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Jing Yan
Haiyan Zhao
Yuan Meng
Xinping Guan

Localization in Underwater Sensor Networks

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Jing Yan • Haiyan Zhao • Yuan Meng •
Xinping Guan

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Jing Yan
Institute of Electrical Engineering
Yanshan University
Qinhuangdao
Hebei, China

Haiyan Zhao
Institute of Electrical Engineering
Yanshan University
Qinhuangdao
Hebei, China

Yuan Meng
Institute of Electrical Engineering
Yanshan University
Qinhuangdao
Hebei, China

Xinping Guan
Department of Automation
Shanghai Jiao Tong University
Shanghai, China

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Preface

The ocean covers 70.8% of the Earth's surface, and it plays a significant role in supporting the system of life on Earth. Nevertheless, more than 80% of the ocean's volume remains unmapped, unobserved, and unexplored. With regard to this, underwater sensor networks (USNs), which incorporate ubiquitous computation, efficient communication, and reliable control, have emerged as a promising solution to understand and explore the ocean. The deployment of USNs can enhance the monitoring capacity for various applications such as intrusion surveillance, marine resource protection, navigation, geographic mapping, and petroleum exploration. In order to support these applications, accurate location information of sensor nodes is required for correctly analyzing and interpreting the sampled data. However, the openness and weak communication characteristics of USNs make underwater localization much more challenging as compared with the terrestrial sensor networks.

In this book, we focus on the localization problem of USNs with consideration of the unique characteristics of USNs. The localization problem is of great necessary and importance since fundamental guidance on design and analysis on the localization of USNs is very limited at present. We first introduce the network architecture and briefly review the prior arts in localization of USNs. Then, we consider the asynchronous clock and node mobility during the localization procedure, through which a mobility prediction-based least squares estimator is developed to seek the locations of sensor nodes. Note that the first-order linearization is required for least squares estimator to calculate the Jacobian matrix; however, it can introduce large model errors. In view of this, we further design a consensus-based unscented Kalman filtering (UKF) localization estimator to relax the linearization requirement and improve the localization accuracy. In addition, we also employ the reinforcement learning (RL) to relax the linearization requirement and avoid the local minimum during the least squares-based localization procedure, such that an RL-based localization algorithm is provided. Besides that, we investigate the privacy-preserving localization issue for USNs. To this end, three privacy-preserving localization protocols are designed to hide the position information of reference nodes. Accordingly, the least squares and deep reinforcement learning (DRL) based localization estimators are developed, respectively, to jointly achieve privacy preservation, asynchronous localization, and stratification compensation for USNs. Finally, rich implications from the book provide guidance on the design for future localization schemes on USNs.

The results in this book reveal from the system perspective that the underwater localization accuracy is closely related to the communication protocol and optimization estimator. Researchers, scientists, and engineers in the field of USNs can benefit a lot from this book. As such, the valuable knowledge, useful methods, and practical algorithms can provide the guidance on understanding and exploring the ocean. To use this book for underwater applications, knowledge of wireless communication and signal processing is needed.

The book is organized as follows.

Chapter 1 provides the network architecture of USNs and briefly reviews the prior arts in localization of USNs. Besides that, the weak communication characteristics of USNs, including asynchronous clock, stratification effect, and node mobility, are also summarized in this chapter.

Chapter 2 considers the asynchronous clock and node mobility. A hybrid network architecture including autonomous underwater vehicles as well as active and passive sensor nodes is constructed. Then, an asynchronous localization solution with mobility prediction is developed for USNs, where iterative least squares estimators are conducted to seek the position information.

Chapter 3 presents a consensus-based UKF localization algorithm. Compared with the results in Chap. 2, the stratification effect is incorporated into the developed localization protocol in this chapter, and more importantly, the model error can be significantly reduced since the first-order linearization is not required by the localization algorithm in Chap. 3.

Chapter 4 covers an RL-based localization algorithm for USNs in weak communication channel. Note that the least squares-related localization estimators are adopted in Chaps. 2 and 3. However, the least squares-related estimators can easily fall into local minimum. In view of this, Chap. 4 employs the RL to seek the global optimization localization solution.

Chapters 2–4 assume the monitoring area is safe and the position privacy is ignored. However, USNs are usually deployed in open environment, and it is necessary to utilize the information-hiding technology to develop a privacy-preserving localization protocol for USNs. In view of this, Chap. 5 presents a privacy-preserving solution for the asynchronous localization of USNs, in which the asynchronous clock and node mobility are also considered.

Chapter 6 further considers the stratification effect and the forging attack in underwater environment, through which a privacy-preserving localization estimator is developed for USNs. It is worth mentioning that the malicious attacks can be detected and the straight-line localization bias can be compensated in this chapter, which are not available in Chap. 5.

Chapters 5–6 employ the least squares-based estimators to seek the position information of sensor nodes, which can easily fall into local minimum. In order to solve this issue, Chap. 7 develops DRL-based privacy-preserving localization protocol and estimator for USNs. Per knowledge of the authors, this is the first work that incorporates DRL and stratification compensation into the privacy-preservation localization of USNs.

Chapter 8 provides the future research direction on the localization of USNs. We have tried to provide complete instructions for the underwater localization and meanwhile share insights into the underwater localization from the system perspective. We hope this book has reached our goal.

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Qinhuangdao, China Jing Yan
Qinhuangdao, China Haiyan Zhao
Qinhuangdao, China Yuan Meng
Shanghai, China Xinping Guan
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About the Authors

Jing Yan received his B.Eng. degree in automation from Henan University, Kaifeng, China, in 2008, and his Ph.D. degree in control theory and control engineering from Yanshan University, Qinhuangdao, China, in 2014. In 2014, he was a research assistant with the Key Laboratory of System Control and Information Processing, Ministry of Education, Shanghai Jiao Tong University, Shanghai, China. From January 2016 to September 2016, he was a postdoc at University of North Texas, Denton, USA. From October 2016 to January 2017, he was a research associate at University of Texas at Arlington, Arlington, USA. Currently, he is a full professor at Yanshan University, Qinhuangdao, China. Meanwhile, he is also an associate editor for IEEE Access. His research interests cover underwater acoustic sensor networks, networked teleoperation systems, and cyber-physical systems. He has published more than 80 peer-reviewed papers in leading academic journals and conferences. He has also received numerous awards, including the Excellence Paper Award from the National Doctoral Academic Forum of System Control and Information Processing in 2012, the Outstanding Doctorate Dissertation of Hebei Province in 2015, the Excellence Paper Award from the National Doctoral Academic Forum of System Control and Information Processing in 2012, the Youth Talent Support Program of Hebei Province in 2019, the Outstanding Young Foundation of Hebei Province in 2020, and the Excellence Adviser from Oceanology International Underwater Robot Competition in 2017.

Haiyan Zhao received her B.S. degree in automation from Yanshan University in 2017. Currently, she is pursuing her Ph.D. degree in control theory and control engineering at Yanshan University, Qinhuangdao, China. Her research interests cover in underwater acoustic sensor networks and autonomous underwater vehicle. She won the national scholarship in 2019 and presided over Postgraduate Innovation Fund Project of Hebei in 2019.

Yuan Meng received her B.S. degree in measurement and control technology and Instruments from Liaoning Technical University, Huludao, China, in 2019.

Currently, she is pursuing her Ph.D. degree in control theory and control engineering at Yanshan University, Qinhuangdao, China. Her research interests include localization of underwater sensor networks and networked underwater robot control. Besides that, she won the national scholarship in 2021 and presided over Postgraduate Innovation Fund Project of Hebei in 2021.

Xinping Guan received his B.S. degree in applied mathematics from Harbin Normal University, Harbin, China, in 1986, and his M.S. degree in applied mathematics as well as Ph.D. degree in electrical engineering from the Harbin Institute of Technology, Harbin, in 1991 and 1999, respectively. He is currently a chair professor at Shanghai Jiao Tong University, Shanghai, China. He has authored and/or co-authored four research monographs, more than 270 papers in IEEE and other peer-reviewed journals, and numerous conference papers. His current research interests include industrial cyber-physical systems, wireless networking and applications in smart city and smart factory, and underwater sensor networks. Dr. Guan was a recipient of the National Outstanding Youth Honored by the NSF of China, the Changjiang Scholar by the Ministry of Education of China, and the State-Level Scholar of New Century Bai Qianwan Talent Program of China. He is an executive committee member of the Chinese Automation Association Council and the Chinese Artificial Intelligence Association Council.

Acronyms

AOA	Angle of arrival
AUVs	Autonomous underwater vehicles
CRLB	Cramér-Rao lower bound
DRL	Deep reinforcement learning
DVL	Doppler velocity log
FOG	Fiber optic gyroscope
GPS	Global positioning system
HAPs	High-altitude platforms
LBL	Long-baseline
LS	Least squares
ML	Maximum likelihood
PPDP	Privacy-preserving diagonal product
PPS	Privacy-preserving summation
RF	Radio frequency
RL	Reinforcement learning
RMSE	Root mean square error
RSS	Received signal strength
SBL	Short-baseline
TDOA	Time difference of arrival
TOA	Time of arrival
TOF	Time of flight
UAVs	Unmanned aerial vehicles
UKF	Unscented Kalman filtering
USNs	Underwater sensor networks
UWB	Ultra-wideband

Symbols

$\mathcal{R}$	Field of real numbers
$\mathcal{R}^n$	n-Dimensional real Euclidean space
$\mathcal{R}^{n\times m}$	Space of $n \times m$ real matrices
$\mathbf{I}$	Identity matrix
$\mathbf{A}$	System matrix
$\mathbf{A}^{-1}$	Inverse of matrix $\mathbf{A}$
$\mathbf{A}^{\mathrm{T}}$	Transpose of matrix $\mathbf{A}$
$\mathrm{argmin}\, f$	Value of the variable that minimizes function f
$\mathrm{argmax}\, f$	Value of the variable that maximizes function f
$\mathrm{tr}(\mathbf{A})$	Trace of matrix $\mathbf{A}$
$\mathrm{rank}(\mathbf{A})$	Rank of matrix $\mathbf{A}$
$\|\cdot\|$	Euclidean norm
$\bigtriangledown f$	The gradient of function f
$\forall$	For all
$\in$	Belong to
$\sum$	Sum
$\mathbf{E}\{\cdot\}$	Mathematical expectation operator
$\mathbf{var}\{\cdot\}$	Mathematical variance operator
$(\mathbf{A})_{\mathrm{s}}$	The sth column of matrix $\mathbf{A}$
$L_f\mathbf{A}$	Lie derivative of $\mathbf{A}$ to f
$\lceil\cdot\rceil$	Ceiling function
$\lfloor\cdot\rfloor$	Floor function
ϕ	Empty set
$\mathrm{diag}\{\cdot\}$	Diagonal matrix

Chapter 1
Introduction

Abstract This chapter presents the network architecture of underwater sensor networks (USNs). According to the different measurement ways, the localization schemes for wireless sensor networks are briefly reviewed. Based on this, the weak communication characteristics of USNs are summarized, through which the problems studied in this book are provided.

Keywords Underwater sensor networks (USNs) · Localization · Underwater · Weak communication

1.1 Underwater On-Line Monitoring System

The twenty-first century is the ocean century, and the development of ocean enterprise will become a main theme in the twenty-first century. In order to understand and explore the ocean, strong ocean observation ability is required to offer technical support. As for this issue, many instruments, e.g., acoustic Doppler current profiler, sonar array and multi-beam swath bathymeter, have been deployed to provide ocean monitoring services. These instruments acquire and store the measurement data, such that the data recovery and analysis can be implemented later based on salvaging the instruments manually. However, the spatial and temporal coverage ability of the above instruments is very limited, because they are bulky and expensive which are not conductive to large scale deployment. Besides that, they are off-line systems, which cannot meet the real-time requirement for some specific scenarios. Therefore, it is necessary to connect underwater instruments by means of wireless networks to enable real-time monitoring of given underwater region.

With the rapid development of communication and network technology, Underwater Sensor Networks (USNs) have made on-line ocean monitoring a reality. To be specific, USNs are consist of a large number of static sensors and mobile vehicles, which are deployed to perform cooperative monitoring tasks (Akyildiz et al. 2005). Compared with the off-line systems, USNs have the advantages of increased data source, improved real-time characteristic and reduced failure rate. Figure 1.1 illustrates a concept of underwater monitoring system via USNs. In

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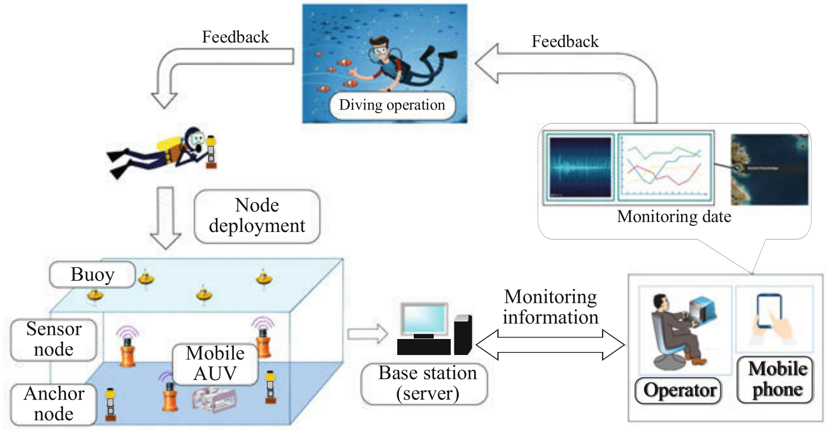

Fig. 1.1 Conceptual sketch of underwater on-line monitoring system via USNs

this system, static sensor nodes deployed in monitoring area periodically collect marine environment information, while the mobile autonomous underwater vehicles (AUVs) collect marine environment information by approaching or passing areas that cannot be monitored by static sensor nodes. Through acoustic and electromagnetic communication links, an operator on coast (or in a vessel on water offshore) collects all available data and then makes mission decision for the monitoring task. Accordingly, the seamless spatial observation and on-line data acquisition can be realized through the cooperation networking of sensor nodes and AUVs.

In such a system, the accurate locations of sensor nodes and AUVs are required for the routing, networking and control of USNs, since these services are valid only when the location information is accurately acquired. Although there exist many recently designed localization schemes for wireless sensor networks, the unique characteristics of USNs, such as asynchronous clock, node mobility, stratification effect and limited bandwidth, require very reliable and efficient new localization solutions for USNs. In view of this, we first present an overview of the localization schemes for wireless sensor networks. Based on this, the unique characteristics of USNs are provided. To address these characteristics, we put forward the problems studied in this book.

1.2 Localization Schemes for Wireless Sensor Networks

According to the different measurement ways, the localization schemes for wireless sensor networks can be classified into the following three categories: (1) angle of arrival (AOA) based localization; (2) distance-related localization; (3) received signal strength (RSS) profiling-based localization.

1.2.1 Localization with AOA Measurements

The localization with AOA measurements is to measure the azimuth of arrival of radio beam signal from the transmitter by using receiver antenna, through which the position of transmitter can be estimated by using optimization algorithm. In general, beamforming is one of the basic types of AOA measurement technology, whose measurement unit can be of small size as compared with the signal wavelength. Suppose that the beam of receiver antenna is rotating, and then the direction of the maximum received signal strength can be considered as the direction of the transmitter. In view of this, an improved polar localization scheme was developed in Wang and Ho (2018), which can make AOA localization unified in the near and far position. Besides that, an AOA-based weighted localization scheme was provided in Zheng et al. (2019) to reduce the median localization error by evaluating the multi-path effect. Also of relevance, some other AOA-based localization schemes can be found in Al-Sadoon et al. (2020) and Huang and Zheng (2018).

In the absence of noise and interference, the azimuth lines from two or more receivers can intersect at a certain unique position, that is, the estimated position of the transmitter, as shown in Fig. 1.2a. However, the noise and interference cannot be ignored in practice, i.e., two or more azimuth lines cannot intersect at a unique position if the noise and interference are considered, as depicted by Fig. 1.2b. Thereby, it is necessary to design localization estimator to reduce the influences of noise and interference.

In the following, the details of two dimensional localization by using AOA measurement are presented. Let $\mathbf{x}_t = [x_t, y_t]^T$ represent the real position vector of the transmitter to be estimated from bearing measurements $\boldsymbol{\beta} = [\beta_1, \beta_2, \beta_3]^T$, and one takes three receivers as the example. Denote $\boldsymbol{\theta}(\mathbf{x}_t) = [\theta_1(\mathbf{x}_t), \theta_2(\mathbf{x}_t), \theta_3(\mathbf{x}_t)]^T$ as the bearing vector of transmitter at position $\mathbf{x}_t$. Particularly, $\theta_i(\mathbf{x}_t) = \arctan \frac{y_t - y_i}{x_t - x_i}$ for $1 \le i \le 3$, and $\hat{\mathbf{x}}_t$ is the estimated position of the transmitter. Besides, $\mathbf{x}_i = [x_i, y_i]^T$ is the real position vector of the receiver i.

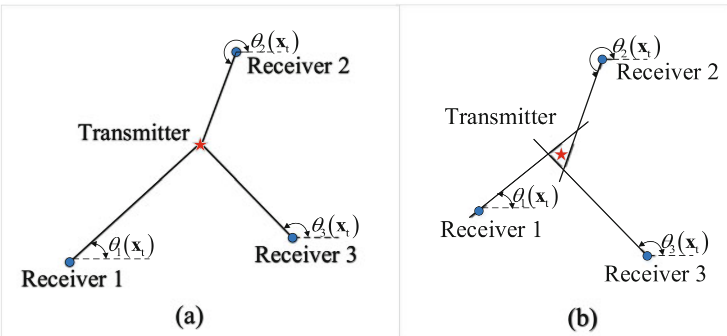

Fig. 1.2 Description of the azimuth lines from three receivers

The measurement bearing of transmitter is composed of true bearing and additional noise $\boldsymbol{\varepsilon} = [\varepsilon_1, \varepsilon_2, \varepsilon_3]^{\mathrm{T}}$ with zero mean and covariance matrices $\mathbf{S} = \mathrm{diag}\{\sigma_1^2, \sigma_2^2, \sigma_3^2\}$, i.e.,

$$\boldsymbol{\beta} = \boldsymbol{\theta}\,(\mathbf{x}_t) + \boldsymbol{\varepsilon}. \tag{1.1}$$

Based on this, the maximum likelihood (ML) estimation of the transmitter position is designed as

$$\begin{aligned}\hat{\mathbf{x}}_{\mathrm{t}} &= \arg\min \frac{1}{2}\,[\boldsymbol{\theta}\,(\mathbf{x}_{\mathrm{t}}) - \boldsymbol{\beta}]^{\mathrm{T}}\,\mathbf{S}^{-1}\,[\boldsymbol{\theta}\,(\mathbf{x}_{\mathrm{t}}) - \boldsymbol{\beta}] \\ &= \arg\min \frac{1}{2}\sum\nolimits_{i=1}^{3} \frac{\left(\theta_i\,(\mathbf{x}_{\mathrm{t}}) - \beta_i\right)^2}{\sigma_i^2}.\end{aligned} \tag{1.2}$$

Stanfield's method assumes that the measurement error is small enough, i.e., $\varepsilon_i \approx \sin\varepsilon_i$, and hence, Eq. (1.2) can be arranged as

$$\hat{\mathbf{x}}_{\mathrm{t}} = \arg\min \frac{1}{2}\sum\nolimits_{i=1}^{3} \frac{\sin^2\left(\theta_i\,(\mathbf{x}_{\mathrm{t}}) - \beta_i\right)}{\sigma_i^2}. \tag{1.3}$$

After trigonometric transformation, Eq. (1.3) is sorted into

$$\hat{\mathbf{x}}_{\mathrm{t}} = \arg\min \frac{1}{2}\sum\nolimits_{i=1}^{3} \frac{[(y_{\mathrm{t}} - y_i)\cos\beta_i - (x_{\mathrm{t}} - x_i)\sin\beta_i]^2}{\sigma_i^2 r_i^2}, \tag{1.4}$$

where $r_i = \sqrt{(x_{\mathrm{t}} - x_i)^2 + (y_{\mathrm{t}} - y_i)^2}$.

Therefore, one can get an estimation of the position $\mathbf{x}_{\mathrm{t}}$, i.e.,

$$\hat{\mathbf{x}}_{\mathrm{t}} = (\mathbf{A}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{S}^{-1}\mathbf{A})^{-1}\mathbf{A}^{\mathrm{T}}\mathbf{R}^{-1}\mathbf{S}^{-1}\mathbf{b}, \tag{1.5}$$

where $\mathbf{A} = [\sin\beta_1, -\cos\beta_1;\ \sin\beta_2, -\cos\beta_2;\ \sin\beta_3, -\cos\beta_3]$, $\mathbf{R} = \mathrm{diag}\{r_1^2, r_2^2, r_3^2\}$ and $\mathbf{b} = [x_1\sin\beta_1 - y_1\cos\beta_1, x_2\sin\beta_2 - y_2\cos\beta_2, x_3\sin\beta_3 - y_3\cos\beta_3]^{\mathrm{T}}$.

1.2.2 Localization with Distance-Related Measurements

Distance-related measurements can be classified into four types: (1) time-of-arrival (TOA) measurement; (2) time-difference-of-arrival (TDOA) measurement; (3) RSS measurement; (4) lighthouse measurement. In the following, the details of these four localization schemes are presented.

1.2.2.1 Localization with TOA Measurement

The main idea of TOA-based localization is to employ the propagation time measurement to obtain the relative distance between transmitter and receiver, through which the position of transmitter can be estimated by trilateral localization or maximum likelihood estimation. In view of this, a channel-aware localization scheme with quantized ToA measurement and transmission uncertainty was developed in Yan et al. (2021). In Yuan et al. (2019), factor graphs were employed to construct a TOA-based passive localization scheme. Also of relevance, some other TOA-based localization schemes were developed in Wu et al. (2019) and Chen et al. (2020).

As shown in Fig. 1.3, the TOA strategy can be divided into one-way propagation time measurement and roundtrip propagation time measurement. For one-way propagation time measurement, the difference between the sending time of transmitter and the receiving time of receiver can be measured, i.e., the difference between t_{t} and t_i for $i \in \{1, 2, 3\}$ as shown in Fig. 1.3a. Accordingly, the TOA between transmitter and receiver under one-way propagation time measurement can be given as

$$\begin{aligned}\Delta T_i &= t_i - t_{\mathrm{t}},\\ &= \frac{1}{\mathrm{c}}\left\|\mathbf{x}_i - \mathbf{x}_{\mathrm{t}}\right\|, i \in \{1, 2, 3\},\end{aligned} \tag{1.6}$$

where t_{t} is the sending time by transmitter, t_i is the receiving time by receiver i for $i \in \{1, 2, 3\}$, c is the propagation speed of the signal, $\mathbf{x}_i$ is the position vector of receiver i, and $\mathbf{x}_{\mathrm{t}}$ is the position vector of transmitter.

Of note, the main drawback of one-way propagation time measurement is that it requires the local time of transmitter and receiver to be accurately synchronized. This requirement may increase the cost and complexity of sensor nodes by requiring a sophisticated synchronization mechanism. In order to relax the

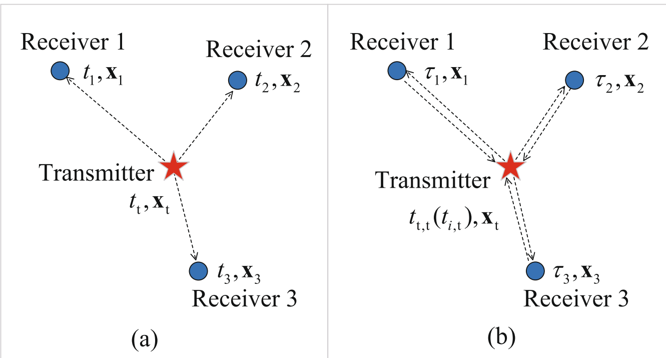

Fig. 1.3 An illustration of the TOA measurement. (**a**) One-way measurement. (**b**) Roundtrip measurement

clock synchronization requirement, the roundtrip propagation time measurement is appreciated. As shown in Fig. 1.3b, the difference between the time when a signal is sent by transmitter and the time when transmitter receives a signal from receiver is measured, i.e., the difference between $t_{t,t}$ and $t_{i,t}$ for $i \in \{1, 2, 3\}$. Accordingly, the TOA between transmitter and receiver under roundtrip propagation time measurement can be given as

$$\begin{aligned}\Delta \mathcal{T}_i &= (t_{i,t} - t_{t,t}) - \tau_i, \\ &= \frac{2}{c} \|\mathbf{x}_i - \mathbf{x}_t\|, i \in \{1, 2, 3\},\end{aligned} \tag{1.7}$$

where $t_{t,t}$ is the sending time by transmitter, $t_{i,t}$ is the time when a signal is received by transmitter from receiver i, and τ_i is the delay for the receiver i to handle the signal. It is noted that the delay is either known by a priori calibration, or measured to be subtracted. The delay measurement is a relatively mature filed, where the most popular method for delay measurement is the generalized cross-correlation (Chen et al. 2011; Zhou et al. 2017).

By applying TOA measurement, the 2D localization problem can be formulated as follows. Define $\Delta\tilde{\mathbf{T}} = [c\Delta T_1, c\Delta T_2, c\Delta T_3]^T$ (or $\Delta\tilde{\mathbf{T}} = [\frac{c}{2}\Delta\mathcal{T}_1, \frac{c}{2}\Delta\mathcal{T}_2, \frac{c}{2}\Delta\mathcal{T}_3]^T$), $h(\mathbf{x}_t) = [\|\mathbf{x}_1 - \mathbf{x}_t\|, \|\mathbf{x}_2 - \mathbf{x}_t\|, \|\mathbf{x}_3 - \mathbf{x}_t\|]^T$, and $\mathbf{w} = [\varepsilon_1, \varepsilon_2, \varepsilon_3]^T$, where $\mathbf{w}$ is measurement noise with zero mean and covariance matrices $\bar{\mathbf{R}}$. Thus, the TOA measurement with noise measurement can be rewritten as $\Delta\tilde{\mathbf{T}} = h(\mathbf{x}_t) + \mathbf{w}$. Based on this, the ML estimator of the transmitter location $\mathbf{x}_t$ can be given as

$$\hat{\mathbf{x}}_t = \arg\min\{[\Delta\tilde{\mathbf{T}} - h(\mathbf{x}_t)]^T \bar{\mathbf{R}}^{-1} [\Delta\tilde{\mathbf{T}} - h(\mathbf{x}_t)]\}. \tag{1.8}$$

According to the principle of trilateration (Zhang et al. 2012), the nonlinear minimization problem is solved, i.e., the position of transmitter can be estimated.

1.2.2.2 Localization with TDOA Measurement

The localization with TDOA measurement is to apply the propagation time measurement to obtain the difference, such that optimization algorithms can be conducted to estimate the position of transmitter. Particularly, some TDOA-based localization schemes can be found in Ge et al. (2020) and Dai et al. (2020).

As shown in Fig. 1.4a, t_t denotes the time when a signal is sent by transmitter, and $\mathbf{x}_t$ denotes the position of transmitter. Similarly, t_i denotes the time when a signal is received by receiver $i \in \{1, 2, 3\}$ from transmitter, while $\mathbf{x}_i$ denotes the position of receiver i. Based on this, the TDOA between receivers i and j can be given as

$$\begin{aligned}\Delta t_{i,j} &= t_i - t_j, \\ &= \frac{1}{c}(\|\mathbf{x}_i - \mathbf{x}_t\| - \|\mathbf{x}_j - \mathbf{x}_t\|), i \neq j.\end{aligned} \tag{1.9}$$

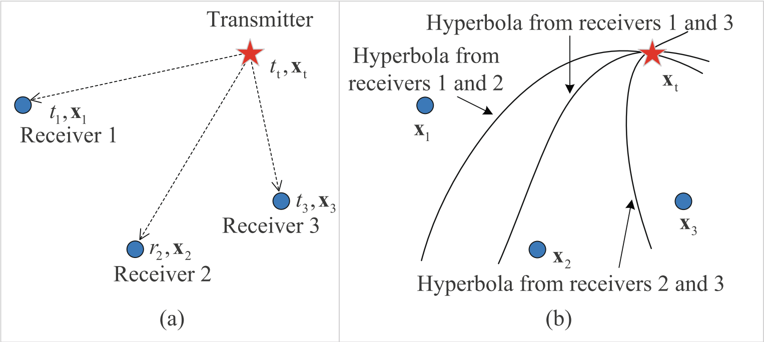

Fig. 1.4 An illustration of (**a**) TDOA and (**b**) intersecting hyperbolas from three receivers

From (1.9), a branch of hyperbola whose foci is at the position of receiver can be defined. Meanwhile, the transmitter must be on the branch, as illustrated in Fig. 1.4b. Because $\Delta t_{i,j}$ is not available, the noisy TDOA measurement of $\Delta\tilde{t}_{i,j}$ can be given as

$$\Delta\tilde{t}_{i,j} = \Delta t_{i,j} + n_{i,j}, \tag{1.10}$$

where $n_{i,j}$ is measurement noise, and it is usually assumed to be an independent zero-mean Gaussian distributed random variable.

Accordingly, TDOA measurements with three receivers can be stacked into

$$\underbrace{\begin{bmatrix} \Delta\tilde{t}_{1,2} \\ \Delta\tilde{t}_{1,3} \\ \Delta\tilde{t}_{2,3} \end{bmatrix}}_{:=\Delta\tilde{\mathbf{t}}} = \underbrace{\begin{bmatrix} \frac{(\|\mathbf{x}_1-\mathbf{x}_t\|-\|\mathbf{x}_2-\mathbf{x}_t\|)}{c} \\ \frac{(\|\mathbf{x}_1-\mathbf{x}_t\|-\|\mathbf{x}_3-\mathbf{x}_t\|)}{c} \\ \frac{(\|\mathbf{x}_2-\mathbf{x}_t\|-\|\mathbf{x}_3-\mathbf{x}_t\|)}{c} \end{bmatrix}}_{:=\varphi(\mathbf{x}_t)} + \underbrace{\begin{bmatrix} \varepsilon_{1,2} \\ \varepsilon_{1,3} \\ \varepsilon_{2,3} \end{bmatrix}}_{:=\bar{\mathbf{w}}} \tag{1.11}$$

where $\Delta\tilde{\mathbf{t}}$ is the TDOA measurement vector, $\varphi(\mathbf{x}_t)$ is the nonlinear vector function about transmitter, and $\bar{\mathbf{w}}$ is measurement noise with zero mean and covariance matrices $\bar{\mathbf{S}}$.

Based on this, the 2D localization problem of TDOA measurement can be formulated as $\Delta\tilde{\mathbf{t}} = \varphi(\mathbf{x}_t) + \bar{\mathbf{w}}$. Thus, the ML estimator of $\mathbf{x}_t$ can be give as

$$\hat{\mathbf{x}}_t = \arg\min\{[\Delta\tilde{\mathbf{t}} - \varphi(\mathbf{x}_t)]^T \bar{\mathbf{S}}^{-1} [\Delta\tilde{\mathbf{t}} - \varphi(\mathbf{x}_t)]\}. \tag{1.12}$$

Clearly, there is no closed solution to (1.12) because of the nonlinear function of $\varphi(\mathbf{x}_t)$. According to the knowledge of Taylor series, one can linearize $\varphi(\mathbf{x}_t)$ around a reference point $\mathbf{x}_0$, i.e.,

$$\varphi(\mathbf{x}_t) \approx \varphi(\mathbf{x}_0) + \nabla\varphi(\mathbf{x}_0)(\mathbf{x}_t - \mathbf{x}_0), \tag{1.13}$$

where $\nabla\varphi(\mathbf{x}_0)$ is the partial derivative of $\varphi(\mathbf{x}_t)$ at the value $\mathbf{x}_0$. Referring to Wang et al. (2020), a recursive solution of ML estimator can be obtained, i.e.,

$$\hat{\mathbf{x}}_{t,k+1} = \hat{\mathbf{x}}_{t,k} + (\nabla^T\varphi(\mathbf{x}_{t,k})\bar{\mathbf{S}}^{-1}\nabla\varphi(\mathbf{x}_{t,k}))^{-1}\nabla^T\varphi(\mathbf{x}_{t,k})\bar{\mathbf{S}}^{-1}[\Delta\tilde{\mathbf{t}} - \varphi(\mathbf{x}_{t,k})]. \tag{1.14}$$

1.2.2.3 Localization with RSS Measurement

The localization with RSS measurement is to employ the RSS to estimate the relative distance between transmitter and receiver, through which optimization algorithms can be conducted to estimate the position of transmitter. In Zhang et al. (2016a), a RSS-based localization solution was developed, where a Newton-Raphson algorithm was provided to seek the position of target. In our previous works (Sebastian and Petros 2018; Yan et al. 2017), RSS was employed to estimate the position of remote unmanned aerial vehicle, thorough which a robust long-range aerial communication channel was established with the assistance of directional antennas. An advantage of this strategy is that the time synchronization is not required. However, RSS is sensitive to man-made and ambient noises.

Next, a brief introduction on RSS-based localization is presented. Particularly, the RSS in dBm on the receiver can be modelled as

$$P_i(d_i) = P_0(d_0) - 10n_p\log_{10}(\frac{d_i}{d_0}) + n_{i,\sigma}, \tag{1.15}$$

where $P_i(d)$ is the received power of receiver i for $i \in \{1, 2, 3\}$, $P_0(d_0)$ is the known reference power value at a reference distance d_0 from the transmitter, d_i is the distance between the transmitter and receiver i, and n_p is the path loss exponent. Besides, $n_{i,\sigma}$ is the zero mean Gaussian measurement noise with variance σ^2, which explains the random effect of shadow (Rappaport 2001).

By using RSS measurement, the 2D localization problem can be formulated as follows. Let $\mathbf{P} = [P_1(d_1), P_2(d_2), P_3(d_3)]^T$ be the measurement vector. Meanwhile, $\mathbf{g}(\mathbf{x}_t) = [P_0(d_0) - 10n_p\log_{10}(\frac{d_1}{d_0}), P_0(d_0) - 10n_p\log_{10}(\frac{d_2}{d_0}), P_0(d_0) - 10n_p\log_{10}(\frac{d_3}{d_0})]^T$ is the nonlinear vector function about transmitter x_t, and $\mathbf{n} = [n_{1,\sigma}, n_{2,\sigma}, n_{3,\sigma}]^T$ is the measurement noise vector, Based on the RSS measurement in (1.15), the likelihood function can be defined as

$$p(\mathbf{P}; \mathbf{x}_t) = \frac{1}{\sqrt{2\pi}\sigma}\exp[-\frac{1}{2\sigma^2}\|\mathbf{P} - \mathbf{g}(\mathbf{x}_t)\|^2]. \tag{1.16}$$

Thus, the ML solution of x_t is given as

$$\hat{\mathbf{x}}_t = \arg\max p(\mathbf{P}; \mathbf{x}_t). \tag{1.17}$$