(t-1)})$, whereas the latter statistically describe the relationship between intra-node measurements and the positional states, $p(\mathbf{z}_{\text{self}}|\,\mathbf{y}^{(t)})$. Once again, the mechanisms used to update beliefs from these models are based on Bayes' rule and marginalization. Specifically, the belief update can be performed in two steps:

(i) Prediction:

$$p\left(\mathbf{y}^{(t)}\middle|\mathbf{z}^{(1:t-1)}\right)=\int p\left(\mathbf{y}^{(t-1)}\middle|\mathbf{z}^{(1:t-1)}\right)p\left(\mathbf{y}^{(t)}\middle|\mathbf{y}^{(t-1)}\right)\mathrm{d}\mathbf{y}^{(t-1)}$$

(ii) Correction:

$$p\left(\mathbf{y}^{(t)}\middle|\mathbf{z}^{(1:t)}\right)\propto p\left(\mathbf{y}^{(t)}\middle|\mathbf{z}^{(1:t-1)}\right)p\left(\mathbf{z}^{(t)}\middle|\mathbf{y}^{(t)}\right)$$

$$\text{where }\; p\left(\mathbf{z}^{(t)}\middle|\mathbf{y}^{(t)}\right)=p\left(\mathbf{z}_{\text{self}}^{(t)}\middle|\mathbf{y}^{(t)}\right)p\left(\mathbf{z}_{\text{rel}}^{(t)}\middle|\mathbf{y}^{(t)}\right).$$

Similar to the above cases, these equations can only be solved analytically for some models. For example, if both measurements and mobility models are linear-Gaussian, and the previous beliefs are also Gaussian, the updated beliefs at each time instant can be evaluated exactly by means of the Kalman filter (KF). However, these assumptions do not hold for nonlinear or non-Gaussian models that arise in many environments. There are several methods to approximately solve the above equations, ranging from Kalman-like methods, such as extended KF or unscented KF, to particle filters (PFs) based on sequential Monte Carlo techniques. Kalman-like methods assume Gaussian beliefs and perform the update similarly to the KF, while PFs compute the update using samples (particles) without a specific model for the beliefs. Kalman-like filters cannot capture the nonlinear and non-Gaussian models, while PFs suffer high computational complexity. To address these problems, a new framework of generalized filters needs to be developed to fill the gap between the Kalman-like filters and PFs in terms of the performance-complexity trade-off.

Remarks

Network localization and navigation by spatio-temporal cooperation open the door to a variety of important, some seemingly inconceivable, applications that rely on position information. Firefighters tracking each other in a smoke-filled building, soldiers determining each other's position in harsh environments, medical staff locating equipment or each other in a busy hospital, and workers finding merchandise in a warehouse

Algorithms for spatio-temporal cooperation are being developed based on graphical models, a new branch of statistics that makes inference possible over highly interrelated random variables.

Network localization and navigation by spatio-temporal cooperation open the door to a variety of important, some seemingly inconceivable, applications that rely on position information.

all need high-accuracy location information. Harnessing the full potential of such a promising paradigm can be achieved by using a combination of methods from communication theory, information theory, signal processing, and statistical inference. Fisher information theory not only provides the fundamental limits attainable by spatio-temporal cooperation, but also guides the algorithm development and network design. Algorithms for spatio-temporal cooperation are being developed based on graphical models, a new branch of statistics that makes inference possible over highly interrelated random variables. Despite the technological advances in the field, there are still several issues that need to be addressed to realize accurate, reliable, and efficient network localization and navigation. In particular, new filtering techniques need to be developed for nonlinear and non-Gaussian system models with sufficient accuracy and affordable complexity. Also needed is the creation of efficient scheduling techniques (access protocols) specifically tailored to network localization and navigation. In addition, secure localization and navigation is crucial for homeland security and military applications. The efficient use of spectrum also calls for new approaches such as cognitive navigation and interference management techniques.

Acknowledgments

This research was supported, in part, by the National Science Foundation under Grant ECCS- 0901034, the Office of Naval Research under Grant N00014-11-1-0397, the Defense University Research Instrumentation Program under Grant N00014-08-1-0826, the MIT Institute for Soldier Nanotechnologies, and the FP7 European Project SELECT under Grant 257544. The authors wish to thank Tianheng Wang and Javier Prieto for their help.

References

[1] M. Dohler *et al.*, "Performance Analysis of Distributed Space-Time Block-Encoded Sensor Networks," *IEEE Trans. Vehic. Tech.*, vol. 55, no. 6, Nov. 2006, pp. 1776–89.

[2] H. Wymeersch, J. Lien, and M. Z. Win, "Cooperative Localization in Wireless Networks," *Proc. IEEE*, vol. 97, no. 2, Feb. 2009, special issue on Ultra-Wide Bandwidth (UWB) Technology & Emerging Applications, pp. 427–50.

[3] N. Patwari *et al.*, "Locating the Nodes: Cooperative Localization in Wireless Sensor Networks," *IEEE Sig. Proc*, vol. 22, no. 4, July 2005, pp. 54–69.

[4] Y. Shen, H. Wymeersch, and M. Z. Win, "Fundamental Limits of Wideband Localization — Part II: Cooperative Networks," *IEEE Trans. Info. Theory*, vol. 56, no. 10, Oct. 2010, pp. 4981–5000.

[5] U. A. Khan, S. Kar, and J. M. F. Moura, "Distributed Sensor Localization in Random Environments Using Minimal Number of Anchor Nodes," *IEEE Trans. Sig. Proc.*, vol. 57, no. 5, May 2009, pp. 2000–16.

[6] I. F. Akyildiz *et al.*, "A Survey on Sensor Networks," *IEEE Commun. Mag.*, vol. 40, no. 8, Aug. 2002, pp. 102–14.

[7] S. Gezici *et al.*, "Localization via Ultra-Wideband Radios: A Look at Positioning Aspects for Future Sensor Networks," *IEEE Sig. Proc.*, vol. 22, no. 4, July 2005, pp. 70–84.

[8] D. Dardari *et al.*, "Ranging with Ultrawide Bandwidth Signals in Multipath Environments," *Proc. IEEE*, vol. 97, no. 2, Feb. 2009, special issue on Ultra-Wide Bandwidth (UWB) Technology & Emerging Applications, pp. 404–26.

[9] D. Chazan, M. Zakai, and J. Ziv, "Improved Lower Bounds On Signal Parameter Estimation," *IEEE Trans. Info. Theory*, vol. 21, no. 1, Jan. 1975, pp. 90–93.

[10] I. Güvenc *et al.*, "NLOS Identification and Weighted Least-Squares Localization for UWB Systems Using Multipath Channel Statistics," *EURASIP J. Adv. Sig. Process.*, vol. 2008, 2008, pp. 1–14.

Biographies

MOE WIN [F] (moewin@mit.edu) is an associate professor at the Massachusetts Institute of Technology and the founding director of the Wireless Communication and Network Sciences Laboratory. His research encompasses developing fundamental theories, designing algorithms, and conducting experimentation for a broad range of real-world problems. He is an elected Member-at-Large on the IEEE Communications Society Board of Governors (2011–2013). He received the Copernicus Fellowship and Laurea Honoris Causa from the University of Ferrara. He is a recipient of the IEEE Kiyo Tomiyasu and IEEE Eric E. Sumner Awards.

ANDREA CONTI (a.conti@ieee.org) is an assistant professor at the University of Ferrara, Italy. His research interests involve theory and experimentation of wireless systems and networks including network localization, adaptive diversity communications, and cooperative relaying techniques. He is serving as an Editor for *IEEE Communications Letters* and served as an Associate Editor for *IEEE Transactions on Wireless Communications* (2003–2009). He is elected Vice-Chair of the IEEE Communications Society's Radio Communications Technical Committee (2011–2012).

SANTIAGO MAZUELAS (mazuelas@mit.edu) received his Ph.D. in mathematics and Ph.D. in telecommunications engineering from the University of Valladolid in 2009 and 2011, respectively. Since September 2009 he has been a postdoctoral fellow in the Wireless Communication and Network Sciences Laboratory at MIT. His research interests are the application of mathematical and statistical theories to communications, localization, and navigation networks.

YUAN SHEN (shenyuan@mit.edu) received his B.S. degree from Tsinghua University in 2005 and his S.M. degree from MIT in 2008, both in electrical engineering. He is now a Ph.D. candidate in the EECS Department at MIT. His research interests include communication theory, information theory, and statistical inference with application to wideband communication systems and network navigation. He is a recipient of the Marconi Young Scholar Award and the MIT Walter A. Rosenblith Presidential Fellowship.

WESLEY M. GIFFORD (wgifford@ieee.org) received his B.S. degree (summa cum laude) from Rensselaer Polytechnic Institute in computer and systems engineering — computer science in 2001. He received his M.S. and Ph.D. degrees in electrical engineering from MIT in 2004 and 2010, respectively. He is currently a research staff member at the IBM Thomas J. Watson Research Center, where he applies mathematical, statistical, and machine learning theories to the modeling and analysis of complex business processes. He received the Rensselaer Medal and a Claude E. Shannon Fellowship.

DAVIDE DARDARI (ddardari@ieee.org) is an associate professor at the University of Bologna at Cesena, Italy. His research interests are in UWB communication and localization, wireless sensor networks, and OFDM systems. He is serving as an Associate Editor for *IEEE Transactions on Wireless Communications*. He is elected Chair of the IEEE Communications Society's Radio Communications Technical Committee (2011–2012), and is serving as General Co-Chair of the 2011 IEEE International Conference on UWB. He is a recipient of IEEE Aerospace and Electronic Systems Society's M. Barry Carlton Award.

MARCO CHIANI [F] (marco.chiani@unibo.it) is a full professor at the University of Bologna at Cesena, where he is also the director of the Center for Industrial Research on ICT (CIRI-ICT). His research interests include wireless communications, MIMO systems, UWB communication, and cognitive radio. He was elected Chair of the IEEE Communications Society's Radio Communications Technical Committee (2003–2004), and is serving as General Co-Chair of the 2011 IEEE International Conference on UWB. He is the recipient of the 2010 IEEE ComSoc RCC Technical Recognition Award.