LOCATION-AWARE VISUAL RADIOS

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ABSTRACT

Location awareness creates a new paradigm for distributing scalable multimedia data over wireless networks, enabling a variety of context-aware applications that require precise location information of network nodes. An emerging concept for robust and accurate network localization is to exploit *cooperation* and *heterogeneous design* for harnessing multimodal fusion of sensing measurements to extract location information. This article gives a brief introduction to vision- and radio-based positioning technologies, and then presents illustrative machine-learning methodology to successfully integrate vision information and radio time-of-arrival measurements for cooperative localization of ultra-wideband visual radios in harsh indoor environments.

INTRODUCTION

With rapid pervasion of smart mobile devices as well as substantial advances in wireless technologies, everyone nowadays is able to create and distribute multimedia content over wireless networks. Since such smart devices integrate GPS, WiFi, mobile Internet, and/or cameras inside, robust and accurate localization ignites a new era of ubiquitous location awareness with the ability to operate in harsh GPS-denied environments, enabling a variety of commercial, military, social, and public service applications. In particular, visual networks are expected to play an important role in facilitating a new family of applications such as security, surveillance, target localization, and tracking [1].

Vision information enables the self- and target localization alternative to radio-based solutions [2–8]. Since imaging sensors and cameras capture directly unique features of targets as a type of image, vision localization provides high accuracy in inferring position information. However, imaging devices usually require large energy and bandwidth resources as well as high computational capability for real-time image processing. In addition, geometric constraints induced by the projective nature of cameras have a direct impact on designing distributed algorithms for object detection, tracking, and recognition [4]. Therefore, it is crucial to exploit cooperation and heterogeneous design for robust and accurate localization in visual networks [5–8].

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Wireless localization is an effective and low-cost approach to determining the locations of network nodes in both outdoor and indoor environments due to the availability of diverse wireless infrastructures and devices, such as GPS, cellular networks, wireless local area networks (WLANs), ultrawide bandwidth (UWB) radios, radio frequency identification (RFID), and Bluetooth [9, 10]. Cooperation between network nodes can significantly improve localization accuracy as well as increase localization coverage [11, 12]. However, suffering from the impacts of radio propagation characteristics on the communication range and quality of measurements, wireless localization is subject to some fundamental limits in its precision and coverage without changing a network topology. Since visual ability provides more precise information for learning about locations as well as radio propagation conditions such as line of sight (LOS) or non-LOS (NLOS), heterogeneous design of vision- and radio-based positioning is highly promising for robust and accurate localization in harsh indoor environments. In this article, an illustrative machine-learning approach is presented to successfully integrate vision information and UWB time-of-arrival (TOA) measurements for cooperative localization.

VISION INFORMATION FOR LOCALIZATION

In a visual network, imaging sensors or cameras provide computer-vision information of a three-dimensional (3D) scene as a type of image or video. Measurements of 3D coordinates of points or distances from two-dimensional (2D) images can be used for various applications in visual networks such as security, surveillance, target localization, and tracking.

COORDINATE TRANSFORMATIONS

The *perspective projection* or central projection describes the mapping of a scene in 3D world coordinates onto a 2D image plane. As illustrated in Fig. 1, a linear perspective camera performs the central projection where the projective transformation consists of three sub-transformations between four different coordinate systems as follows.

World to Camera — The world coordinates can be transformed into camera coordinates by a rotation matrix $\mathbf{R}$ and a translation vector $\mathbf{t}$. The quantities $\mathbf{R}$ and $\mathbf{t}$ are called *extrinsic camera cal-*

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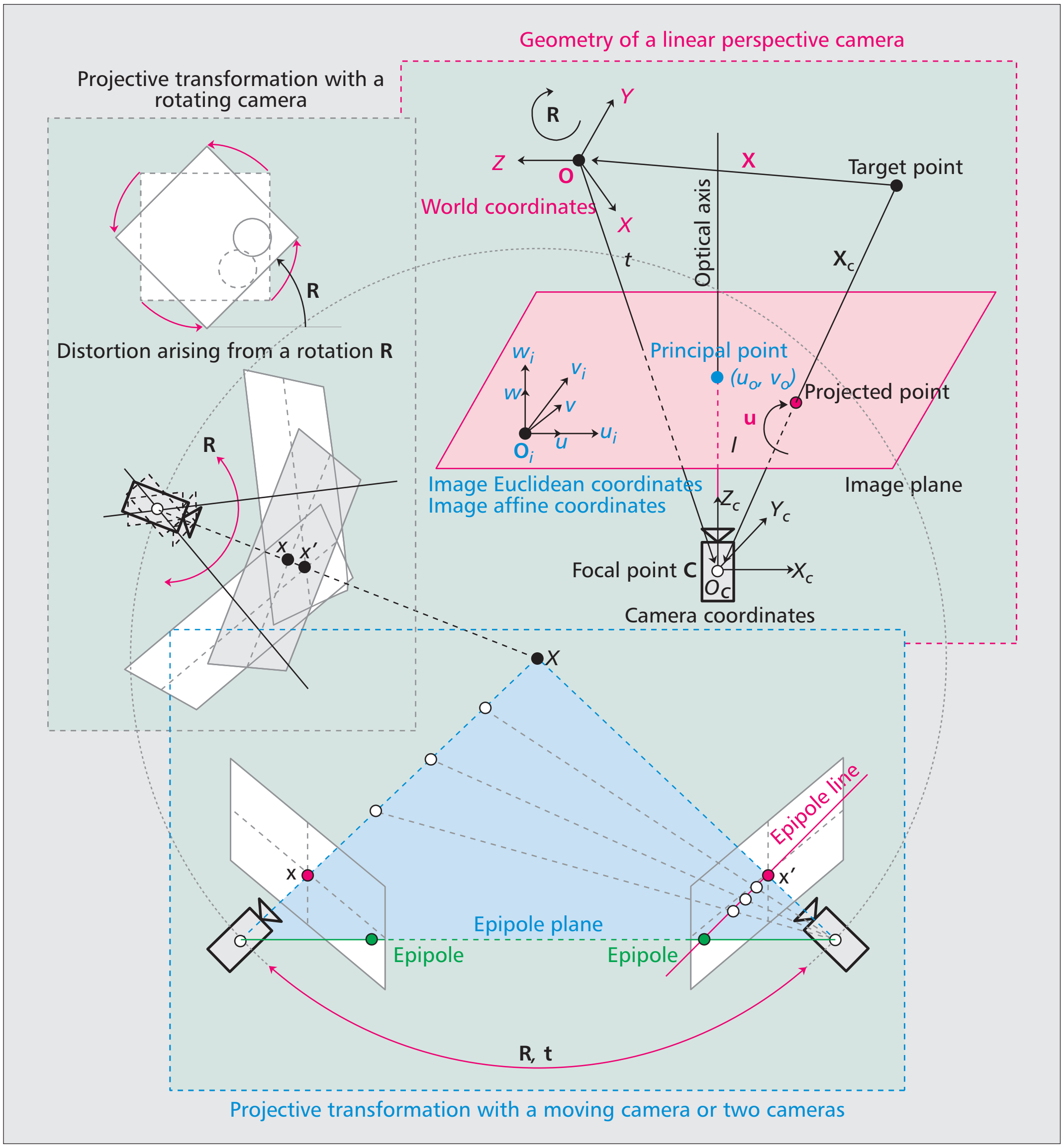

Figure 1. Projective geometry and transformations of a camera.

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ibration parameters, which describe the orientation and position of the camera in the world coordinates and transform the point $\mathbf{X}$ to the point $\mathbf{X}_c$ in the camera coordinate system.

***Camera to Image Euclidean* —** This transformation projects the 3D target point $\mathbf{X}_c$ in the camera coordinates to the point $\mathbf{u}_i$ in the image Euclidean coordinate system. The projection scales 3D camera coordinate points by the camera focal length ℓ, which is the distance from the origin $\mathbf{O}_c$ of camera coordinates to the image plane along the optical axis.

***Image Euclidean to Image Affine* —** The 2D image coordinate point $\mathbf{u}_i$ is transformed to the point $\mathbf{u}$ in the image affine (homogeneous) coordinates. This transformation can be characterized by the intrinsic calibration matrix containing *five intrinsic camera calibration parameters*: two scaling parameters f and g along the u and v axes, which are often equal to the focal length; the shear parameter s, which gives the degree of shear of the coordinate axes in the image plane; and the principal points u_o and v_o.

In the homogeneous image plane, the perspective projection can be written in a linear transformation

$$\mathbf{u} \simeq \begin{bmatrix} f & s & -u_o \\ 0 & g & -v_o \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \ell & 0 & 0 & 0 \\ 0 & \ell & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{R} & -\mathbf{Rt} \\ 0^T & 1 \end{bmatrix} \mathbf{X} = \mathbf{PX}$$

where $\mathbf{P}$ is the *projection matrix* and T denotes transpose.

Camera Calibration and Self-Localization

The *camera calibration* — also called camera resectioning — is the process of retrieving information on intrinsic and extrinsic parameters of a camera to estimate the camera projection matrix

Localization accuracy can be further enhanced by cooperating with other nodes in the network. Some applications of wireless localization can be listed as location-based cellular services, search-and-rescue operations, solder tracking, animal tracking, logistics, and patient treatment.

P from a set of feature point correspondences among the camera images [2–4]. The projection matrix gives the position and orientation information of the camera in the world coordinates defined by scene geometry. Accurate estimation of the projection matrix enables the camera to self-localize and provides simple alignment of all cameras to the same coordinate frame in the network. Therefore, an object seen by a camera with multiview images or by pairs of cameras with overlapped fields of view (FOVs) is autonomously localizable [4].

Calibration with One Camera — The epipolar structure can be made using two images taken from different views with a moving camera (Fig. 1). However, this implementation is often unreliable since the camera movement causes occlusion, aspect changes, and/or lighting changes. On the other hand, some work suggests self-calibration with multiple views of a rotating camera at a fixed location.

Calibration with Two Cameras — Classical calibration of two cameras usually requires a set of feature point correspondences in stereo vision as well as the detection of high-quality features. If there are no known 3D locations in the world coordinates, the two cameras can be calibrated up to a similarity transformation. In this case, the *relative* positions and orientations of both cameras can be estimated. For example, when the intrinsic camera parameters of each camera are known, the epipolar geometry between two cameras can be used to extract estimates of the rotation and translation between each camera pair.

Network Calibration with More than Two Cameras — The objective of network camera calibration is to estimate calibration parameters for each camera with cooperation of more than two cameras. The camera network can be modeled as two undirected graphs: a *communication graph* and a *vision graph*. The communication graph is determined by the camera locations and communication topology. Using communication protocols, all cameras share their calibration parameters for cooperation. An edge of the vision graph appears between two cameras that have overlapped FOVs from different perspectives. The belief propagation algorithm on these graphs enables network camera calibration in a distributed manner [3].

Target Localization and Tracking

Object localization and tracking is a common task for a variety of applications of visual sensor or camera networks where the use of vision information relies strongly on the ability of imaging devices to acquire accurate location information within the least amount of time [4, 5]. Such real-time image processing and sensing require high computational capability and energy consumption. Since visual sensors are in general resource- and energy-limited, the use of imaging is restricted, especially in ad hoc networks, and multiview localization and tracking algorithms aim to optimize a trade-off between the network energy consumption and the quality of self- and/or target localization. To circumvent these limitations, a combination of heterogeneous measurements is attractive for localization (e.g., see [5]).

The basic methods for target localization and tracking exploit the correlation between multiview images with areas of overlapped FOVs, where intersections are created from back projection in order to localize all the individual targets. To remove the uncertainty about target existence at the intersections, the inverse approach with a progressive certainty map shrinks the uncertain regions as local certainty maps are fused [6]. While the use of multiple cameras improves the reliability of multiview localization and tracking, the communication overload also increases with the number of active cameras. Therefore, under the constraints of resource and energy, it is crucial to balance the trade-off between localization accuracy and resource/energy consumption [7, 8].

Wireless Localization

Wireless localization is to determine the locations of network nodes or agents with efficient and low-cost implementation [9, 10]. In outdoor environments, agent nodes can infer their positions with the aid of cellular base stations or GPS, because their communication range is typically large enough to cover most outdoor locations. In indoor environments, the availability of access points or anchors with known positions enables the agent nodes to estimate their locations using a variety of localization algorithms. With some scale of radio propagation coverage, the agents in a wireless network are localizable for any complicated terrains. Localization accuracy can be further enhanced by cooperating with other nodes in the network [11, 12]. Some applications of wireless localization can be listed as location-based cellular services, search-and-rescue operations, solder tracking, animal tracking, logistics, and patient treatment.

Challenges

Wireless localization suffers uncertainty due to random phenomena of radio propagations such as path loss, multipath fading, and shadowing. In addition, the signal is also corrupted at the receiver by additive noise, interference, and a clock drift. These impairments cause undesirable errors in measuring distances, angles, phases, or received signal strength (RSS). UWB radios are highlighted to overcome these drawbacks due to such beneficial characteristics as obstacle passing, fine delay resolution, and robust signaling [13]. However, NLOS propagations still limit high-accuracy location awareness. Furthermore, since a general localization problem is typically nonconvex, it is still open and challenging to develop its optimal solution as well as efficient and economical deployment of a localization network.

Measurement Techniques

In a measurement phase, network nodes exchange packets to retrieve information necessary for localization such as the RSS, distance, angle, velocity, acceleration, and/or orientation. This information can be extracted from the received waveforms by observing one or more signal metrics. The localization accuracy depends highly on the quality of measurements, which are typically classified into three types: range-, direction-, and proximity-based measurements [12]. Time- or RSS-based ranging is commonly used in wireless positioning systems due to its simplicity and low cost, whereas angle of arrival (AOA) is often used for direction-based localization; and internal measurements such as velocity, acceleration, and orientation are used for proximity-based localization.

Time-Based Ranging — TOA, time difference of arrival (TDOA), and round-trip time of arrival (RTOA) are three types of time metrics for ranging, which rely on the time of flight (one-way or rough-trip) from node (node A) to node (node B) to estimate their pairwise distance. In particular, the RTOA is more practical since the time synchronization between nodes is not essential. In this case, node A requires only to know the RTOA and the processing time at node B without time synchronization to infer the distance from node B. Since the range estimation in NLOS environments produces a positive bias that causes significant localization errors, identification and mitigation of NLOS signals are essential to partially remove this detrimental effect on localization accuracy. One of the effective ways to reduce this impact is to use machine learning approaches (e.g., neural networks and sparse kernel machines [14]) for identifying NLOS signals with classifiers and mitigating them with regressors [15].

RSS-Based Ranging — The distance between nodes can also be estimated by exploiting RSS measurements and a path-loss model such that $\mathrm{RSS} = \mathrm{RSS}_0 - 10\alpha\log_{10}d_{\mathrm{AB}} + X$, where RSS_0 is the RSS value at 1 m, α is the power path-loss exponent, d_{AB} is the distance between nodes A and B, and X is the shadowing variable. The RSS ranging often has a larger error than time-based ranging due to the random shadowing effect as well as the path-loss mismatch. Therefore, a robust range-free technique, called *fingerprinting*, has been proposed to improve the localization accuracy using the concept of radio (RSS) maps. The drawback of this method is high dependence on specific localization geometry and the number of reference points.

Localization Algorithms

Using measurement information, agent nodes self-localize or cooperate with other agents to estimate their locations. Localization algorithms can be formularized as estimation, optimization, and/or machine learning problems, depending on node behavior and the amount of prior information. The localization algorithms can be classified into taxonomy as follows [11].

Centralized vs. Distributed — In a centralized algorithm, measurement information gathered in the first phase at agents is sent to a central processor where all the locations of agents are determined and fed back to each agent. Due to high traffic and burden at the central processor, this approach is only attractive for small-scale localization networks. In a distributed algorithm, each agent self-computes its position using locally collected information. This approach is scalable to large localization networks.

Absolute vs. Relative — Absolute localization uses a single predetermined coordinate system, while relative localization uses a specific coordinate system for each node in the context of its neighbors or local environment.

Noncooperative vs. Cooperative — In a noncooperative algorithm, agents only communicate with anchors to get information for localization. For 2D positioning, each agent must be connected with at least three anchors. In cooperative localization, agents can communicate with both anchors and other agents in order to reduce the limitations of peer-to-peer localization. Since more information is gathered in this mode, cooperative algorithms can improve localization accuracy and coverage.

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Wireless Localization Systems

Wireless localization can be enabled by using available wireless network infrastructures such as GPS, cellular, and WLAN, or designing a new infrastructure according to the localization geometry and criteria [9]. Some common localization systems for both indoors and outdoors are as follows.

GPS — The GPS is a global positioning system that uses 24 satellites to cover anywhere on or near the Earth by at least four satellites. This is currently the most robust and efficient positioning system in outdoor environments. In good conditions, GPS-based systems can achieve the accuracy up to 5–50 m. However, the localization accuracy is dramatically degraded in indoor environments where GPS signals are very unreliable due to attenuation or blockage by obstacles. In this situation, assisted-GPS (A-GPS) positioning improves the quality of indoor GPS-based localization by combining GPS signals and assistance information from an A-GPS server through a wireless mobile network.

Cellular — Cellular networks such as Global System for Mobile Communications (GSM), code-division multiple access (CDMA), and Long Term Evolution (LTE) and LTE-Advanced can be used to find the locations of mobile clients. By using Cell-ID or Enhance Observed Time Difference (E-OTD), a mobile user can estimate its location within accuracy of 50–200 m if the cell deployment is dense. In indoor environments, wide RSS fingerprinting is a robust method to enhance the localization accuracy.

UWB — The UWB technology uses ultrashort-pulse signals with a high relative bandwidth more than 20 percent or a large absolute bandwidth more than 500 MHz. Due to very large bandwidths, UWB signals can provide high time resolution and facilitate accurate ranging. In addition, UWB radios produce little interference to other systems since they operate at a very low transmission power and convey information over a large spectrum. Therefore, UWB TOA-based

Since most mobile devices are equipped with WiFi cards and most indoor spaces are covered by WiFi access points, it becomes easier and more practical than ever to localize agent nodes using WLAN infrastructures. The WLAN utilizes two common radio-frequency (RF) bands of 2.4 GHz and 5 GHz with coverage of 50–100 m.

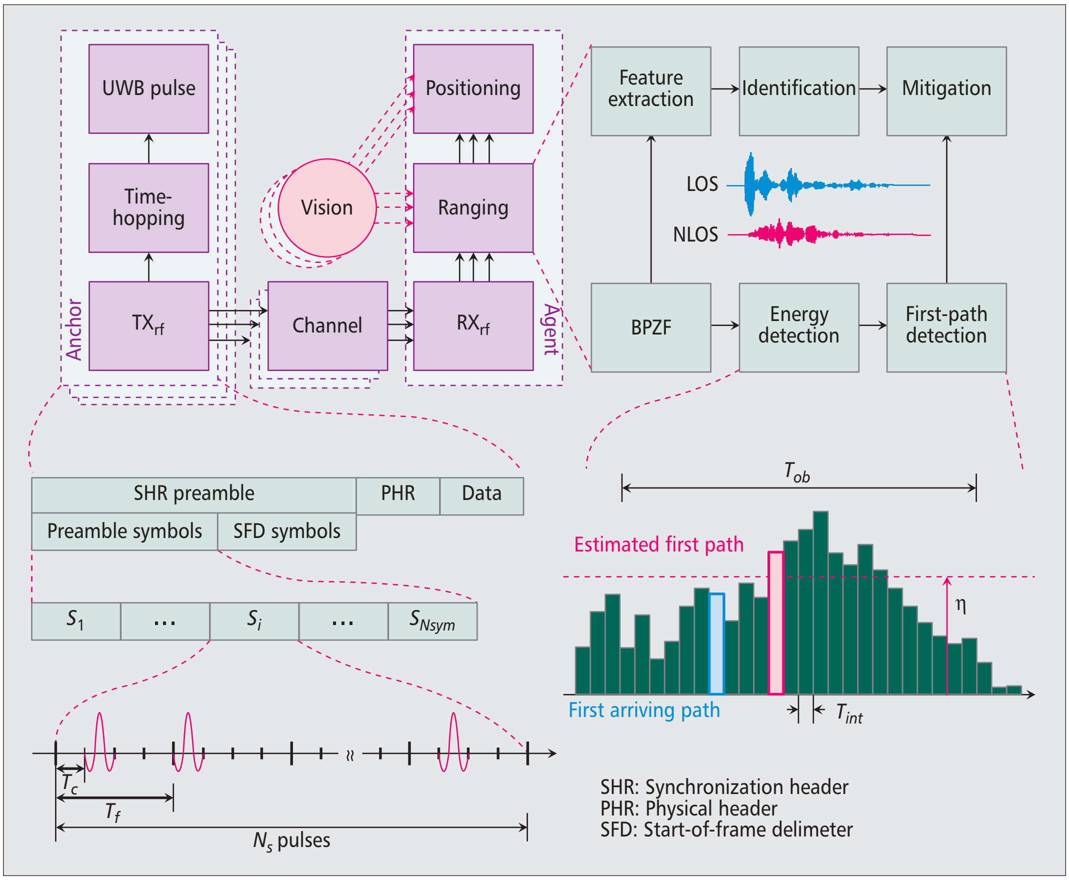

Figure 2. An IEEE 802.15.4-2011 standard-compliant UWB TOA positioning system with vision information.

positioning is attractive for indoor LOS environments, achieving high accuracy of less than 1 m.

WLAN — Since most mobile devices are equipped with WiFi cards and most indoor spaces are covered by WiFi access points, it becomes easier and more practical than ever to localize agent nodes using WLAN infrastructures. A WLAN utilizes two common RF bands of 2.4 GHz and 5 GHz with coverage of 50–100 m. Typically, WLAN RSS-based positioning can achieve the accuracy of 3–30 m, which can be improved by RSS fingerprinting methods.

RFID and Bluetooth — In indoor environments, RFID or Bluetooth signals can also be used to localize devices [9]. In RFID-based localization, RFID tags and readers play a role as anchors and agents, respectively. The coverage of RFID tags is 1–10 m, and the localization accuracy can gain around 1 m, while the coverage of Bluetooth signals is 10–15 m, and the localization error is within 2 m with 95 percent reliability.

Visual Radio Localization

In this section, heterogeneous design of vision- and radio-based positioning is illustrated for robust and accurate network localization in GPS-denied environments. Specifically, a machine-learning approach is used to integrate vision information and UWB TOA measurements where:

- The support vector machine (SVM) classifier/regressor identifies/mitigates NLOS propagations in UWB TOA-based ranging [15].
- The variational message passing (VMP) algorithm implements cooperative localization [14].

IEEE 802.15.4-2011 UWB Visual Radios

Figure 2 shows an IEEE 802.15.4-2011 standard-compliant UWB TOA positioning system where an agent node receives LOS or NLOS signals from a set of anchors knowing their positions a priori, and is capable of imaging objects in LOS conditions or self-localizing through the calibration process if it sees more than one anchor or vision-localized node (*virtual* anchor). When the agent is not vision-localizable, the received waveforms from anchors are first passed through a bandpass zonal filter (BPZF) with center frequency f_0 and bandwidth W to extract features for NLOS identification with vision information. Then the agent estimates TOA with energy detection (ED) for NLOS mitigation, ranging, and positioning. The UWB ranging is set up as in [13] with the following parameters:

- Carrier frequency (f_0): 4492.8 MHz
- Pulse bandwidth (W): 499.2 MHz
- Roll-off factor of root-raised cosine pulse shaping (ν): 0.6
- Pulse width (τ_p): 3.2 ns
- Chip duration (T_c): 4 ns
- Frame duration (T_f): 128 ns
- Noise spectral density: –198.93 dBW/Hz
- Integration time (T_{int}): 2 ns

- TOA search window (T_{ob}): 120 ns
- ED threshold (η): 34.19 dBJ
- The number of pulses per symbol (N_s): 4
- The number of preamble symbols (N_{sym}): 400
- Path loss at 1 m: LOS 43.80 dB, NLOS 48.22 dB
- Path loss exponent: LOS 1.49, NLOS 2.92
- Shadowing spread: LOS 1.15 dB, NLOS 5.12 dB
- Power delay profile: IEEE 802.15.4a CM3 (LOS), CM4 (NLOS)
- Small-scale fading: IEEE 802.15.4a CM3 (LOS), CM4 (NLOS)
- Received SNR at 1 m: LOS 56.8 dB, NLOS 52.47 dB
- Communication range: 20 m

In the presence of imaging devices at agents, vision information becomes useful to reduce NLOS identification errors, leading to decreasing errors in NLOS mitigation. In addition, two vision sources of anchors with known positions enable the agent to self-localize with high accuracy. In this article, the root mean square error (RMSE) of position errors for vision localization is chosen to 0.209 m [3, Table 2].

Ranging: SVM NLOS Identification and Mitigation

Identification and mitigation of NLOS signals are realized by SVM classifiers and regressors using 200 LOS and 200 NLOS realizations for training, and 10^5 LOS and 10^5 NLOS realization for testing. The distances are generated at random between 1 and 20 m. The received energy $\mathcal{E}_{rx}$ and the kurtosis κ of the received waveform are chosen as two features for SVM classification, while the TOA ranging estimate is selected as a feature for SVM regression [15]. To reduce identification errors, vision information is fused as a feature for the SVM classifier, where an agent's camera is assumed to detect anchors or agents in LOS conditions at 95 percent accuracy with ignoring false alarms. As shown in Table 1, the vision information improves the SVM classification performance in terms of both accuracy and complexity: it reduces the identification error from 2.27 to 0.48 percent and the number of support vectors (SVs) from 56 to 19.

SVM classifier					
Feature set	Error	Number of SVs	Feature set	Error	Number of SVs
$\{\mathcal{E}_{rx}\}$	7.17 %	242	$\{\mathcal{E}_{rx}$,Vision $\}$	2.75 %	60
$\{\mathcal{E}_{rx},\kappa\}$	2.27 %	56	$\{\mathcal{E}_{rx},\kappa$,Vision$\}$	0.48 %	19

Table 1. Misidentification and sparsity of SVM classifiers for NLOS identification.

Figure 3 shows the SVM NLOS identification, mitigation, and range RMSE for UWB TOA-based ranging. For the feature set $\{\mathcal{E}_{rx}, \kappa, \text{Vision}\}$, two boundaries are established to classify LOS and NLOS signals depending on the vision feature, whereas only a single boundary exists for the feature set $\{\mathcal{E}_{rx}, \kappa\}$, as depicted in Fig. 3a. The accuracy of NLOS identification with vision information improves, in turn, the quality of NLOS mitigation, and hence reduces the range RMSE, as shown in Fig. 3c, where the range RMSE is depicted as a function of the NLOS probability for no mitigation, SVM mitigation with only radio features, and SVM mitigation with both radio and vision features. A machine learning approach typically consists of two phases for wireless applications: *training* (offline) and *testing* (online). In the training phase, offline data collected for a system setup are used to determine the learning parameters (e.g., weighting vectors for the SVM classifier and regressor). Then these parameters are used to identify or mitigate NLOS signals for testing in the online phase (real-time operation). Therefore, the computational complexity involved in machine learning tasks for NLOS identification and mitigation depends mainly on the training procedure for the learning model setup. One of the more typical examples is a fingerprinting technique for localization.

Vision-Enhanced Wireless Localization

Figure 4a shows a floor plan for a localization network to demonstrate a potential gain in vision-radio fusion to improve localization accuracy, where four anchors A, B, C, and D are located at (–12,5), (–12,–5), (0,0), and (17,5), respectively.

A Noncooperative Solution — Agents that receive UWB signals from at least three anchors are localizable by a trilateration algorithm with TOA ranging. In particular, agents that have vision detection of at least two anchors are vision-localizable with position RMSE of 0.209 m (uniform position errors at the mean of true locations). Hence, without cooperation between agents, an agent located in the shadowed region of Fig.4a is nonlocalizable due to deficiency of anchors within its visible region as well as its 20 m radio communication range. Figures 4b and 4c show the contour plots of position RMSE and outage probability at 2 m position accuracy in the localizable region for no mitigation, SVM mitigation with only radio features, and SVM mitigation with both radio and vision features.

A Cooperative VMP Solution — Since vision-localizable agents can play a role as *virtual* anchors due to their precise self-localization, the vision-radio fusion for localization accuracy and robustness is more attractive in a cooperative localization network. To demonstrate this gain, 10 agents, 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10, are deployed at (–12,0), (–5,0), (–5,–5), (5,0), (2,5), (10,5), (10,–5), (15,0), (25,5), (25,0), respectively, in the floor plan with four anchors in Fig. 4a. In this scenario, agent 1 is self-localizable with vision information of anchors B and C. Then agents 2, 4, 8, and 10 are successively vision-localized with vision information of anchor C and other self-localized agents. Agents 3, 5, 6, 7, and 9 can only localize by wireless cooperation with anchors and neighboring agents. In this example, the VMP algorithm realizes a cooperative process to infer the location information in a distributed manner.

Figure 5 shows the localization performance of the aforementioned cooperative localization

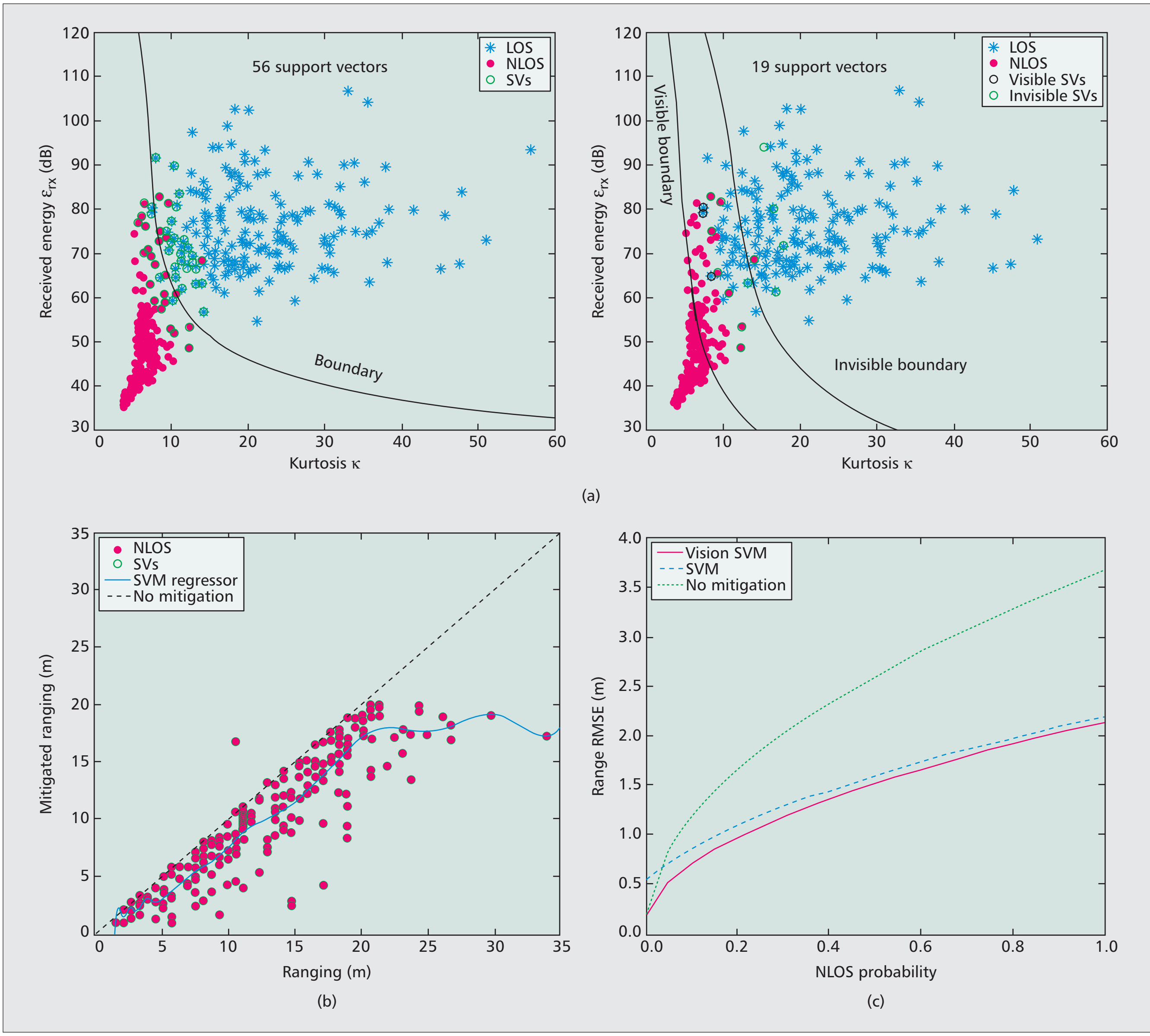

Figure 3. SVM NLOS identification, mitigation, and range RMSE for UWB TOA-based ranging: a) SVM classifier; b) SVM regressor; c) range RMSE as a function of NLOS probability.

network with four anchors and 10 agents, where the cumulative distribution function (CDF) of the average network position error and outage probability at 2 m position accuracy for each agent are depicted in Figs. 5a and 5b, respectively. This example demonstrates that the cooperation between network nodes and the heterogeneity in multimodal sensing constitute an efficient solution to overcome the fundamental limitations of wireless localization systems.

Remarks and Open Research Challenges

Cooperative and heterogeneous design of network localization is a promising solution for location-aware services in wireless multimedia networks. In visual radio systems, vision information can be integrated with radio measurements to enhance localization accuracy, coverage, and robustness. The illustrative examples have demonstrated that vision-radio fusion substantially increases machine-learning accuracy in SVM classification/regression for NLOS identification/mitigation and VMP implementation for distributed cooperative localization. This study also opens a variety of interesting but challenging directions for future work, for example:

- Experimental work on location-aware visual radios to verify fusion advantages for localization
- Design with effective processing of vision information and radio measurements for localization
- Practical issues of visual devices in localization such as sensitivity, resolution, and detection capability
- Design with robust sparse kernel machines such as relevance vector machines

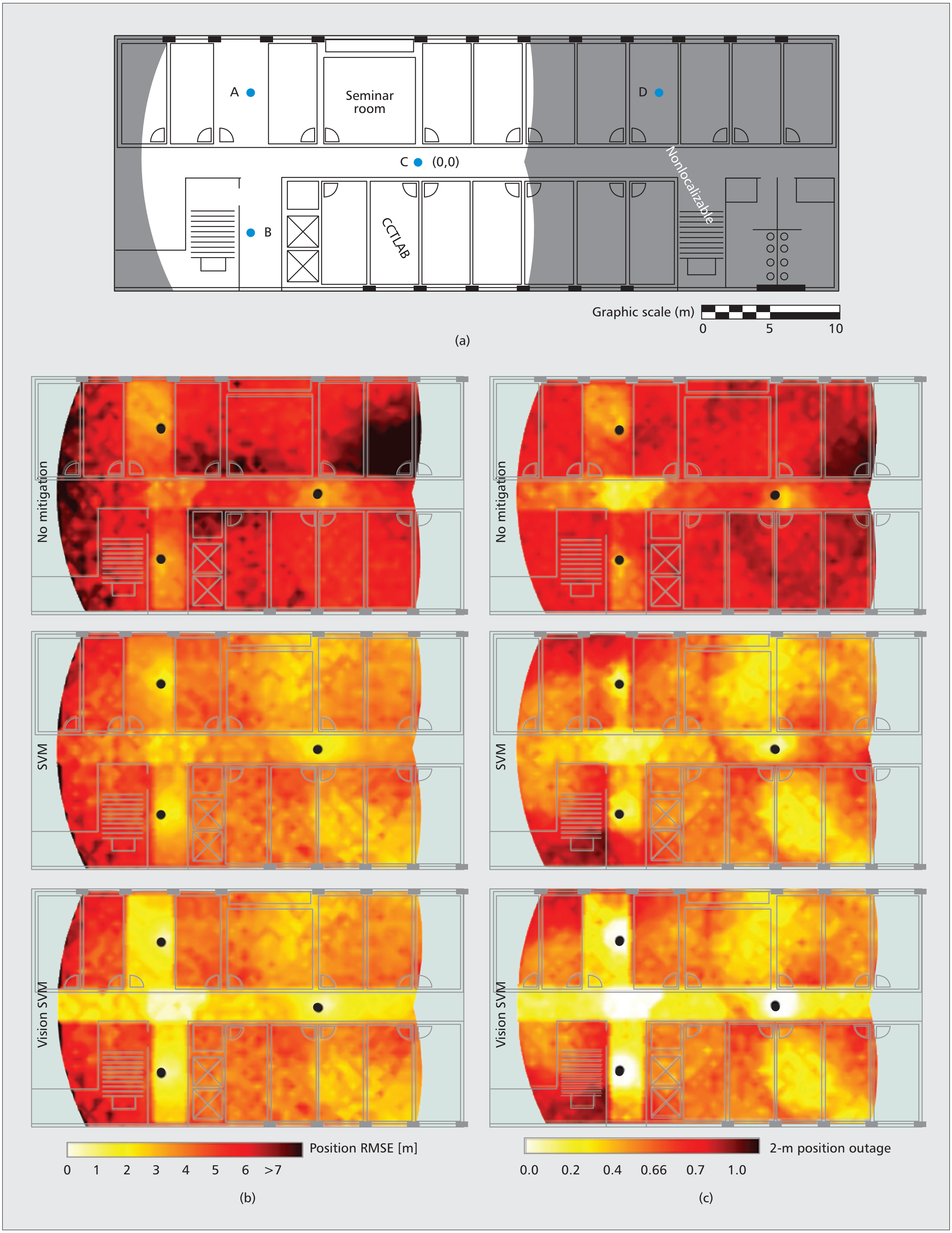

Figure 4. A noncooperative localization network: a) a floor plan; b) position RMSE; c) outage probability at 2 m position accuracy.

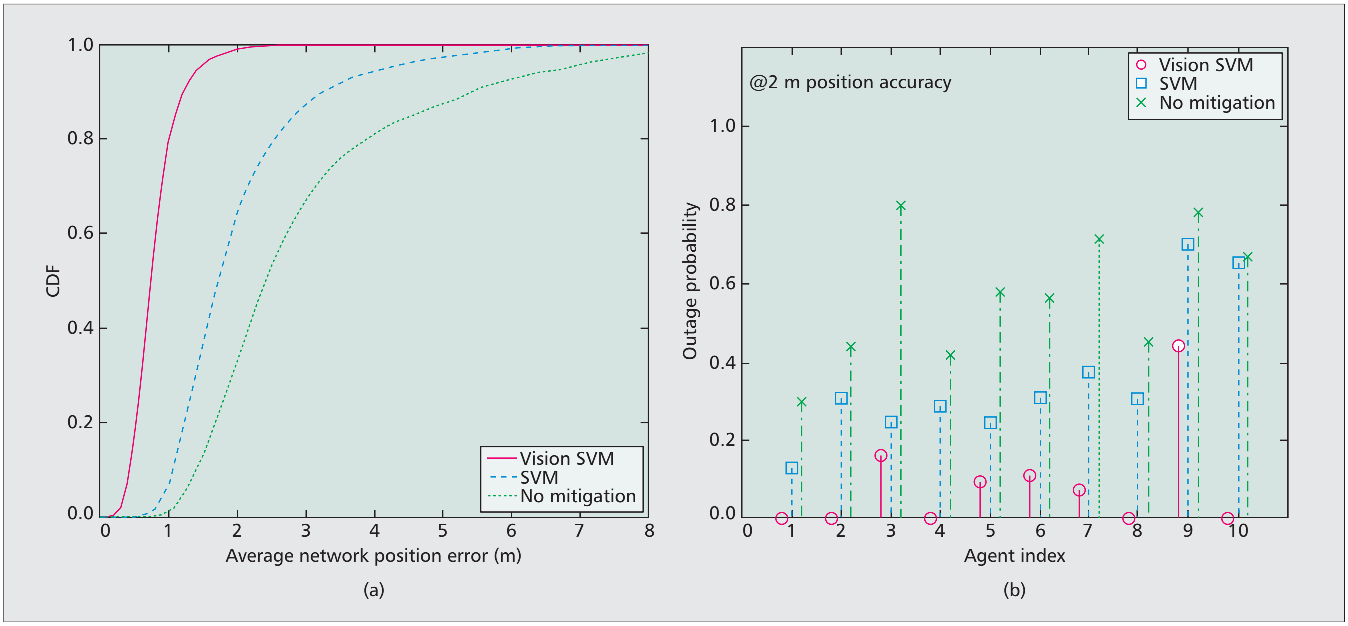

Figure 5. A cooperative localization network: a) CDF of average network position error; b) outage probability at 2 m position accuracy.

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