Linköping Studies in Science and Technology. Licentiate Thesis No. 2039

Channel Modeling for Target Detection, Localization, and Tracking in Underwater Environments

Ashwani Koul

LINKÖPING UNIVERSITY

Linköping studies in science and technology. Licentiate Thesis
No. 2039

Channel Modeling for Target Detection, Localization, and Tracking in Underwater Environments

Ashwani Koul

LINKÖPING UNIVERSITY

This is a Swedish Licentiate's Thesis.

Swedish postgraduate education leads to a Doctor's degree and/or a Licentiate's degree.
A Doctor's Degree comprises 240 ECTS credits (4 years of full-time studies).
A Licentiate's degree comprises 120 ECTS credits,
of which at least 60 ECTS credits constitute a Licentiate's thesis.

Linköping studies in science and technology. Licentiate Thesis
No. 2039

Channel Modeling for Target Detection, Localization, and Tracking in Underwater Environments

Ashwani Koul

ashwani.koul@liu.se
https://www.control.isy.liu.se
Department of Electrical Engineering
Linköping University
SE-581 83 Linköping
Sweden

ISBN 978-91-8118-718-2 (print)
ISBN 978-91-8118-719-9 (PDF)
https://doi.org/10.3384/9789181187199
ISSN 0280-7971

Unless otherwise stated, this work is licensed under the Creative Commons Attribution 4.0 International License. To view a copy of this license, visit https://creativecommons.org/licenses/by/4.0/.

Copyright © 2026 Ashwani Koul

Printed by LiU-Tryck, Linköping, Sweden 2026

To those who made this fool see nothing but the truth.

Abstract

Acquiring accurate and reliable target information over large areas is crucial for various underwater applications. This can be achieved by deploying underwater wireless sensor networks (UWSN), in which spatially distributed sensor nodes detect targets and communicate the acquired information. Traditionally, sensing and communication are performed separately, requiring dedicated waveforms, hardware, and signal-processing resources. Given the limited resources available in underwater systems, this separation can be inefficient. To reduce this inefficiency, an integrated sensing and communication (ISAC) framework enables shared waveform and system resources to be used for both sensing and communication. However, sharing these resources does not remove the effects of the underwater propagation environment on the received signals.

Appropriate modeling of underwater acoustic propagation is also important for reliable target detection, localization, and tracking. In shallow-water active sonar systems, the received signal may contain the target-reflected signal, the direct-path signal, and reflections from the sea surface and seabed, along with ambient noise. These multipath components vary over time and can mask weak target reflections, motivating models that account for their structure and temporal variation. Therefore, this thesis investigates how modeling underwater acoustic propagation, and particularly the time-varying propagation channel, can support target localization, detection, and tracking.

First, a simplified channel model is used to investigate the feasibility of communication-centric signals for underwater target localization in a bistatic sonar setup. The localization performance is evaluated using the Cramér-Rao lower bound (CRLB), while the delay and Doppler resolution characteristics are assessed using the wideband ambiguity function. The results show that combining bistatic target-reflected information with passive bearing measurements improves the theoretical localization accuracy without requiring an additional sensing transmission. Under the considered conditions, the localization bounds are comparable to those obtained using a conventional linear frequency-modulated (LFM) waveform.

Second, a wideband Doppler linearization method is used to obtain a statistical model of the time-varying multipath channel. The approximate model enables recursive tracking of the structured multipath components using an extended Kalman filter. BELLHOP-based evaluations show that explicitly modeling and tracking the time-varying multipath channel improves detection performance.

Finally, the inferred channel statistics are used to approximate the raw sensor measurement likelihood, enabling computationally efficient target tracking within a Bernoulli track-before-detect framework. Evaluations using datasets representing both model-matched and model-mismatched conditions show improved target-confirmation and localization performance compared with constant-false-alarm-rate (CFAR)-based tracking approaches.

Populärvetenskaplig sammanfattning

Mycket av den information som vi använder på land överförs med hjälp av elektromagnetiska vågor. Under vatten dämpas dock radiovågor kraftigt och har därför begränsad räckvidd. I stället använder undervattenssystem vanligtvis ljud för att kommunicera och för att avbilda eller känna av sin omgivning. Akustiska signaler kan användas för att överföra information mellan sensornoder under vatten, men också för att upptäcka och lokalisera objekt i omgivningen.

Undervattensbaserade sensorsystem har ofta begränsad batterikapacitet, beräkningsförmåga och kommunikationsbandbredd. Det är därför viktigt att använda de tillgängliga resurserna så effektivt som möjligt. Om en signal redan sänds för kommunikation är det naturligt att fråga om samma signal även kan användas för att få information om ett mål. Genom att återanvända en befintlig kommunikationssignal för avkänning kan behovet av ytterligare sändningar minska och samma undervattenssystem kan användas för flera olika uppgifter.

Det är dock svårt att utvinna tillförlitlig information ur akustiska signaler under vatten. Ljud färdas inte enbart direkt från en sändare till en mottagare. När en akustisk signal fortplantar sig genom vattnet försvagas den och påverkas av den omgivande miljön. Havsytan och havsbotten reflekterar den utsända signalen, vilket gör att flera kopior av samma signal når mottagaren vid olika tidpunkter. Detta fenomen kallas flervägsutbredning. Rörelser hos havsytan, sändarna och mottagarna kan dessutom sträcka ut eller komprimera signalerna och göra att de mottagna flervägskomponenterna förändras över tid. Mottagaren observerar därför en blandning av flera signalkomponenter vars egenskaper kan variera från en sändning till nästa. Om reflektionen från ett mål är svag kan den vara svår att skilja från dessa andra komponenter, vilket gör svaga mål svåra att upptäcka, lokalisera och följa över tid.

En viktig fråga är därför hur kunskap om ljudets fortplantning under vatten kan användas för att få bättre information om mål. Denna avhandling undersöker frågan på olika nivåer av komplexitet. I den första studien används en förenklad modell av ljudutbredningen under vatten för att undersöka om en signal som redan sänds för kommunikation också kan användas för mållokalisering. Information från kommunikationssignalen som reflekteras från målet kombineras med passiva riktningsmätningar som erhålls genom att lyssna på ljud som avges från målet. Resultaten visar att kombinationen av dessa två informationskällor förbättrar den teoretiska lokaliseringsnoggrannheten. Under de studerade förhållandena kan kommunikationssignaler även ge en lokaliseringsnoggrannhet och upplösning som är jämförbar med en konventionell sonarsignal.

Avhandlingen behandlar därefter ett mer utmanande fall där flervägsutbredningen förändras över tid. En approximativ matematisk modell utvecklas för att beskriva hur kanalen förändras från en utsänd signal till nästa. Genom att uppskatta dessa förändringar får mottagaren information om de aktuella fortplantningsförhållandena i stället för att anta att kanalen är oföränderlig. Resultaten visar att hänsyn till dessa kanalvariationer förbättrar möjligheten att upptäcka svaga målreflektioner. Slutligen används den uppskattade kanalinformationen för målföljning, där information från flera mättillfällen kombineras för att för-

stärka evidensen för svaga mål. I de utvärderade scenarierna kan den föreslagna metoden bekräfta mål mer konsekvent och ger bättre lokaliseringsprestanda än de konventionella detektionsbaserade metoder som används som jämförelse.

Acknowledgments

I would like to express my sincere gratitude to my supervisor, Assoc. Prof. Isaac Skog, and co-supervisor, Assoc. Prof. Gustaf Hendeby, for their invaluable guidance, encouragement, and support throughout this work. I am also thankful to Assoc. Prof. Martin Enqvist, head of division, for fostering a friendly and open working environment. I am grateful to Ms. Ninna Stensgård for taking care of the practical matters and for her support in many other ways. My sincere thanks go to my colleagues, Reza J., Joel We., and Rasmus, for their comments and feedback on the manuscript. I would like to thank Gustav Z. and Johanna W. for their guidance and support in navigating the administrative procedures and ensuring that all requirements for the successful submission of my licentiate thesis were fulfilled. Finally, I am deeply grateful to my family, without whose sacrifices and blessings I would not be where I am today. My special thanks go to Maa and Grandma, who I know would be very proud.

This work has been supported by the Wallenberg AI, Autonomous Systems and Software Program (WASP), funded by the Knut and Alice Wallenberg Foundation.

Linköping, December 2026
Ashwani Koul

Contents

Notation **xv**

I Background

1 Introduction **3**
1.1 Background and Motivation 3
1.2 Research Questions 6
1.3 Publications and Contributions 6
1.4 Thesis Outline 8

2 Sonar Systems and Measurement Models **9**
2.1 Sonar Systems 9
2.1.1 Passive Sonar 9
2.1.2 Active Sonar 10
2.2 Measurement Models 12
2.2.1 Passive-Sonar Measurement Model 12
2.2.2 Active-Sonar Measurement Model 13
2.2.3 Ambient Noise 13
2.3 Localization Performance Characterization 14
2.3.1 Fisher Information and Cramér-Rao Lower Bound 14
2.3.2 Wideband Ambiguity Function 15

3 Modeling and Tracking Time-Varying Multipath Channels **17**
3.1 Time-Varying Multipath Channel 17
3.2 Modeling the Multipath Channel 19
3.2.1 Modeling the Doppler Variations 20
3.2.2 Tracking the Multipath Channel 21

4 Tracking Targets using the Multipath Channel Model **23**
4.1 Target and Background State Inference 23
4.1.1 Assumptions and Approximations 24
4.1.2 Switching Logic 25

5 Conclusions and Future Research 27
5.1 Future Research Directions 28

Bibliography 29

II Publications

A Performance Analysis of Communication Signals for Localization in Underwater Sensor Networks 35
1 Introduction 37
2 Methodology 38
2.1 Assumptions 39
2.2 Signal Model 40
2.3 Performance Metrics 41
2.4 SNR Equations 42
2.5 Considered Scenarios 42
2.6 Wideband Ambiguity Analysis 43
3 Simulation Setup 43
3.1 SNR Design 43
3.2 Evaluated Communication Signals 43
4 Results and Discussion 44
5 Conclusions and Future Work 47
A Details on the Signal Model 50
Bibliography 52

B Tracking Time-Varying Multipath Channels for Active Sonar Applications 55
1 Introduction 58
2 Signal Model 59
2.1 General Continuous Time Channel Model 59
2.2 Wideband Linearized Model 61
2.3 Discrete-Time Linearized Channel Model 61
2.4 Stochastic Multipath Background Model 61
2.5 State-Space Model 62
3 State Estimation 63
3.1 Amplitude Tracking 63
3.2 Hyperparameter Learning 63
4 Evaluation Methodology 63
4.1 P-value Significance Test 64
4.2 Target Detection Performance 65
4.3 Simulation Setup 67
5 Results and Discussion 69
6 Conclusion 73
A Wideband linearization of time-varying multipath signal 74
Bibliography 75

C A Computationally Efficient Likelihood Approximation for Target Tracking in Time-Varying Multipath Channels **77**
1 Introduction 80
2 Problem Formulation 82
3 Measurement Model and Background Tracking 82
3.1 Multipath Propagation Model 83
3.2 Multipath Approximation for the Target 83
3.3 Discrete-Time Measurement Model 84
3.4 Statistical Channel Model 85
3.5 Low-Dimensional Representation 85
3.6 Background Tracking 86
4 Bernoulli Filter-Based Target Tracking 87
4.1 Bernoulli Filter Overview 87
4.2 Likelihood with CFAR-Based Detections 88
4.3 Likelihood for the Proposed Method 90
5 Target State Dynamics and Birth Model 91
5.1 Motion Model 91
5.2 Birth Model 93
6 Evaluation 93
6.1 Performance Evaluation Metrics 94
6.2 Simulation Setup 95
6.3 Parameter Settings 97
7 Results and Discussion 98
7.1 Evaluation 1 99
7.2 Evaluation 2 100
8 Conclusion 101
A Wideband linearization of time-varying multipath signal 102
Bibliography 104

Notation

Mathematical Notations

Notation	Meaning
$(\cdot)^\top$	Transpose operator
$(\cdot)^{-1}$	Inverse operator

Abbreviations

Abbreviation	Meaning
AR	Autoregressive
CFAR	Constant-false-alarm rate
CIR	Channel impulse response
CRLB	Cramér-Rao lower bound
EKF	Extended Kalman filter
FIM	Fisher information matrix
GOSPA	Generalized optimal subpattern assignment
ISAC	Integrated sensing and communication
LFM	Linear frequency modulated
SNR	Signal-to-noise ratio
SONAR	Sound navigation and ranging
TRBD	Track-before-detect
UWSN	Underwater wireless sensor network
WBAF	Wideband ambiguity function

Part I

Background

1 Introduction

This chapter introduces the background and motivation for the research, formulates the research questions, summarizes the publications and the author's contributions, and outlines the structure of the thesis.

1.1 Background and Motivation

Accurate and reliable estimates of the location and motion of underwater targets are important for applications in maritime surveillance, autonomous navigation, and environmental monitoring [1–3]. To monitor large areas, spatially distributed sensor nodes can be deployed in the ocean and interconnected to form an underwater wireless sensor network (UWSN) as shown in Figure 1.1. The nodes collect measurements from different locations and exchange relevant information through communication links. By combining measurements from multiple nodes, a UWSN can not only extend the sensing coverage but also improve the accuracy and reliability of the estimated target location and motion.

Acquiring target information and communicating it across the network require sensor nodes to support both sensing and communication. Since the nodes are typically battery-operated, these functionalities need to be implemented efficiently to ensure a long operational lifetime. Traditionally, sensing and communication have been treated as separate functionalities. A sensing system transmits a sensing waveform such as a linear frequency-modulated (LFM) signal for target detection, localization, and tracking, whereas a communication system transmits information encoded in signals between different sensor nodes. This separation commonly requires dedicated waveform designs, signal-processing chains, and hardware components [4–7].

However, the underwater environment presents substantial challenges for both sensing and communication. Radio-frequency-based signaling systems suf-

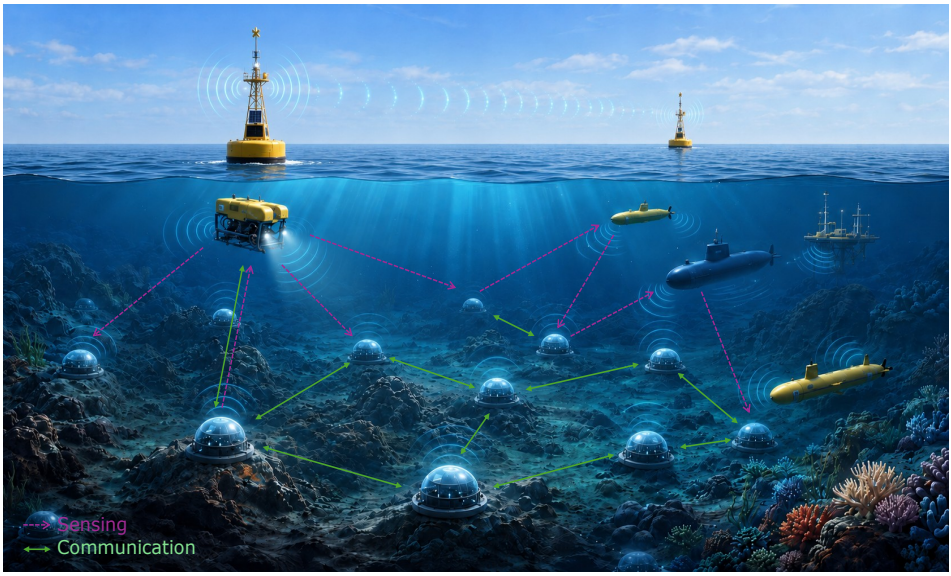

Figure 1.1: *Illustration of an underwater wireless sensor network consisting of spatially distributed sensor nodes, autonomous underwater vehicles, and surface platforms that perform sensing and exchange information through acoustic links.*

fer severe attenuation due to conductivity and absorption. This attenuation generally increases with frequency, so only very-low-frequency electromagnetic waves can propagate over large distances [2]. Optical waves can support much higher data rates, but their propagation range is restricted mainly by absorption and scattering in the water column [8]. Consequently, UWSN rely primarily on acoustic-wave propagation for medium- and long-range operations.

Furthermore, underwater acoustic propagation is affected by several physical phenomena that can degrade the received signal. Variations in temperature, salinity, and pressure produce spatially and temporally varying sound-speed profiles, resulting in refraction, shadow zones, and uncertain propagation paths. Reflections and scattering from the sea surface and seabed generate severe multipath propagation, while geometric spreading and frequency-dependent absorption cause substantial propagation losses. Moreover, the relatively low speed of sound results in long propagation delays and high communication latency. Ambient noise generated by sources such as snapping shrimp, bubbles, shipping activity, and wind also exhibits frequency-dependent characteristics. Consequently, underwater acoustic systems operate with limited bandwidth and energy resources while also experiencing long propagation delays, frequency-dependent attenuation, strong multipath propagation, and Doppler effects [2, 9].

Integrated sensing and communication (ISAC) is considered one of the key enabling technologies for sixth-generation communication systems [10]. With ISAC, sensing and communication functions can be realized using shared wave-

forms, hardware, and signal-processing resources [11, 12]. For underwater sensing and communication applications, ISAC offers a means to use the limited spectral, energy, and hardware resources more efficiently. A communication signal transmitted between two sensor nodes may reach the receiver through a direct path and multiple reflected and refracted propagation paths. The same signal may also interact with an underwater target and produce a delayed and Doppler-scaled bistatic reflection at the receiving node. After the communication signal has been successfully decoded, the transmitted waveform can be reconstructed at the receiver and reused for sensing. The target-reflected component can provide additional information about the target's location and motion.

Recent studies have increasingly explored ISAC for underwater applications. In [13], a comprehensive survey of integrated sonar and communication systems is presented, covering system architectures, hardware constraints, waveform design, channel modeling, and receiver signal-processing techniques. Much of the existing underwater ISAC literature has focused on integrated waveform design, receiver processing, and the evaluation of communication and sensing performance [14–17]. In [18, 19], multi-carrier waveforms have been investigated in terms of communication reliability and target-detection performance. In [20–22], sonar-centric approaches based on LFM and acoustic-frequency-comb waveforms have also been developed to embed communication information while retaining target-sensing capabilities. Related underwater localization studies have considered network-node localization, in which the location and clock parameters of underwater nodes are estimated [4, 23], rather than localization of an external target using a communication waveform reflected by the target.

These studies demonstrate that integrated waveforms can support both sensing and communication, but do not directly quantify the achievable target-localization accuracy provided by a target-reflected communication signal. The target information that can be extracted from underwater acoustic measurements depends jointly on the transmitted waveform, the transmitter-receiver-target geometry, the propagation channel, and how the available measurements are combined. However, in shallow-water environments, the received signal may contain strong multipath components generated by interactions with the sea surface and seabed, together with ambient noise. Since the target-reflected signal and the multipath components are both formed from delayed and Doppler-scaled versions of the transmitted waveform, a weak target reflection can be difficult to distinguish from stronger multipath components. This makes reliable target detection, localization, and tracking particularly challenging in shallow water.

Various channel-estimation and signal-processing methods have been developed to improve weak-target detection in multipath and reverberation environments. In [24], the sparse structure of the channel impulse response is exploited to recursively estimate the time-varying channel and facilitate weak-target detection. In [25], a non-negative matrix factorization method is used to suppress reverberation in the received signal, whereas in [26], measurements are decomposed into a low-rank reverberation component and a sparse target-echo component to reduce reverberation. These methods primarily address channel estimation, reverberation suppression, or target detection, but do not incorporate the

estimated multipath channel within a recursive target-tracking framework. Similarly, many sonar tracking frameworks have been developed in which targets are tracked using processed measurements derived from the received signal [27–29]. In these frameworks, measurements not associated with the target are typically treated as clutter and modeled statistically, rather than through an explicit, physics-motivated model of the time-varying multipath channel. Consequently, strong multipath components may produce target-like measurements, whereas weak target echoes may be suppressed or remain below a detection threshold. This can lead to false or missed tracks and degrade the accuracy of the estimated target location and velocity.

Therefore, this thesis investigates how different underwater acoustic channel modeling methods can improve target detection, localization, and tracking performance. First, a simplified underwater ISAC channel model is considered to evaluate the localization information provided by a target-reflected communication signal and how this information can be combined with passive measurements obtained from the target-radiated signal, without requiring an additional sensing transmission. Next, an approximate channel model is developed in which the time-varying multipath channel is statistically modeled and recursively tracked from the received sensor measurements. The channel tracking is performed using a background state that characterizes the structured multipath component, while the Doppler-induced variations are captured through a state-dependent measurement covariance. Finally, a computationally efficient target-tracking methodology is developed using the inferred background statistics.

1.2 Research Questions

The thesis investigates how underwater acoustic channel models support target detection, localization, and tracking of weak targets. More specifically, the thesis addresses the following research questions.

- What theoretical target-localization accuracy can be provided by a known communication-centric waveform under a simplified underwater channel model?
- How can the time-varying multipath channel be modeled and recursively tracked from raw sensor measurements?
- How can the inferred background statistics be used to approximate the raw sensor-measurement likelihood for target tracking applications?

1.3 Publications and Contributions

The content of this licentiate thesis is based on the following three publications. The papers have been either published, accepted for publication, or submitted for peer review. The following abbreviations are used to refer to the author and co-authors: Ashwani Koul (AK), Gustaf Hendeby (GH), and Isaac Skog (IS).

Paper A: Performance Analysis of Communication Signals for Localization in Underwater Sensor Networks.

> Ashwani Koul, Gustaf Hendeby, and Isaac Skog. Performance analysis of communication signals for localization in underwater sensor networks. In *IEEE OCEANS - Great Lakes*, pages 1–7, Chicago, IL, USA, September 2025.

Paper A investigates the feasibility of using communication-centric waveforms for underwater localization within an ISAC framework. The study evaluates super-permutated frequency-shift keying and multiple frequency-shift keying signals in a simplified bistatic scenario using the Cramér-Rao lower bound to characterize theoretical target-localization accuracy. The localization performance of the communication waveforms is also compared with that of a conventional linear frequency-modulated (LFM) sonar waveform. The results indicate the potential of communication signals to support dual-purpose sensing and communication in underwater environments.
Contribution: IS and GH had the research idea and provided help with improving the manuscript. AK implemented the idea, carried out the simulation experiments, and wrote the paper.

Paper B: Tracking Time-Varying Multipath Channels for Active Sonar Applications

> Ashwani Koul, Gustaf Hendeby, and Isaac Skog. Tracking time-varying multipath channels for active sonar applications. In *29th International Conference on Information Fusion (FUSION)*, Trondheim, Norway, June 2026. Accepted for publication.

Paper B investigates the modeling and tracking of a time-varying multipath channel in the raw sensor measurement domain for active-sonar target detection. The study derives a state-space model with a heteroscedastic measurement model based on the wideband Doppler linearization of the time-varying multipath channel. The resulting model enables recursive channel tracking using an extended Kalman filter. The statistical adequacy of the proposed models is evaluated using a p-value significance test. The inferred background statistics are then incorporated into a sequential likelihood-ratio test for target detection. BELLHOP-based simulations show that the proposed framework more accurately captures channel variations caused by sea-surface fluctuations and transmitter and receiver drift, thereby improving target-detection reliability in time-varying shallow-water environments.
Contribution: IS and GH had the research idea, provided research discussions, and helped improve the manuscript. AK implemented the idea, carried out the simulation analysis, and wrote the paper.

Paper C: A Computationally Efficient Likelihood Approximation for Target Tracking in Time-Varying Multipath Channels

Ashwani Koul, Gustaf Hendeby, and Isaac Skog. A computationally efficient likelihood approximation for target tracking in time-varying multipath channels, 2026. URL https://arxiv.org/abs/2608.20206. Submitted for possible publication in IEEE Transactions on Aerospace and Electronic Systems.

Paper C investigates the effectiveness of a computationally efficient likelihood approximation for target tracking in time-varying multipath channels. This paper builds on the methodology developed in Paper B for recursively tracking a time-varying multipath channel and uses the inferred background statistics to construct approximate target-present and target-absent likelihoods. The approximation neglects the posterior dependence between the target and background states, thereby enabling the target-existence probability and target state to be estimated recursively from the raw sensor measurements without requiring full joint target-background inference. The proposed method is evaluated using measurements generated from both the assumed statistical model and BELLHOP-generated time-varying multipath propagation. The results demonstrate improved target-confirmation and localization performance compared with CFAR-based tracking methods.
Contribution: IS and GH had the research idea, provided research discussions, and helped improve the manuscript. AK implemented the idea, carried out the simulation analysis, and wrote the paper.

1.4 Thesis Outline

The thesis is divided into two parts. Part I provides the background, theoretical foundations, and methodological framework required to understand the research contributions. Part II contains the publications summarized in Section 1.3.

Chapter 2 introduces different sonar systems and the corresponding measurement models. It also introduces the signal and noise characteristics required to evaluate target-localization performance. Chapter 3 presents a methodology for modeling and recursively tracking a time-varying multipath channel. The inferred background statistics provide the basis for constructing a physics-motivated measurement likelihood for target detection and tracking. Chapter 4 presents a framework for a computationally efficient approximation to the joint Bayesian inference problem involving the target and background states. Chapter 5 concludes Part I by summarizing the main findings of the thesis and discussing possible directions for future research. The remaining part of the thesis contains the edited versions of the publications listed in Section 1.3.

2

Sonar Systems and Measurement Models

This chapter provides a brief background on the sonar systems considered in this thesis, introduces the corresponding measurement models, and presents the performance measures used to characterize target-localization information. For notational convenience, scalar, vector, and matrix quantities are written using ordinary symbols throughout Part I. The appended papers retain their original notation and conventions.

2.1 Sonar Systems

Sound navigation and ranging (SONAR) systems use acoustic signals to detect, localize, and track underwater targets. Depending on the configuration, these systems comprise transducers, hydrophones, and processing units that generate, receive, and process acoustic signals, respectively. They are broadly classified as passive or active systems, based on whether the sensing system transmits a probing acoustic signal [9]. Passive sonar listens to signals radiated by a target or other sources in the environment, whereas active sonar transmits an acoustic signal and processes the resulting reflections. These sensing configurations provide different information about the target and lead to different measurement models.

2.1.1 Passive Sonar

Passive sonar systems perform sensing, localization, and tracking based on the acoustic signals received by the sensor nodes. Since there is no active transmission of signals from the sensor nodes, passive sonar can observe the environment without revealing the sensor location through its own transmissions. This type of sonar system is used by military vessels requiring covert operation and for scientific applications involving passive acoustic monitoring of marine life and the

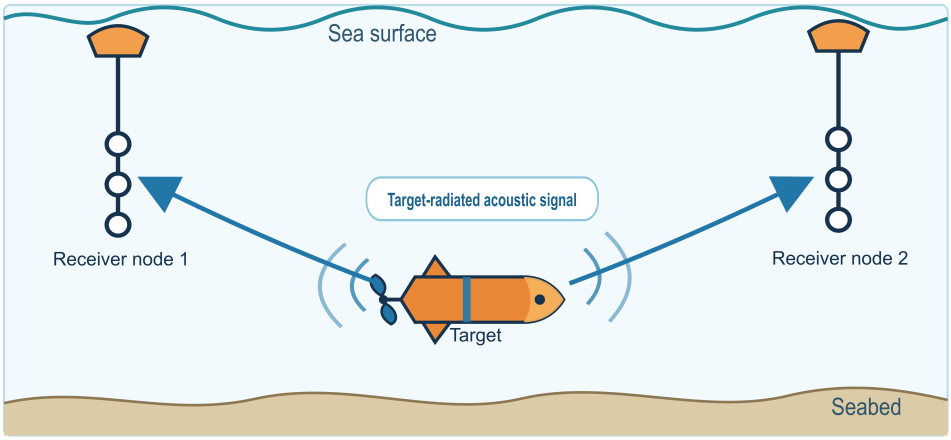

Figure 2.1: *Illustration of a passive sonar configuration in which spatially separated receiver nodes observe acoustic signals radiated by a target.*

underwater environment. An example of a passive sonar system is illustrated in Figure 2.1.

In passive sonar, the signal radiated from the target and ambient noise form the main components of the received signal. However, the statistical characteristics of the signal radiated from the target and its emission time are generally unknown. In order to localize the target, the direction of arrival of the incoming signal can be estimated using a hydrophone array installed at each sensor node, and bearing measurements from multiple spatially separated nodes can be combined to triangulate the target location.

2.1.2 Active Sonar

An active sonar system performs target detection, localization, and tracking by transmitting a known acoustic signal and processing the reflected signals received at the sensor nodes. An advantage of active sonar is that the transmitted signal is known and its energy can be controlled within operational constraints. Increasing the transmitted signal energy generally increases the energy of the received target-reflected signal, and knowledge of the transmitted waveform enables matched-filter processing, which provides processing gain [32]. However, reverberation may also increase with transmitted signal energy, limiting the improvement in reverberation-dominated environments. Moreover, the transmitted signal may be detected by other acoustic receivers, making active sonar less suitable for covert applications.

The propagation delay of the target-reflected signal provides range-related information, while its direction of arrival provides bearing information when a hydrophone array is used. With known sensor node locations, the delay and bearing information can be combined to estimate the target location. Additionally, the Doppler scaling of the target-reflected signal provides information about the

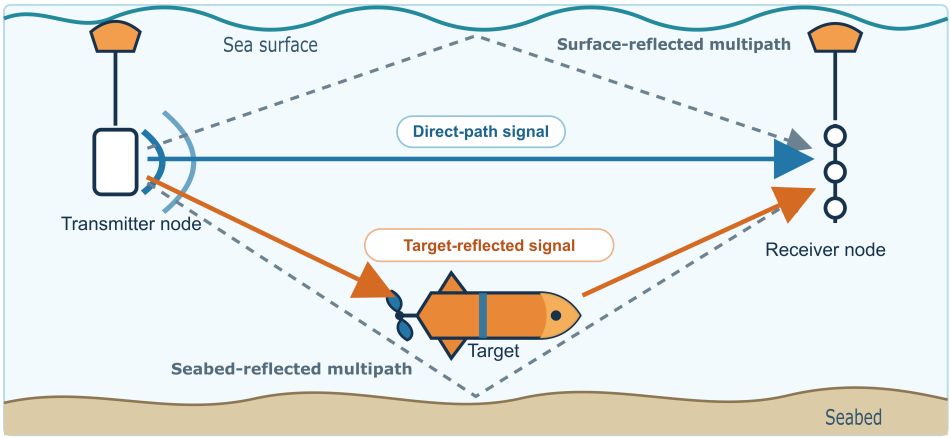

Figure 2.2: *Illustration of an active bistatic sonar configuration showing the direct path signal, target-reflected signal, and multipath components generated by interactions with the sea surface and seabed.*

relative motion of the target with respect to the sensing system. By combining delay, bearing, and Doppler measurements over successive time intervals, the target location and motion can be tracked. A simplified active sonar configuration is illustrated in Figure 2.2, where the transmitted signal is received via the direct path, target-reflected path, and sea surface and seabed reflected paths.

Active sonar can be classified into monostatic and bistatic systems based on the location of the transmitter and the receiver. For monostatic systems, the transmitter and the receiver are collocated, whereas for the bistatic configuration, the transmitter and the receiver are spatially separated. In both configurations, the received signal may contain surface- and seabed-reflected multipath components, whereas in the bistatic configuration, the receiver may additionally observe a strong direct path signal from the transmitter. Moreover, bistatic systems can provide geometric diversity and extend the sensing coverage, although the resulting performance depends on the transmitter-receiver-target geometry and the propagation environment [33].

Active sensing systems can further be classified as dedicated and opportunistic systems based on the primary purpose of the transmitted signal. This distinction determines how the signal and system resources are used, although the target information is obtained through the same target-reflected signal mechanism.

Dedicated Sensing

In a dedicated active-sonar system, the transmitted signal and associated system resources are used for a specific application. For example, an LFM signal can be designed to provide suitable processing gain, delay, and Doppler properties for target detection and localization. The available bandwidth, transmitted en-

ergy, hardware, and signal-processing resources are allocated specifically to one particular task.

Opportunistic Sensing

In an opportunistic system, a signal transmitted primarily for one application can also be reused for another application. For example, in an underwater ISAC framework, a communication signal transmitted between two sensor nodes can be reused to obtain information about a target. If the communication signal is successfully decoded, the transmitted waveform can be reconstructed at the receiving node and used as a known probing signal. Alternatively, the direct-path signal can itself serve as a reference signal. A target-reflected component of the communication signal may also reach the receiver. By processing the target-reflected signal relative to the reference signal, delay and Doppler-scaling information can be extracted to provide information about the target location and relative motion without requiring an additional sensing transmission. However, because the communication waveform is not designed solely for sensing, the target information it provides depends on its waveform characteristics, sensor geometry, and propagation environment.

2.2 Measurement Models

Depending on the sonar configuration and the underwater environment, the received measurements may have different statistical characteristics. To describe these measurements, let y_k denote the measurement vector collected by the receiver node during the measurement interval k.

2.2.1 Passive-Sonar Measurement Model

For passive sonar, the discrete-time measurement vector is modeled as

$$y_k = s_p(z_k) + e_k, \tag{2.1}$$

where $s_p(z_k)$ and e_k represent the acoustic signal radiated by the target and the ambient noise, respectively. Here, z_k denotes the unknown target parameters, such as the target location and motion. Further, the signal and the noise components can be modeled as

$$s_p(z_k) \sim \mathcal{N}\left(0, R_s(z_k)\right), \tag{2.2a}$$

$$e_k \sim \mathcal{N}\left(0, R_{e,k}\right), \tag{2.2b}$$

where $R_s(z_k)$ and $R_{e,k}$ are the covariance matrices for the radiated signal and the ambient noise, respectively. Assuming that the target-radiated signal and ambient noise are statistically independent, the conditional distribution of the measurement is

$$\begin{aligned} p\left(y_k \mid z_k\right) &= \mathcal{N}\left(y_k; 0, R(z_k)\right) \\ &= \mathcal{N}\left(y_k; 0, R_s(z_k) + R_{e,k}\right). \end{aligned} \tag{2.3}$$

The acoustic signal radiated by the target can originate from onboard machinery and the propulsion system of the target. It may contain tonal components associated with rotating machinery and propeller motion, together with broadband components generated by cavitation and hydrodynamic flow around the hull and propeller [9]. For the statistical measurement model, $s_p(z_k)$ is modeled as zero-mean Gaussian with covariance $R_s(z_k)$. The covariance captures the received signal power and the array-dependent structure induced by the relative propagation delays across the hydrophones, which depend on the target's direction of arrival. Further details about the construction and use of $R_s(z_k)$ are provided in [7, 34].

2.2.2 Active-Sonar Measurement Model

For active sonar, the receiver node may receive multiple delayed and Doppler-scaled copies of the transmitted signal in addition to the same target-radiated signal and ambient-noise components as in passive sonar. In this case, the received measurements can be described as

$$y_k = x_k^{\mathrm{m}} + x_k^{\mathrm{o}}(z_k) + s_p(z_k) + e_k, \tag{2.4}$$

where x_k^{m} denotes the multipath signal component, which may contain the direct transmitter-receiver signal and signal components generated by interactions with the sea surface and seabed. The component $x_k^{\mathrm{o}}(z_k)$ denotes the target-reflected component of the transmitted signal, while $s_p(z_k)$ and e_k denote the target-radiated signal and ambient noise, respectively.

For the given signal, the conditional distribution of the measurement becomes

$$p\left(y_k \mid z_k\right) = \mathcal{N}\left(y_k; \mu_k(z_k), R(z_k)\right). \tag{2.5}$$

Here, the mean $\mu_k(z_k)$ and the covariance matrix $R(z_k)$ can be described as

$$\mu_k(z_k) = x_k^{\mathrm{m}} + x_k^{\mathrm{o}}(z_k), \tag{2.6}$$

$$R(z_k) = R_s(z_k) + R_{e,k}. \tag{2.7}$$

The multipath and target-reflected signal components are both formed from delayed and Doppler-scaled versions of the transmitted signal, although they generally exhibit different propagation delays and Doppler scaling factors.

2.2.3 Ambient Noise

Ambient noise in the underwater domain is generated by various natural and anthropogenic sources such as wind, rain, biological activity, and shipping. Its characteristics depend on the time, location, and depth at which the noise is measured. A statistical characterization of ambient noise generally involves modeling its probability distribution and its temporal and spatial correlation structure. A Gaussian distribution may be appropriate for noise resulting from the combination of many weak, approximately independent sources, whereas impulsive noise may require a non-Gaussian heavy-tailed model. In this thesis, impulsive noise is not considered.

The temporal correlation of ambient noise is characterized by its autocorrelation function and, under a wide-sense stationarity assumption, is related to the power spectral density through the Fourier transform. If the power spectral density is approximately constant over the operational bandwidth, a temporally white-noise approximation may be appropriate. However, if the power spectral density varies over the operational bandwidth, the ambient noise is colored and temporally correlated. This thesis models ambient noise as zero-mean Gaussian and considers both temporally white and colored noise models. Further details on the spatial and temporal characteristics of underwater ambient noise are provided in [9, 35].

2.3 Localization Performance Characterization

Underwater sensor nodes operating with limited spectral, energy, and hardware resources motivate reusing existing communication signals for opportunistic active sensing. Paper A investigates this approach by characterizing the theoretical target-localization performance using communication signals. In the considered setup, the target is assumed to have been detected from the passively received target-radiated signal, from which the bearing estimates are obtained. Then, these bearing estimates are communicated to the other sensor node using the communication signal. For underwater propagation, a simplified channel model is considered, where the signal reflections from the sea surface and the seabed are neglected. From the target-reflected communication signal, additional delay and Doppler information can be extracted and combined with the passive bearing information to improve localization accuracy. The lower bound on the achievable localization accuracy is obtained using the Cramér-Rao lower bound (CRLB), while the delay and Doppler resolution characteristics are assessed using the wideband ambiguity function (WBAF). These quantities are described briefly below.

2.3.1 Fisher Information and Cramér-Rao Lower Bound

The Fisher information matrix (FIM) quantifies how much information the observed measurements carry about the unknown target parameters [36]. The CRLB, given by the inverse of the FIM, provides a lower bound on the covariance of any unbiased estimator. For a Gaussian measurement model with parameter-dependent mean $\mu_k(z)$ and covariance $R_k(z)$, the (q, r):th element of the Fisher information matrix is [37]

$$[I(z)]_{q,r} = \frac{\partial \mu_k^\top(z)}{\partial z_q} R_k^{-1}(z) \frac{\partial \mu_k(z)}{\partial z_r} + \frac{1}{2} \operatorname{tr}\left(R_k^{-1}(z) \frac{\partial R_k(z)}{\partial z_q} R_k^{-1}(z) \frac{\partial R_k(z)}{\partial z_r} \right). \quad (2.8)$$

The first term captures the information contributed by the parameter-dependent measurement mean, while the second captures that contributed by the parameter-dependent covariance. The covariance of any unbiased estimator $\hat{z}$ of the target-

parameter vector z satisfies

$$\mathrm{cov}(\hat{z}) \succeq I^{-1}(z). \tag{2.9}$$

The diagonal elements of $I^{-1}(z)$ yield the theoretical lower bounds on the variance of each estimated target parameter, providing a measure of the best achievable localization accuracy.

2.3.2 Wideband Ambiguity Function

The WBAF characterizes the similarity between the transmitted signal and its delayed and Doppler-scaled replicas. For a real-valued signal $s(t)$, it is defined as

$$\chi(\tau, \beta) = \sqrt{\beta} \int_{-\infty}^{\infty} s(t) s\Big(\beta(t - \tau)\Big) dt, \qquad \beta > 0. \tag{2.10}$$

The shape of the main lobe and sidelobes depends on the waveform design, while the delay and Doppler resolution are primarily related to signal bandwidth and duration, respectively. Consequently, signals with similar localization bounds may still exhibit different ambiguity characteristics.

The CRLB and WBAF provide complementary characterizations of sensing performance. The CRLB is a local measure that provides a lower bound on the estimation-error covariance of the target parameters, whereas the WBAF provides a global characterization of the waveform over the delay-Doppler domain, including its resolution and sidelobe properties. The CRLB depends on the complete statistical measurement model, including the sensor geometry and SNR, whereas the WBAF primarily characterizes properties of the transmitted waveform. Thus, Paper A evaluates the CRLB for different measurement-availability scenarios and uses the WBAF to investigate the delay-Doppler resolution and sidelobe characteristics of the considered communication waveforms.

3

Modeling and Tracking Time-Varying Multipath Channels

The previous chapter introduced different sonar systems and their corresponding measurement models. For the localization analysis in Paper A, a simplified underwater channel model was considered in which the non-target signal components of the transmitted signal were represented only by the direct transmitter-receiver path, while reflections from the sea surface and seabed were neglected. However, this approximation may be inadequate for active sonar in shallow-water environments. The received signal can contain direct, surface-reflected, and seabed-reflected components that may be considerably stronger than a weak target reflection. Moreover, the delays, amplitudes, and phases of these components may vary over time because of sea-surface dynamics and the relative motion of the transmitter and receiver. Consequently, a static and deterministic representation of the multipath channel can become mismatched to the received measurements, causing weak target reflections to be missed or multipath components to be mistaken for targets.

Thus, this chapter motivates modeling the time-varying multipath channel and presents a framework for recursively tracking its temporal evolution. For the dedicated active-sonar scenario considered here, passive target-radiated emissions are neglected, and the ambient noise is modeled as independent, identically distributed zero-mean Gaussian noise.

3.1 Time-Varying Multipath Channel

Consider the bistatic active sonar configuration in a shallow-water environment shown in Figure 3.1. The transmitted signal may reach the receiver through the direct path and through multiple paths involving reflections and scattering from the sea surface and seabed. When the transmitter and receiver are supported by surface platforms, wind-driven surface-wave motion and platform drift can

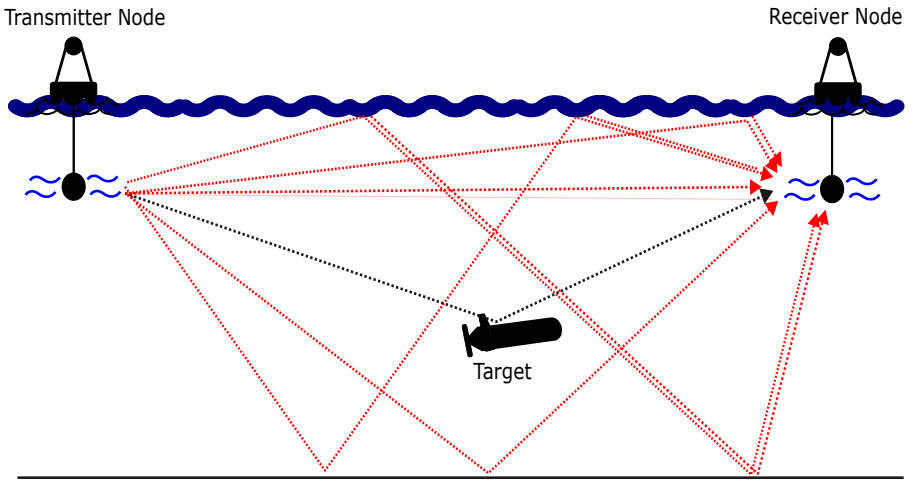

Figure 3.1: *Illustration of the considered sonar scenario with a time-varying multipath channel. Reproduced from [30].*

change the positions of sensor nodes over time. Consequently, the delays, amplitudes, and phases of the multipath components vary over successive measurement intervals. Further, due to the motion of the sea surface and the relative motion of the sensor nodes, the propagation delays of the multipath signal components vary over time, resulting in Doppler effects in the received signal. For wideband signals, the received signal is not only delayed but also Doppler-scaled differently for each multipath component. For a given relative velocity, the low speed of sound in water makes Doppler effects pronounced in underwater acoustic systems. Moreover, the multipath components can be considerably stronger than a weak target reflection. Since both the multipath signal components and the target reflection consist of delayed and Doppler-scaled versions of the transmitted waveform, changes in the multipath channel can mask a target reflection or produce target-like responses. Consequently, reliable target detection, localization, and tracking become highly challenging.

To illustrate the effects of time-varying multipath propagation, two measured underwater acoustic channels are shown in Figure 3.2. The squared magnitude of the channel impulse response (CIR) shows how the channel strength varies with propagation delay and time, while the squared magnitude of the delay-Doppler spread function shows its distribution over delay and Doppler. For the `BCH1_002` channel, the power is concentrated in a relatively small number of distinct multipath arrivals, whereas the `KAU2_010` channel exhibits a much denser distribution over delay, indicating a more diffuse multipath structure. In the delay-Doppler representation, the energy for `BCH1_002` is concentrated around distinct delay regions and close to zero Doppler, whereas `KAU2_010` exhibits a more diffuse distribution. This is reflected in the Doppler spectra, where most of the power in both channels is concentrated near zero Doppler, while the broader Doppler spread for `KAU2_010` indicates greater temporal variability of the chan-

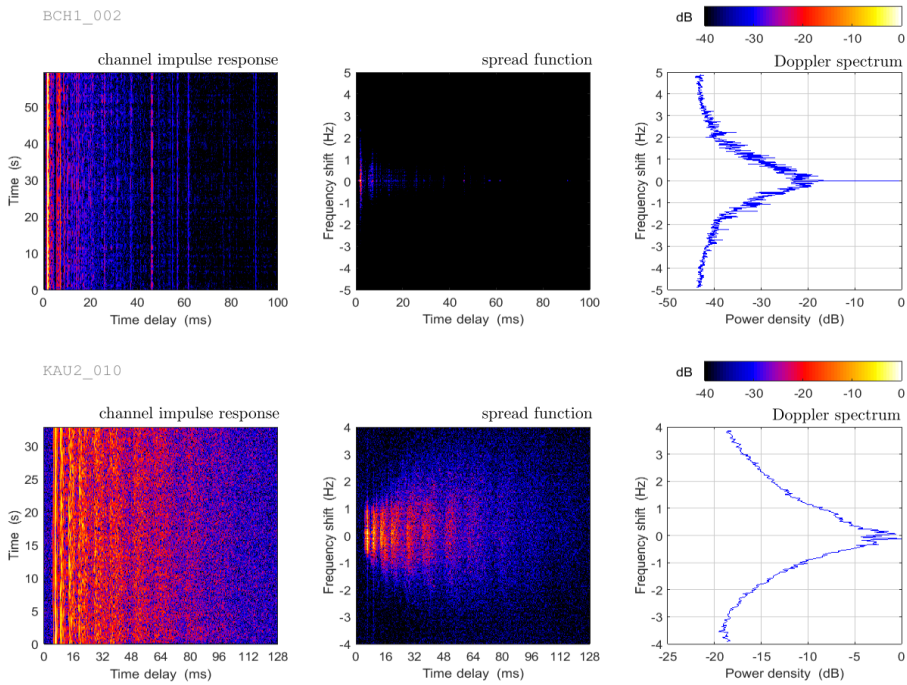

Figure 3.2: *Measured time-varying channel characteristics of two Watermark datasets. The panels show the squared magnitudes of the channel impulse response and delay-Doppler spread function, together with the Doppler spectrum. Reproduced from the Watermark manual and user's guide [38].*

nel.

These characteristics illustrate the structured and time-varying nature of underwater multipath signal propagation and motivate modeling the time-varying multipath channel for target detection and tracking applications.

3.2 Modeling the Multipath Channel

The structured multipath component in the received signal is formed by delayed and Doppler-scaled replicas of the transmitted waveform. From (2.4), the multipath signal components x_k^{m} can be described in continuous time as

$$x_k^{\mathrm{m}}(t) = \sum_{i=1}^{N_b} a_{i,k}\, s\left(\beta_{i,k}(t - \tau_{i,k})\right), \tag{3.1}$$

where $a_{i,k}$, $\tau_{i,k}$, and $\beta_{i,k}$ are the amplitude, delay, and Doppler scaling parameters for the i:th path, respectively. Here, N_b denotes the number of propagation paths,

including the direct path and paths involving reflections from the sea surface and seabed.

For relatively small velocities, the Doppler-scaling factor is close to unity. Defining $r = \ln \beta$, a first-order approximation of a Doppler-scaled waveform can be written as

$$s(\beta(t-\tau)) \approx s(t-\tau) + (t-\tau) r \dot{s}(t-\tau). \tag{3.2}$$

After sampling the received signal and representing the possible propagation delays on a discrete delay grid, the linearized multipath signal can be written as

$$x_k^{\mathrm{m}} \approx S a_k + U \Lambda_{a_k} r_k, \tag{3.3}$$

where S is a Toeplitz matrix constructed from the sampled transmitted waveform and U is constructed from its time-weighted first-order derivative. Further, a_k is the vector containing the multipath signal amplitudes, $\Lambda_{a_k} = \mathrm{diag}(a_k)$, and r_k contains the logarithmic Doppler-scaling parameters associated with the delay-grid components.

Here, the multipath-amplitude vector a_k may be high-dimensional because it is represented over a fine propagation-delay grid. Moreover, diffuse reverberation can distribute the received energy over several neighboring delay samples. To obtain a compact representation, the multipath-amplitude vector can be represented as

$$a_k \triangleq B\theta_k,$$

where B is a fixed basis dictionary of radial basis functions defined over the delay grid, and θ_k is a low-dimensional vector of basis coefficients. In the remainder of this thesis, θ_k is referred to as the background state. It parametrizes the structured multipath signal component through $a_k = B\theta_k$. The random Doppler variations r_k and ambient noise e_k are not included in the background state. However, their effects are represented through the measurement covariance.

3.2.1 Modeling the Doppler Variations

The vector r_k representing the logarithmic Doppler-scaling variations is decomposed as

$$r_k = c_k + d_k, \tag{3.4}$$

where c_k represents path-dependent Doppler variations, while d_k represents a Doppler variation that affects the multipath components coherently. These components are assumed to be mutually independent and are modeled as

$$c_k \sim \mathcal{N}(0, \sigma_c^2 I), \tag{3.5a}$$

$$d_k \sim \mathcal{N}(0, \sigma_d^2 \mathbb{1}\mathbb{1}^\top), \tag{3.5b}$$

where $\mathbb{1}$ denotes a vector of ones. This decomposition is motivated by the physical conditions of the considered underwater environment. The relative motion of the transmitter and receiver can produce an approximately common Doppler variation across the propagation paths. In contrast, differences in path geometry

and interactions with different moving regions of the sea surface can produce path-specific Doppler variations.

Now, based on the approximated multipath channel model, the distribution of the discrete-time measurement model can be described as

$$p\left(y_k \mid z_k, \theta_k\right) = \mathcal{N}\left(y_k; H\theta_k + x_k^o(z_k), R(\theta_k)\right), \tag{3.6}$$

where $H = SB$ and

$$R(\theta_k) = \sigma_e^2 I + \sigma_c^2 U \Lambda_{B\theta_k} \Lambda_{B\theta_k}^\top U^\top + \sigma_d^2 U(B\theta_k)(B\theta_k)^\top U^\top. \tag{3.7}$$

As shown in (3.6), the mean is linear in the background state θ_k, whereas the covariance $R(\theta_k)$ depends on θ_k, resulting in a heteroscedastic measurement model. Here, the three terms in $R(\theta_k)$ represent ambient noise, path-specific Doppler fluctuations, and common Doppler fluctuations, respectively. Their dependence on the channel amplitudes reflects that stronger multipath components produce larger signal variations for the same Doppler perturbation.

3.2.2 Tracking the Multipath Channel

The structured multipath signal components can be tracked by recursively estimating the background state θ_k from measurements. A random-walk model represents the temporal evolution of θ_k to account for gradual changes in the multipath amplitudes between successive measurement intervals, given as

$$\theta_{k+1} = \theta_k + w_k, \qquad w_k \sim \mathcal{N}(0, Q_\theta), \tag{3.8}$$

where w_k is the process noise and Q_θ represents the process noise covariance matrix. An EKF is used to recursively obtain the predicted background-state mean and covariance while evaluating $R(\theta_k)$ at the predicted state estimate.

Paper B builds on the Doppler modeling and compares different candidate measurement covariance models that capture the resulting Doppler-induced background fluctuations to different degrees. It evaluates the statistical significance of these models on BELLHOP-generated datasets using the p-value significance test. BELLHOP is a ray-tracing program used to simulate acoustic propagation and multipath channel characteristics in underwater environments [39]. Furthermore, the paper presents a framework for recursively tracking the background state θ_k, and subsequently using the inferred background statistics for target detection.

4

Tracking Targets using the Multipath Channel Model

The previous chapter introduced the wideband Doppler-linearized model for the time-varying multipath channel. It presented a physics-motivated approach to account for the channel's temporal variation by statistically modeling the Doppler scaling factor in the raw sensor measurement domain. Furthermore, a tracking framework was briefly described to infer the background state from the received measurements. The next step is to integrate the time-varying multipath channel model into a target-tracking framework.

In principle, tracking a target in a time-varying multipath channel using an exact Bayesian framework requires jointly inferring the target and background states from the received measurements. This joint inference can be computationally demanding, especially when the background state is high-dimensional. Another issue is that using measurements containing a target-reflected signal to infer the background state may cause some target-reflected energy to be absorbed into the background-state estimate. This can reduce the target evidence available to the tracking filter, particularly under low SNR conditions.

Therefore, this chapter provides a framework in which the target and background states can be inferred separately, thereby avoiding direct joint inference. Additionally, a strategy to reduce the incorporation of target-reflected energy into the background-state estimate is discussed.

4.1 Target and Background State Inference

The target-tracking framework is based on a set of assumptions and approximations that allow the background and target inference problems to be treated separately. The background state can be recursively inferred using an EKF based on the measurement model for the time-varying multipath channel, whereas the target can be tracked using a single-target Bernoulli track-before-detect (TRBD) filter.

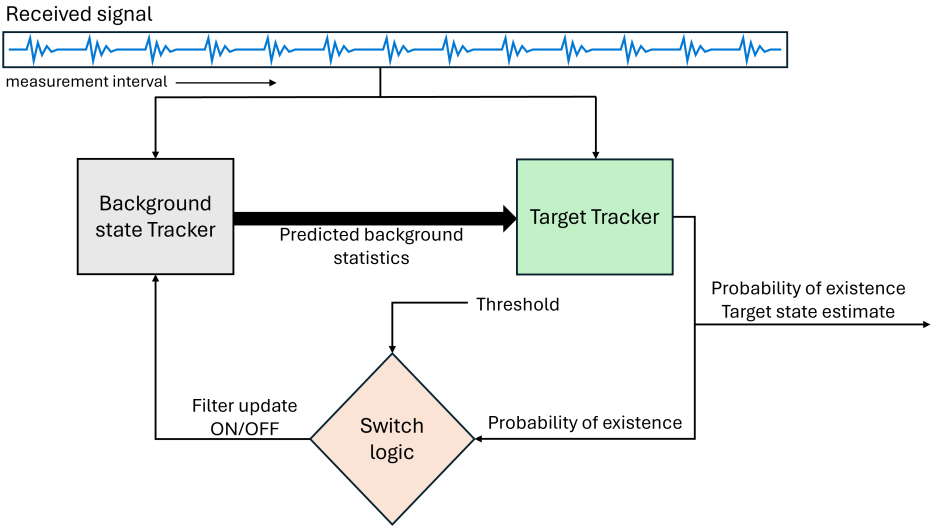

Figure 4.1: *Overview of the target-tracking framework with separate background-state and target tracking. The target tracker uses the predicted background statistics, while the target-existence probability controls the background-state measurement update through the switch logic.*

In the Bernoulli filter, both the target-existence probability and the target state are inferred recursively from the raw sensor measurements. The probability of existence represents the uncertainty regarding whether a target is present based on the received measurements. A detailed description of Bernoulli filtering is given in [40].

An overview of the proposed target-tracking framework is shown in Figure 4.1. The received measurements are provided to both the background-state tracker and the target tracker. The predicted background statistics obtained from the background-state tracker are used by the target tracker to construct the measurement likelihood to infer the target state and estimate the existence probability. Further, to reduce the incorporation of target-reflected energy into the background-state estimate, switching logic is introduced based on the estimated target's probability of existence.

4.1.1 Assumptions and Approximations

The separate inference of the background and target states is enabled by neglecting their dependence in the predictive distribution and by assuming that the background state can be inferred from target-free measurements. Using the probability product rule, the predictive joint distribution can be written as

$$p(z_k, \theta_k \mid y_{1:k-1}) = p(z_k \mid \theta_k, y_{1:k-1}) p(\theta_k \mid y_{1:k-1}), \tag{4.1}$$

and

$$p(z_k \mid \theta_k, y_{1:k-1}) \approx p(z_k \mid y_{1:k-1}) \tag{4.2a}$$
$$p(\theta_k \mid y_{1:k-1}) \approx p(\theta_k \mid y_{1:k-1}, x_k^{\mathrm{o}}(z_k) = 0). \tag{4.2b}$$

The approximation in (4.2a) is motivated by the physical characteristics of the considered sensing problem. The background state evolves primarily due to changes in the underwater propagation environment, whereas the target state evolves according to the target's location and motion relative to the sensor nodes. Furthermore, in the considered setup, the multipath signal components are observed following each transmission, whereas the target may or may not be present from the first measurement interval and can enter the monitored region at an unknown time. This motivates the assumption in (4.2b), as measurements collected during target-absent intervals can be used to infer the background state without contamination from the target-reflected signal.

Additionally, the predicted background-state distribution is approximated as Gaussian, with its mean and covariance obtained recursively from the EKF. It is given as

$$p(\theta_k \mid y_{1:k-1}, x_k^{\mathrm{o}}(z_k) = 0) \approx \mathcal{N}(\theta_k; \hat{\theta}_{k|k-1}, P_{k|k-1}), \tag{4.3}$$

where $\hat{\theta}_{k|k-1}$ and $P_{k|k-1}$ are the predicted background-state mean and covariance matrix, respectively.

The predicted background statistics obtained from the EKF are used to construct an approximate measurement likelihood for the Bernoulli TRBD filter by marginalizing the conditional measurement likelihood over the predicted background state. This likelihood enables the target-existence probability and target state to be recursively inferred from the raw sensor measurements.

4.1.2 Switching Logic

Since the target-arrival time is generally unknown, the background-state filter may continue to update after the target appears, which can cause part of the target-reflected energy to be absorbed into the background-state estimate. To mitigate this effect, a switching logic is introduced based on the estimated target-existence probability. At each measurement interval, the probability of existence is compared with a predefined threshold. If the probability exceeds this threshold, the target is assumed to be present, and the measurement update of the background-state filter is skipped. If the probability subsequently falls below the threshold, the measurement update is resumed. This provides a practical mechanism for reducing the absorption of target-reflected energy into the background-state estimate.

Paper C provides a detailed methodological formulation and investigates different switching logics. The tracking methodology is evaluated using datasets corresponding to both background-model-matched and background-model-mismatched conditions. Moreover, the resulting tracking performance is compared with conventional and background-compensated CFAR-based detect-before-track approaches.

5

Conclusions and Future Research

This thesis investigated underwater acoustic channel models for target detection, localization, and tracking. For resource-limited sonar systems, suitable communication signals can also support target localization. Under the simplified channel conditions considered, the theoretical localization bounds are comparable to those obtained using a dedicated sensing waveform. Paper A shows that combining passive bearing information with bistatic information from the communication signal provides location-error lower bounds of approximately 4–15 m over a substantial part of the considered region. This supports opportunistic sensing as a means to obtain target location information from existing communication transmissions, reducing the need for separate sensing transmissions.

Additionally, a sonar system benefits from statistically modeling underwater signal propagation and its temporal variation. The wideband Doppler linearization method in Paper B provides a tractable and physically motivated statistical model of the time-varying multipath channel. The model enables recursive tracking and compensation for structured, time-varying background.

For sonar systems operating in time-varying multipath environments, incorporating the statistical channel model into a target-tracking framework improves target detection and tracking. The inferred background statistics allow the system to account for the time-varying multipath channel while inferring the target location and motion information. Improvements relative to the evaluated CFAR-based approaches are observed under both model-matched and model-mismatched conditions. As shown in Paper C, in the model-mismatched evaluation at $\mathrm{SNR}_{\mathrm{eff}} = 26.3$ dB, two of the proposed background-update logics achieve GOSPA values of approximately 28–35 m at ping 60, compared with approximately 85 m for the conventional CFAR-based tracker.

Taken together, these findings support a sonar-system design that makes effective use of available transmissions and incorporates the time-varying multipath

channel into target inference.

5.1 Future Research Directions

The proposed framework approximates the joint predictive distribution by neglecting the dependence between the target and background states. It remains unclear under which conditions the resulting target-background decoupling provides an accurate approximation to the joint inference problem. Therefore, an important direction for future research is to characterize the validity of this approximation and to investigate its effect on the target inference.

Further, the background state is assumed to be inferred from target-free measurements, and its predictive distribution is approximated as Gaussian, with its mean and covariance obtained using an EKF. A second direction is to investigate under which conditions this Gaussian approximation adequately represents the background-state predictive distribution and how deviations from this approximation affect target inference.

A third direction concerns the first-order approximation used in the wideband Doppler linearization. Future research could investigate under which propagation conditions this approximation is sufficient and whether higher-order approximations improve the representation of the time-varying multipath channel. Any improvements in detection and tracking could then be evaluated against the additional computational cost.

Bibliography

[1] Emad Felemban, Faisal Karim Shaikh, Umair Mujtaba Qureshi, Adil A. Sheikh, and Saad Bin Qaisar. Underwater sensor network applications: A comprehensive survey. *Int. J. Distrib. Sens. N.*, 11(11):896832, November 2015. ISSN 1550-1477. doi: 10.1155/2015/896832.

[2] Ian F. Akyildiz, Dario Pompili, and Tommaso Melodia. Underwater acoustic sensor networks: research challenges. *Ad Hoc Netw.*, 3(3):257–279, May 2005. ISSN 1570-8705. doi: 10.1016/j.adhoc.2005.01.004.

[3] Huma Ghafoor and Youngtae Noh. An overview of next-generation underwater target detection and tracking: An integrated underwater architecture. *IEEE Access*, 7:98841–98853, 2019. ISSN 2169-3536. doi: 10.1109/access.2019.2929932.

[4] Asiya Jehangir, S. M. Majid Ashraf, Ruhul Amin Khalil, and Nasir Saeed. ISAC-enabled underwater IoT network localization: Overcoming asynchrony, mobility, and stratification issues. *IEEE Open J. of the Commun. Soc.*, 5:3277–3288, 2024. ISSN 2644-125X. doi: 10.1109/ojcoms.2024.3401745.

[5] He Huang and Wen-Qin Wang. FDA-OFDM for integrated navigation, sensing, and communication systems. *IEEE Aerosp. Electron. Syst. Mag.*, 33(5-6):34–42, 2018.

[6] An Liu, Zhe Huang, Min Li, Yubo Wan, Wenrui Li, Tony Xiao Han, Chenchen Liu, Rui Du, Danny Kai Pin Tan, Jianmin Lu, et al. A survey on fundamental limits of integrated sensing and communication. *IEEE Communications Surveys & Tutorials*, 24(2):994–1034, 2022.

[7] Ashwani Koul, Gustaf Hendeby, and Isaac Skog. Performance analysis of communication signals for localization in underwater sensor networks. In *IEEE OCEANS - Great Lakes*, pages 1–7, Chicago, IL, USA, September 2025.

[8] Zhaoquan Zeng, Shu Fu, Huihui Zhang, Yuhan Dong, and Julian Cheng. A survey of underwater optical wireless communications. *IEEE Communications Surveys and Tutorials*, 19(1):204–238, October 2016. doi: 10.1109/COMST.2016.2618841.

[9] D. A. Abraham. *Underwater Acoustic Signal Processing: Modeling, Detection, and Estimation*. Springer, Cham, Switzerland, February 2019. ISBN 9783319929835. doi: 10.1007/978-3-319-92983-5.

[10] Shixiong Wang, Wei Dai, Haowei Wang, and Geoffrey Ye Li. Robust waveform design for integrated sensing and communication. *IEEE Trans. Signal Process.*, 72:3122–3138, 2024. ISSN 1941-0476. doi: 10.1109/tsp.2024.3410142.

[11] Zhiqing Wei, Hanyang Qu, Yuan Wang, Xin Yuan, Huici Wu, Ying Du, Kaifeng Han, Ning Zhang, and Zhiyong Feng. Integrated sensing and communication signals toward 5G-A and 6G: A survey. *IEEE Internet Things J.*, 10(13):11068–11092, 2023. doi: 10.1109/JIOT.2023.3235618.

[12] Fan Liu, Christos Masouros, Athina P. Petropulu, Hugh Griffiths, and Lajos Hanzo. Joint radar and communication design: Applications, state-of-the-art, and the road ahead. *IEEE Trans. Comm.*, 68(6):3834–3862, 2020. doi: 10.1109/TCOMM.2020.2973976.

[13] Junlong Wang, Qing Wang, Quan Tao, and Xiaomei Fu. Integrated sonar and communication: A survey. *IEEE Comm. Surveys and Tutorials*, 28:4127–4155, 2026. ISSN 2373-745X. doi: 10.1109/comst.2025.3645053.

[14] Wei Men, Liang Zhang, Longxiang Guo, and Hongyu Yin. Waveform design and processing for joint detection and communication based on MIMO sonar systems. In *IEEE 5th Int. Conf. on Inf. Commun. and Signal Process. (ICICSP)*, pages 523–527, November 2022. doi: 10.1109/icicsp55539.2022.10050704.

[15] Qixiang Niu, Qunfei Zhang, and Wentao Shi. Integrated waveform design scheme based on underwater detection and communication. In *IEEE Int. Conf. on Signal Process., Commun. and Comput. (ICSPCC)*, pages 1–5, October 2022. doi: 10.1109/icspcc55723.2022.9984531.

[16] Jingwei Yin, Wei Men, Xiao Han, and Longxiang Guo. Integrated waveform for continuous active sonar detection and communication. *IET Radar Sonar Navig.*, 14(9):1382–1390, 2020. doi: https://doi.org/10.1049/iet-rsn.2020.0099.

[17] Jiale Wang, Jie Lian, and Guolei Zhu. A weighted Mahalanobis distance target sensing strategy for underwater integrated sensing and communication systems. *IEEE Wireless Commun. Lett.*, 13(1):79–83, January 2024. ISSN 2162-2345. doi: 10.1109/lwc.2023.3320121.

[18] Yiyin Wang, Zhenyu Shi, Xiaoli Ma, and Lingya Liu. A joint sonar-communication system based on multicarrier waveforms. *IEEE Signal Process Lett.*, 29:777–781, 2022. ISSN 1558-2361. doi: 10.1109/lsp.2021.3106889.

[19] Junlong Wang, Qing Wang, Quan Tao, and Xiaomei Fu. Dictionary-theory-based orthogonal chirp division multiplexing signal for integrated sonar and communication system. *IEEE Trans. Veh. Technol.*, 74(5):7005–7019, May 2025. ISSN 1939-9359. doi: 10.1109/tvt.2025.3527971.

[20] Jixin Bao, Junlong Wang, Quan Tao, Guangyao Han, and Xiaomei Fu. Fresnel domain sector modulation lfm signal for underwater integrated communication and detection. *IEEE Internet Things J.*, 12(3):3017–3027, February 2025. ISSN 2372-2541. doi: 10.1109/jiot.2024.3477576.

[21] Shuai Liu, Junlong Wang, Zhiwen Qian, and Xiaomei Fu. A novel sonar-communication system based on incremental-frequency-interval acoustic frequency comb signal. *IEEE Internet Things J.*, 12(5):5834–5846, March 2025. ISSN 2372-2541. doi: 10.1109/jiot.2024.3489636.

[22] Wei Men, Jun Du, Jingwei Yin, Liang Zhang, Lei Liu, Yong Ren, and Dusit Niyato. Joint detection and communication system design via combination of index and phase modulations. *IEEE Trans. Wireless Commun.*, 23 (10):15690–15704, October 2024. ISSN 1558-2248. doi: 10.1109/twc.2024.3432777.

[23] Jun Liu, Zhaohui Wang, Jun-Hong Cui, Shengli Zhou, and Bo Yang. A joint time synchronization and localization design for mobile underwater sensor networks. *IEEE Trans. Mob. Comput.*, 15(3):530–543, March 2016. ISSN 2161-9875. doi: 10.1109/tmc.2015.2410777.

[24] Chaoran Yang, Qing Ling, Xueli Sheng, Mengfei Mu, and Andreas Jakobsson. Detecting weak underwater targets using block updating of sparse and structured channel impulse responses. *Remote Sensing*, 16(3):476, January 2024. ISSN 2072-4292. doi: 10.3390/rs16030476.

[25] Hongjian Jia and Xiukun Li. Underwater reverberation suppression based on non-negative matrix factorisation. *J. Sound Vib.*, 506:116166, August 2021. ISSN 0022-460X. doi: 10.1016/j.jsv.2021.116166.

[26] Yunchao Zhu, Rui Duan, and Kunde Yang. Robust shallow water reverberation reduction methods based on low-rank and sparsity decomposition. *J. Acoust. Soc. Am*, 151(5):2826–2842, April 2022. ISSN 1520-8524. doi: 10.1121/10.0010353.

[27] Xiaohua Li, Yaan Li, Jing Yu, Xiao Chen, and Miao Dai. PMHT approach for multi-target multi-sensor sonar tracking in clutter. *Sensors*, 15(11):28177–28192, November 2015. ISSN 1424-8220. doi: 10.3390/s151128177.

[28] Xiaohua Li, Bo Lu, Wasiq Ali, and Haiyan Jin. Passive tracking of multiple underwater targets in incomplete detection and clutter environment. *Entropy*, 23(8):1082, August 2021. ISSN 1099-4300. doi: 10.3390/e23081082.

[29] Jonghoek Kim. Tracking multiple underwater targets using adaptive Gaussian mixture probability hypothesis density filter with unknown clutter rate.

IEEE Trans. Aerosp. Electron. Syst., 60(6):9154–9162, December 2024. ISSN 2371-9877. doi: 10.1109/taes.2024.3437343.

[30] Ashwani Koul, Gustaf Hendeby, and Isaac Skog. Tracking time-varying multipath channels for active sonar applications. In *29th International Conference on Information Fusion (FUSION)*, Trondheim, Norway, June 2026. Accepted for publication.

[31] Ashwani Koul, Gustaf Hendeby, and Isaac Skog. A computationally efficient likelihood approximation for target tracking in time-varying multipath channels, 2026. URL `https://arxiv.org/abs/2608.20206`. Submitted for possible publication in IEEE Transactions on Aerospace and Electronic Systems.

[32] S. M. Kay. *Fundamentals of Statistical Signal Processing: Detection Theory*. Prentice Hall, 1998.

[33] Henry Cox. Fundamentals of bistatic active sonar. In *Underwater acoustic data processing*, pages 3–24. Springer, 1989.

[34] Daniel Bossér, Gustaf Hendeby, Magnus Lundberg Nordenvaad, and Isaac Skog. A statistically motivated likelihood for track-before-detect. In *IEEE Int. Conf. on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, pages 1–6, Bedford, United Kingdom, September 2022.

[35] Finn B. Jensen, William A. Kuperman, Michael B. Porter, and Henrik Schmidt. *Computational Ocean Acoustics*. Modern Acoustics and Signal Processing. Springer, New York, NY, 2 edition, 2011. ISBN 978-1-4419-8677-1. doi: 10.1007/978-1-4419-8678-8.

[36] S. M. Kay. *Fundamentals of Statistical Signal Processing: Estimation Theory*. Prentice Hall, 1993.

[37] Harry L Van Trees. *Optimum array processing: Part IV of detection, estimation, and modulation theory*. John Wiley & Sons, 2002.

[38] Paul van Walree, Roald Otnes, and Trond Jenserud. The Watermark manual and user's guide: Version 1.0. FFI Report 16/01378, Norwegian Defence Research Establishment (FFI), Kjeller, Norway, November 2016.

[39] Michael B Porter. The BELLHOP Manual and User's Guide: PRELIMINARY DRAFT. *Heat, Light, and Sound Research, Inc., La Jolla, CA, USA, Tech. Rep*, 260, 2011.

[40] Branko Ristic, Ba-Tuong Vo, Ba-Ngu Vo, and Alfonso Farina. A tutorial on Bernoulli filters: Theory, implementation and applications. *IEEE Trans. Signal Process.*, 61(13):3406–3430, July 2013. ISSN 1941-0476. doi: 10.1109/tsp.2013.2257765.

Part II

Publications

Papers

The papers associated with this thesis have been removed for copyright reasons. For more details about these see:

https://doi.org/10.3384/9789181187199

FACULTY OF SCIENCE AND ENGINEERING

Linköping studies in science and technology. Licentiate Thesis No. 2039, 2026
Department of Electrical Engineering

Linköping University
SE-581 83 Linköping, Sweden

www.liu.se

LINKÖPING UNIVERSITY