
by

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B.A.Sc., University of British Columbia, 2018

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

Master of Applied Science

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES
(Electrical and Computer Engineering)

The University of British Columbia
(Vancouver)

July 2020

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The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the thesis entitled:


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Abstract

Achieving high data rate and reliable communication in shallow and harbour underwater acoustic (UA) environments can be a demanding task in the presence of ship-radiated noise. However, few research studies have examined the properties of ship-radiated noise in terms of its time-domain statistical characteristics and its negative effects on UA communication systems. From the observation of spectrograms and the temporal signals of various acoustic shipping noise recordings, high frequency and impulsive characteristics are visible. These impulsive agitations can be detrimental to the performance of multi-carrier UA communication systems, thus impulse noise cancellation methods are necessary to reduce errors. In this thesis, we investigate the impulsive and correlative interference generated due to nearby shipping activity and its effects on orthogonal frequency-division multiplexing (OFDM) systems. The research objectives are twofold: (1) model the time-domain stochastic characteristics of ship-radiated noise, and (2) achieve shipping noise cancellation for UA OFDM systems.

We propose the use of unsupervised learning techniques to train generative models that capture the time-domain stochastic behaviours of ship-radiated noise using a publicly available database of long-term acoustic shipping noise recordings. These models can then be used for further analysis of ship-radiated noise and performance evaluation of UA OFDM systems in the presence of such interference. The results indicate a two component Gaussian mixture model serves as a better approximation for high frequency ship-radiated noise while generative adversarial networks produce improved realizations of shipping noise in lower frequencies.

We offer sparsity and deep learning-based ship-radiated noise cancellation so-
tions that are constructed under a compressed sensing framework. Obtained results show that the sparsity-based estimation and cancellation algorithms demonstrate competitive mitigation capabilities for high frequency impulsive ship-radiated noise. The deep learning-based cancellation methods depict measurable shipping noise mitigation results to the sparsity-based techniques, but with superior runtime performance. In addition, the deep learning-based methods outperform the sparsity-based approaches in lower frequency ship-radiated noise due to the supplementary correlative structure. Furthermore, experimental results indicate the deep learning-based cancellation approaches scale better to new realizations of high frequency and low frequency shipping noise signals compared to the sparsity-based methods.
Lay Summary

Nearby passing ships in harbour and shallow water environments can cause severe degradation to wireless underwater acoustic signals that are necessary in transferring relevant information between underwater sources. However, effective means of simulating and cancelling the interfering effects of shipping noise remains a challenge. The inability to simulate and mitigate the effects of shipping noise produces difficulties when designing and implementing wireless communication systems that reliably transfer information between underwater sources in the presence of such interference. Inspired by the publicly available database of underwater acoustic shipping noise recordings, we conduct a data driven study to address the above challenges. The objectives of this thesis focus on modelling the statistical characteristics of shipping noise and cancelling its interfering effects. We address the objectives by producing a time-domain statistical model for shipping noise and devise machine learning driven noise cancellation algorithms that reduce the effects of the respective interference.
Preface

The research content presented in this thesis was completed in the Department of Electrical and Computer Engineering at the University of British Columbia under the supervision of Dr. Lutz Lampe. Below, the conference publications that make up the content of this thesis are outlined.

A version of Chapter 2 and Chapter 3 has previously been published in the following conference paper:


Ruoyu Zhang initiated this project and was a main contributor of the original idea generation. Lutz Lampe was the supervisor on this work and provided help in the early stages of idea formation in addition to help in manuscript editing. Roee Diamant provided idea suggestions at the later stages of manuscript writing as well as participated in manuscript editing.

A version of Chapter 4 has been accepted for publication to the following conference:


Roee Diamant facilitated and participated in the experimental design, sea trial organization, and helped in conducting the experimental tests necessary for acquiring relevant experimental data that was used for validation of the models in this work.
Lutz Lampe was the supervisor on this project and aided in the initial stages of idea generation and in manuscript editing.

A version of Chapter 5 has been accepted for publication to the following conference:


Vala Vakilian and Dryden Wiebe constructed the initial body work of code that was utilized as a template in producing and designing a model training framework and result generation. Roee Diamant aided in the experimental sea trials for acquiring experimental data for further validation of this work. Lutz Lampe was the supervisor of this project and helped in the idea formation stage and in manuscript editing.

I have completed majority of the work that embodies the content of the listed conference publications and I am the primary research author of all three publications. The completed tasks include but are not limited to, idea formation, literature review, experimental data acquisition, simulation design, simulation implementation, generation of results, analysis of results, and manuscript writing and editing.

The copyright regarding the publications listed above has been transferred to the Institution of Electrical and Electronic Engineers (IEEE). However, I retain permission to use the work associated with the listed publications in the content of this thesis.
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<td>1-NN</td>
<td>1-nearest neighbours</td>
</tr>
<tr>
<td>AIS</td>
<td>Automatic identification system</td>
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<tr>
<td>AMP</td>
<td>Approximate message passing</td>
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<tr>
<td>ANN</td>
<td>Artificial neural network</td>
</tr>
<tr>
<td>AWGN</td>
<td>Additive white Gaussian noise</td>
</tr>
<tr>
<td>BP</td>
<td>Basis pursuit</td>
</tr>
<tr>
<td>BP DN</td>
<td>Basic pursuit de-noise</td>
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<tr>
<td>CDF</td>
<td>Cumulative distribution function</td>
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<tr>
<td>CNN</td>
<td>Convolutional neural network</td>
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<tr>
<td>CS</td>
<td>Compressed sensing</td>
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<tr>
<td>CSC</td>
<td>Circularly-symmetric complex</td>
</tr>
<tr>
<td>DCGAN</td>
<td>Deep convolutional generative adversarial network</td>
</tr>
<tr>
<td>DFT</td>
<td>Discrete Fourier transform</td>
</tr>
<tr>
<td>DIL</td>
<td>Dictionary learning</td>
</tr>
<tr>
<td>DIL-BP</td>
<td>Dictionary learning and basis pursuit</td>
</tr>
<tr>
<td>DL</td>
<td>Deep learning</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
<td>DNN</td>
<td>Deep neural network</td>
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<tr>
<td>EM</td>
<td>Expectation-maximization</td>
</tr>
<tr>
<td>GAMP</td>
<td>Generalized approximate message passing</td>
</tr>
<tr>
<td>GAN</td>
<td>Generative adversarial network</td>
</tr>
<tr>
<td>GMM</td>
<td>Gaussian mixture model</td>
</tr>
<tr>
<td>GM-GAMP</td>
<td>Gaussian mixture generalized approximate message passing</td>
</tr>
<tr>
<td>HF</td>
<td>High frequency</td>
</tr>
<tr>
<td>IDFT</td>
<td>Inverse discrete Fourier transform</td>
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<tr>
<td>K-SVD</td>
<td>K-singular value decomposition</td>
</tr>
<tr>
<td>LF</td>
<td>Low frequency</td>
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<tr>
<td>LOO</td>
<td>Leave-one-out</td>
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<tr>
<td>LPF</td>
<td>Low-pass filter</td>
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<tr>
<td>L-SDA</td>
<td>Linear stacked de-noising autoencoder</td>
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<tr>
<td>MSE</td>
<td>Mean squared error</td>
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<tr>
<td>ML</td>
<td>Maximum likelihood</td>
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<tr>
<td>NL-SDA</td>
<td>Non-linear stacked de-noising autoencoder</td>
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<td>ONC</td>
<td>Ocean Networks Canada</td>
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<tr>
<td>OFDM</td>
<td>Orthogonal frequency-division multiplexing</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability distribution function</td>
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<td>QPSK</td>
<td>Quadrature phase shift keying</td>
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<tr>
<td>QQ</td>
<td>Quantile-quantile</td>
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<tr>
<td>RIP</td>
<td>Restricted isometric property</td>
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<td>Abbreviation</td>
<td>Full Form</td>
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<tr>
<td>SDA</td>
<td>Stacked de-noising autoencoder</td>
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<tr>
<td>SER</td>
<td>Symbol error rate</td>
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<tr>
<td>SNR</td>
<td>Signal to noise ratio</td>
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<tr>
<td>SVD</td>
<td>Singular value decomposition</td>
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<tr>
<td>UA</td>
<td>Underwater acoustic</td>
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<tr>
<td>UAC</td>
<td>Underwater acoustic communication</td>
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<td>VLF</td>
<td>Very low frequency</td>
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Acknowledgments

First and foremost, I would like to express sincere gratitude to Dr. Lutz Lampe for his guidance, mentorship, and supervision throughout the duration of my Master of Applied Science degree as well as my undergraduate research assistantship. Dr. Lampe’s patient approach to academic research and insightful knowledge in the field of digital communications has been a source of inspiration towards my own academic progress.

I would like to thank Dr. Roee Diamant for his extensive support and mentorship in underwater acoustic communication theory, experimental engineering, and for facilitating the opportunity to visit the Marine Technologies Lab at the University of Haifa, Israel, which enabled me to participate in experimental sea trials during my visitation.

This thesis research has been funded by the National Sciences and Engineering Research Council (NSERC) of Canada Discovery Grant and the North Atlantic Treaty Organization (NATO) Science for Peace and Security Programme awarded to Dr. Lampe. I would also like to gratefully acknowledge the funding support received towards my Master’s research from the NSERC Canadian Graduate Scholarship - Master’s Program Award and the province of British Columbia for supporting my Master’s research through the British Columbia Graduate Scholarship. Moreover, I would like to thank the Electrical and Computer Engineering Department at the University of British Columbia for further supplementing my Master’s research through the Graduate Support Initiative Award.

To Ocean Networks Canada, thank you for providing help with the data collection and preparation process that made this study possible.

My appreciation and gratitude goes out towards my friends and colleagues in
the Data Communications Group that made the journey that much better.

Last but not least, I would like to express special thanks to my mother and father who have always provided me with support and motivation to pursue my professional and academic aspirations. Without them, this would have not been possible.
Chapter 1

Introduction

1.1 Overview

The realm of underwater acoustics (UAs) focuses on studying the propagation of sound waves in water, which in turn has laid the forefront for research in the fields of UA marine science and engineering. Research in UA marine science and engineering encompasses applications such as oceanography, environmental monitoring, sonar, and wireless underwater acoustic communication (UAC) [5]. Of the latter, research trends in UAC continue to evolve [6] due to its continuous needs in naval defense, diver to diver communication, autonomous underwater vehicle tracking, and more [7]. However, there remain continuous challenges in designing high data rate and robust wireless UAC systems.

The UA channel consists of linear and non-linear distortions and additive perturbations that create challenging conditions for achieving high data rate robust wireless communication. These factors include multipath fading, Doppler shifts, time varying channel characteristics, high attenuation, and various sources of noise and interference [8] [9]. Among the latter, the ramifications of ambient noise and interference on UAC signals in ocean and marine environments has attracted significant research attention [10–18]. Shipping activity, marine life, wind, seismic activity, and other natural phenomena all contribute in producing background noise and interference amid the high time variability of the UA channel. Noise in the UA channel rarely takes the form of pure additive white Gaussian noise (AWGN) [10].
thus research in this area continues to flourish as UA noise models prove invaluable when assessing the performance UAC systems.

The constant presence of noise requires effective mitigation techniques that either eliminate or suppress the additive perturbing effects of acoustic noise to UAC signals. One particular area of interest is the suppression and cancellation of the impulse noise found in the UA channel, predominately produced from shipping activity and/or snapping shrimp [17, 19–21]. Noise due to snapping shrimp is typically considered when investigating the effects of impulse noise on UAC systems. However, few research studies address the high frequency (HF) and impulsive contributions associated with ship-radiated noise, yet from observation, there are evident HF and impulsive attributes. Figure 1.1 illustrates a typical spectrogram obtained in the presence of a nearby passing ship, demonstrating key HF identifiers. Figure 1.2 (a) and Figure 1.2 (b) show the accompanying raw acoustic recording and complex baseband noise signal respectively, of a nearby passing ship, visibly displaying impulsive characteristics. Due to these observed characteristics, and the lack of research studies on ship-radiated noise interference in the UA environment, investigating the effects of shipping noise would provide beneficial insights in future design and evaluation of UAC systems. Therefore, the main goal of this thesis focuses on the impulsive and correlative interference generated due to ship-radiated noise and its effects on high data rate UAC systems.

1.2 Scope and Motivation

In this section, we give introductory overviews of the existing literature in the domains of ship-radiated noise analysis, UAC noise cancellation, and introduce the publicly available database of long-term acoustic shipping noise recordings. Likewise, the motivations behind the research content of this thesis are presented.

1.2.1 Ship-radiated Noise

Ship-radiated noise is a major contributor of additive perturbations in harbour and shallow water environments, limiting the data rate performance and reliability of UAC systems. There have been various research studies that explore the ambient and spectral characteristics associated with shipping activity in the UA channel.
Figure 1.1: Spectrogram of a ship (labelled “ship 64802”) passing in the Strait of Georgia, BC, Canada, within a distance of 1 km from the underwater listening station. This figure is obtained from the Ocean Networks Canada “Hydrophone Data Search” Directory [1].

yet the development of a stochastic model for ship-radiated noise has not received much attention. Additionally, the HF and impulsive noise attributes exhibited in the presence of shipping activity is evident from observation of acoustic recordings, as exemplified in Figure 1.1 and Figure 1.2, but few research study have investigated these properties. The lack of an adequate stochastic model introduces challenges when designing and evaluating the performance of high data rate UAC systems for implementation in the presence of such interference. Thus, investigating the temporal statistical characteristics of ship-radiated noise would be beneficial in producing a time-domain stochastic model for ship-radiated noise.
1.2.2 Noise Cancellation for UAC Systems

Some receiver designs are specifically constructed to handle the harsh and variable sea environment, such as [20] which proposes the use of a method based on a new modulation constellation that is carefully tailored to the noise statistics of the UA channel. However, this method requires accurate channel state information to adapt to the varying UA channel conditions, which may be difficult to acquire.

Orthogonal frequency-division multiplexing (OFDM) is a popular multi-carrier technique for high data rate communication utilized to combat the frequency selectivity present in the UA channel [18] [24]. However, OFDM is known to be susceptible to degradation in the presence of impulse noise [25] [26]. Considering this challenge, several research studies have proposed methods for impulse noise
cancellation under a compressed sensing (CS) framework for OFDM systems, e.g. [26–30].

These approaches exploit the sparsity of impulse noise and utilize convex optimization and iterative solvers to estimate and cancel the impulsive interfering contributions. An iterative empirical Bayesian solver was implemented [30] to exploit additional statistical information regarding the impulse noise, yielding improved cancellation performance to existing CS approaches. However, the aforementioned methods explore the case of impulse noise interference primarily generated due to snapping shrimp. Therefore, work on interference cancellation of ship-radiated noise for UA OFDM systems is also necessary in order to address the various cases of correlative noise in the UA channel.

1.2.3 Database of Long-term Acoustic Recordings

Typically, the acquisition of UA recordings, either of received UAC signals or of UA noise, require tedious and expensive experimental configurations that are carried out over the course of extensive sea trials. To combat these experimental limitations, UAC systems can be modelled and simulated via analytic relationships that represent the behaviour of the UA channel, then later verified experimentally [5] [12]. Likewise, on-line databases of long-term acoustic recordings can be utilized to investigate the statistical properties of ambient noise in marine environments.

Ocean Networks Canada (ONC) [31] provides an on-line publically available database of long term acoustic recordings from their hydrophone listening stations [1]. Amongst a variety of aquatic data records and acoustic measurements, the ONC database contains acoustic recordings of nearby passing ships. Thus, the public availability of acoustic recordings of ship-radiated noise prompts a data driven study focussing on the noise properties of ship-radiated noise, in terms of statistical characterization and interference cancellation.

1.3 Objectives and Contributions

Given the above research gaps and the access to a large publicly available database of acoustic shipping noise recordings, we address the problems associated with ship-radiated noise interference in UA OFDM systems. The primary objective is
to evaluate and improve the performance of UA OFDM systems in the presence of ship-radiated noise. In order to achieve this objective, a sound understanding of the stochastic characteristics of ship-radiated noise is required, thus with the access to the ONC database we conduct a data driven study utilizing numerous acoustic recordings of nearby passing ships.

The objectives and contributions of this thesis are two-fold:

1. **Objective:** Develop a time-domain stochastic model for ship-radiated noise.

   **Contribution:** With the absence of a time-domain stochastic model for ship-radiated noise, we propose the use of unsupervised learning methods to fit probabilistic generative models that approximate the stochastic behaviour of the shipping noise dataset [32]. We consider two approaches: (1) assuming the ship-radiated noise follows a Gaussian mixture model (GMM) distribution [33], we learn the GMM parameters via expectation-maximization (EM) [34], and (2) taking advantage of new advances in deep learning (DL), we train a generative adversarial network (GAN) that learns the distribution of the dataset with minimal assumptions [35]. Once trained, these models produce new probabilistic realizations of ship-radiated noise signals drawn from the distribution of the shipping noise dataset. Our offered solutions enable performance evaluations of UA OFDM systems in the presence of ship-radiated noise interference by producing time-domain stochastic models of shipping noise.

2. **Objective:** Mitigate the perturbing effects of ship-radiated noise on UA OFDM systems.

   **Contribution:** The success of CS-based methods for impulse noise cancellation in OFDM systems [26–30] and the observable impulsive attributes of shipping noise suggest the applicability of these CS approaches for mitigating ship-radiated noise interference in UA OFDM systems. Therefore, we propose the use of the CS framework for UA OFDM systems in order to cancel the interfering effects of ship-radiated noise. Under this framework, we consider two categories of approaches: (1) iterative CS-based algorithms,
and (2) DL-based methods that utilize data to learn a non-linear mapping to solve the CS problem. The proposed solutions facilitate the cancellation of ship-radiated noise in UA OFDM systems by providing noise estimation from a minimal quantity of measurements.

In addition to the acoustic shipping noise recordings acquired from the ONC database, we devise an experimental procedure to collect supplementary data of ship-radiated noise. The experiment is carried out through a set of various sea trials off the Coast of Caesarea, Israel. The additional experimentally acquired data is used for further evaluation of the ship-radiated noise time-domain stochastic models and the noise cancellations methods for UA OFDM systems. The experimental ship-radiated noise data help demonstrate the scalability of our proposed time-domain stochastic models and noise cancellation methods to new never before seen shipping noise examples.

1.4 Organization

The remainder of this thesis is organized as follows. We discuss the OFDM system model for noise cancellation, the acoustic shipping noise data collection process, and the characterization of ship-radiated noise via the GMM in Chapter 2. In Chapter 3, the cancellation of ship-radiated noise via iterative CS solvers is investigated. Next, the DL-based methods for CS estimation and cancellation of ship-radiated noise are presented in Chapter 4. In Chapter 5, we introduce the GAN for probabilistic modelling of shipping noise and investigate the suitability of the GMM and GAN for producing time-domain stochastic models of ship-radiated noise. Finally, we concluded this thesis by providing a summary of the overall obtained results and suggest avenues for future research directions in Chapter 6.
Chapter 2

Methodology, System Formulation, and Ship-radiated Noise Characterization

Fundamentally, this thesis requires the access to ship-radiated noise data. Thus, the acquisition and pre-processing of acoustic shipping noise recordings is essential to the methodology of this work. In this chapter, we first introduce the noise cancellation framework for OFDM systems. This framework defines the necessary pre-processing structure of the ship-radiated noise recordings. We then outline the on-line and experimental data acquisition procedures and introduce the pre-processing steps that emulate signal reception in OFDM systems. Then, we introduce the GMM for the statistical characterization of ship-radiated noise in UA OFDM systems. Finally, we discuss the results of the statistical characterization of ship-radiated noise and draw relevant conclusions.

2.1 Noise Cancellation Framework

We consider the use of an OFDM system for data transmission, where the zero and pilot sub-carriers are used as sampling points to probe the interference. We may further expand the necessary amount of sampling points by utilizing a joint channel estimation and impulse noise estimation method as proposed by [27], where
initially detected data carriers are additionally exploited. The overall goal is to realize interference estimation using as few of the aforementioned sampling points as possible. Since the aim is to estimate impulsive interference with a limited quantity of sampling points, we employ a CS framework where the inherent sparsity of temporal impulsive noise is exploited.

### 2.1.1 CS-based Signal Estimation

CS utilizes a set of randomized linear measurements sampled far below the Nyquist rate, to achieve accurate reconstruction of a desired signal given it is sparse [36]. Let us consider the recovery of an $L$ dimensional $s$-sparse vector $s$ from $k < L$ noisy measurements

$$v = As + n$$  \hspace{1cm} (2.1)

where $A$ is the $k \times L$ random measurement matrix and $n$ is AWGN. Using the knowledge that $s$ is a sparse vector, we can formulate reconstruction as a convex optimization problem enforcing the constraint on sparsity using the $\ell_1$ norm [36]:

$$\text{minimize } s \quad \|s\|_1$$

subject to

$$\|v - As\|_2 \leq \varepsilon$$ \hspace{1cm} (P1)

The parameter $\varepsilon$ is determined based on the variance of the measurement noise $n$ [37]. We adopt (P1) as a benchmark algorithm for impulse interference estimation, formally known as basis pursuit de-noise (BPDN). A common and equivalent formulation of (P1), known as Lasso, can be expressed as:

$$\text{minimize } s \quad \frac{1}{2}\|v - As\|_2^2 + \lambda \|s\|_1$$ \hspace{1cm} (P2)

In order to achieve reconstruction guarantees based on the $s$-sparse vector $s$, the sensing matrix $A$ must satisfy the restricted isometric property (RIP) with high probability [38]. Likewise, it has been shown that some deterministic matrices, such as the discrete Fourier transform (DFT) matrix under the condition that the matrix is sub-sampled uniformly at random, satisfy the RIP [38]. We utilize this result to formulate the interference estimation problem through employing OFDM
sub-carriers as sampling points in conjunction with the sub-sampled DFT matrix.

### 2.1.2 OFDM Model and System Formulation

OFDM is a multi-carrier transmission technique which partitions the total bandwidth $W$ into $N$ individual sub-channels each separated by a narrow frequency interval $\Delta f = W/N$, ultimately leading to transmission rates that are close to channel capacity [39]. Each OFDM sub-channel may be individually modulated and coded, thus by denoting the complex-valued information symbols at each independent sub-channel as $x[k]$, where $k = 0, 1, \ldots, N - 1$, the time-domain complex baseband transmission signal is expressed as

$$d(t) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} x[k] e^{j2\pi ft/T}, \quad 0 \leq t \leq T \quad (2.2)$$

where $T = 1/\Delta f$ is the symbol duration. Likewise, equation (2.2), which utilizes the inverse discrete Fourier transform (IDFT), can be defined as a linear system

$$d = F^H x \quad (2.3)$$

where $d$ is the discrete time data transmission vector and $F^H$ is the IDFT matrix, with $(\cdot)^H$ defining the Hermitian transpose. The OFDM signal reception process is reverse to the transmission steps as defined by (2.2), using the DFT to re-acquire the transmitted symbols $x[k]$.

Our goal is to utilize some partition of the OFDM sub-carriers, which may include a combination of null sub-carriers, pilot sub-carriers, and in some instances prior detected known data sub-carriers [27], to estimate the respective impulse interference. To simplify the system formulation we consider the case where we use only null and pilot sub-carriers to probe the perturbing interference. We denote the set of data sub-carriers used for transmission as $S$, and the set of sub-carriers used for impulse noise estimation as $S^c$. Then, from an $N \times N$ DFT matrix $F$, we can construct an $m \times N$ partial DFT matrix $F_n$ by selecting the rows of $F$ from the set of row index locations defined in $S^c$. Here, the subscript in $F_n$ signifies that the selected rows of the DFT matrix $F$ adhere from the null sub-carrier locations of the OFDM system. The row selection process of $F_n$ must be drawn to some extent
uniformly at random in order for the DFT measurement matrix to satisfy the RIP [38].

We denote the vector of time domain received samples as $z$, which carry the desired signal component $d$ and some additive interference $w$, and probe the aforementioned interference via the partial DFT matrix $F_n$ as

$$r_n' = F_nz = F_n(d + w)$$

(2.4)

where $w$ can be split into an impulse component $i$ and AWGN component $\zeta$. Then, we can further simplify the received vector $r_n'$ to

$$r_n = F_n(i + \zeta)$$

$$= F_ni + \tilde{\zeta}$$

(2.5)

where the contribution from pilot-data has been subtracted from $r_n'$ and $\tilde{\zeta} = F_n\zeta$. From the construction in (2.5), and under the assumption that the impulse interference $i$ is sparse, we can deduce an estimate for $i$ that follows from (P1)

$$\minimize \| i \|_1$$

subject to

$$\| r_n - F_n i \|_2 \leq \varepsilon$$

(P3)

where identical to the manner of (P1) we select $\varepsilon$ based on the noise parameter $\tilde{\zeta}$, and thus pose the problem of estimating impulse interference for OFDM systems under a CS framework.

### 2.2 Data Acquisition and Pre-processing

This thesis comprises various data driven algorithmic mechanisms for the statistical characterization and modelling of shipping noise as well as learning-based methods for ship-radiated noise estimation and cancellation, which demand a large volume of data. Therefore, well defined data acquisition procedures, both from the ONC on-line database and from experimental sea trials, is necessary. This section summarizes these data acquisition procedures as well as the data pre-processing stage of the acoustic shipping noise recordings.
2.2.1 ONC Ship-radiated Noise Data

The ONC data acquisition procedure is outlined as follows:

1. Using the “Data Search” directory on the ONC website [1], we acquire the location of the underwater listening station:
   
   - Depth: 170 meters
   - Location: Strait of Georgia, East, 49.04° latitude, −123.32° longitude

2. According to the location of the underwater listening station, we use automatic identification system (AIS) data to locate and identify respective ships within a 1 km radius and record the time of passing.

3. From the “Search Hydrophone Data” directory on the ONC website, and based on the time and ship details acquired in Step 2, we collect data from JASCO M36 Hydrophone-2372, JASCO M36 Hydrophone 2373, JASCO M36 Hydrophone 2375, and JASCO M36 Hydrophone 2379, from the 4 respective hydrophone sets at the underwater listening station located in Step 1.

   We focus on shipping noise recordings from the period between January 2016 to September 2016, yielding an overall data set of 48 acoustic ship-radiated noise recordings. As there are 4 hydrophone sets, we have a total of 192 shipping noise recordings for analysis.

2.2.2 Experimental Ship-radiated Noise Data

The sea trials took place off the coast of Caesarea, Israel, over a two day period of May 20th and May 21st, 2019. The experimental set-up for the acquisition of acoustic shipping noise recordings is presented in Figure 2.1. We use a linear array of 6 hydrophones placed at approximately equal spacing over 10 meters of length with the first hydrophone starting at a depth of approximately 15 meters. The “noise generating ship” follows a continuous elliptical trajectory around the acoustic recording station, situated on the primary ship, producing acoustic ship-radiated noise, as shown in Figure 2.1. The experimental data acquisition procedure is outlined as follows:
Figure 2.1: Experimental set-up for acoustic acquisition of ship-radiated noise recordings.

1. With the “noise generating ship”, we encircle the main ship in an elliptical trajectory and begin the acoustic recording via the linear hydrophone array. This step is carried out for approximately 1 minute in duration.

2. We record the time of day of the acoustic recording, later used to filter and find relevant data files.

We repeat Steps 1 and 2 at several occasions to gather an assortment of acoustic ship-radiated noise recordings over the duration of the 2 day sea trial.

2.2.3 Data Pre-processing

The ONC acquired raw data encompasses 300 seconds of acoustic recordings for each hydrophone, sampled at 64 kHz. To reduce the computational needs of our data driven study, and emulate signal reception, pre-processing of the raw data is
necessary. We select segments of 20 seconds corresponding to the most prominent HF behaviour of the shipping noise signals. This can be seen via the respective spectrogram of each hydrophone recording, as per Figure 1.1. We consider the use of OFDM for transmission in the UA channel with $N = 1024$ sub-carriers, and re-sample the raw recordings based on the respective bands of interest: the very-low frequency (VLF), low frequency (LF), and HF bands. The acoustic recordings are down-converted and filtered via a low-pass filter (LPF), specifically a Kaiser window. Table 2.1 outlines the specifications of the corresponding frequency bands.

In a similar fashion, the acquired experimental acoustic recordings are also down-converted and filtered via a LPF. However, since each experimental acoustic recording is significantly lesser in duration and due to the total smaller quantity of experimental recordings compared to the ONC data, we utilize the full signals for analysis. In addition, from the experimental set-up and procedure, the proximity of the “noise generating ship” is known, thus the full acoustic recordings consist primarily of only ship-radiated noise from the generating source.

### 2.3 Statistical Characterization of Ship-radiated Noise

After the pre-processing stage, we analyse all 48 acoustic ship-radiated noise recordings from the ONC database in terms of the statistical characterization of shipping noise. Characterizing ship-radiated noise in the complex baseband to a GMM facilitates for the later use in producing new realistic realization of shipping noise like signals. These newly generated probabilistic realizations of ship-radiated noise can then be used in evaluation of UA OFDM systems in the presence of such interference. Furthermore, this stage is critical in determining the most effective algorithmic procedure via an empirical Bayesian approach for ship-radiated noise.

### Table 2.1: Acoustic recording pre-processing frequency bands

<table>
<thead>
<tr>
<th>Frequency Band</th>
<th>Center Frequency</th>
<th>Bandwidth</th>
<th>LPF Cut-off</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low Frequency</td>
<td>100 Hz</td>
<td>200 Hz</td>
<td>100 Hz</td>
</tr>
<tr>
<td>Low Frequency</td>
<td>2 kHz</td>
<td>4 kHz</td>
<td>2 kHz</td>
</tr>
<tr>
<td>High Frequency</td>
<td>12 kHz</td>
<td>8 kHz</td>
<td>4 kHz</td>
</tr>
</tbody>
</table>
2.3.1 Gaussian Mixture Noise Model

GMMs are a well known stochastic model used in evaluating the performance of UA communication systems in the presence of impulse noise [18]. In addition, with the analysis conducted in [15], and the observation of temporal acoustic recordings such as from Figure 1.1 and Figure 1.2 we propose to model the noise contributions from shipping activity as a GMM distribution. Prior works such as [10] model impulse noise in UA channel via an alpha distribution. However, learning the statistical parameters of some distributions via EM, such as an alpha distribution, cannot be accomplished in closed form, hence increasing the computational complexity of the algorithm. Therefore, approximating the signal with a GMM distribution provides an efficient means for parameter estimation. In particular, considering the equivalent complex baseband signal, we assume a GMM consisting of two components, each of which is circularly-symmetric complex (CSC) Gaussian distributed. Hence,

\[
f(w; \rho, \sigma_n^2, \tilde{\sigma}_i^2) = (1 - \rho)N\mathcal{C}(w; 0, \sigma_n^2) + \rho N\mathcal{C}(w; 0, \tilde{\sigma}_i^2) \quad (2.6)
\]

where \(N\mathcal{C}\) is the complex normal distribution, \(\tilde{\sigma}_i^2 = \sigma_n^2 + \sigma_i^2\) where \(\sigma_n^2\) is the AWGN variance and \(\sigma_i^2\) is the impulse variance, \(\rho\) controls the sparsity of the impulses and is in the range of \([0, 1]\).

We apply the EM algorithm to learn the parameters \(\theta = [\rho, \sigma_n^2, \sigma_i^2]\) [34]. For the initialization of the EM algorithm, we use the k-means method [32, Chapter 11.4] based on the magnitude of the samples of \(w\).

2.3.2 The Expectation-maximization Algorithm

EM is a well known algorithm for iteratively computing maximum likelihood (ML) estimates given a set of observations drawn from incomplete data [32] [34] [40]. In principle, EM alternates between an expectation step (E-step) and a maximization step (M-step), first inferring the latent variables given the distribution parameters of the current iteration, then optimizing the parameters given the in-
ferred latent variables\footnote{In the setting of mixture models, the latent variables define the hidden states of each cluster $k$ of a given mixture model, i.e. the knowledge of whether a certain data point $i$ is part of cluster $k$ is “missing”. The latent variables are then used in determining the responsibility of cluster $k$ for a given data point $i$, computed in the $E$-step\cite[Chapter 11.4]{32}.} \cite[Chapter 11.4]{32}. The mathematical framework behind EM is provided below.

We denote $\theta = [\rho, \sigma_n^2, \alpha_i^2]$ as the set of parameters to be estimated. Let $w_i$ denote the observed variables, i.e. the data points, and $u_i$ the latent states of the mixture model. Then, given $N$ observed data points, the complete data log likelihood is defined as:

$$L_c(\theta) = \sum_{i=1}^{N} \log f(w_i, u_i | \theta)$$  \hspace{1cm} (2.7)

However, as the $u_i$'s are unknown, equation (2.7) cannot be computed. Instead, EM computes the expected complete-data log likelihood $L_c(\theta)$ in the $E$-step, given the data observations and the previous estimate of $\theta$. Therefore, for the $t^{th}$ iteration, we denote $\theta^{[t]}$ as the estimate of the parameters and $W$ as the set of observations. Then in general form, the expectation step and maximization step are denoted as:

**E-Step**

$$Q(\theta | \theta^{[t]}) = \mathbb{E}[L_c(\theta) | W, \theta^{[t]}]$$  \hspace{1cm} (2.8)

**M-Step**

$$\theta^{[t+1]} = \arg\max_{\theta} \{ Q(\theta | \theta^{[t]}) \}$$  \hspace{1cm} (2.9)

The algorithm is iterated until some convergence is met, i.e. when $\| \theta^{[t]} - \theta^{[t-1]} \| < \eta$, for some set value of $\eta$.

### 2.3.3 EM for GMM

When fitting distributions from the exponential family via EM, each $M$-step is easily computed via closed form expressions \cite{34}. For instance, fitting GMMs with EM falls under this category. The $E$-step can be simplified to the following...
form, consistent with any mixture model
\[ r_{ik} \triangleq p(u_i = k|w, \theta^{[i]}) = \frac{\pi_k p(w_i|\theta_k^{[i]})}{\sum_{k'} \pi_{k'} p(w_i|\theta_{k'}^{[i]})} \]  \hspace{1cm} (2.10)
where \( \pi_k \) defines the probabilistic weight of each mixture model component and \( \sum_{k'} \) denotes the sum over all components [32, Chapter 11.4]. The result of equation (2.10) is then utilized in the M-step to determine the respective GMM probabilistic components weights \( \pi_k \), mean \( \mu_k \), and covariance matrix \( \Sigma_k \). The computations simplify to:
\[ \pi_k = \frac{1}{N} \sum_{i=1}^{N} r_{ik} \]  \hspace{1cm} (2.11)
\[ \mu_k = \frac{\sum_{i=1}^{N} r_{ik} w_i}{r_k} \]  \hspace{1cm} (2.12)
\[ \Sigma_k = \frac{\sum_{i=1}^{N} r_{ik} (w_i - \mu_k)(w_i - \mu_k)^H}{r_k} \]  \hspace{1cm} (2.13)
In our specific case of a CSC GMM as defined in equation (2.6), the means are assumed to be zero, the real and imaginary variances are equal, and the cross-diagonal entries of the covariance matrix are zero, i.e., \( \Sigma_k = \sigma_k^2 I \), where \( I \) is the \( 2 \times 2 \) identity matrix and \( \sigma_k^2 \) is the respective GMM component variance.

### 2.3.4 K-means Initialization

Prior to EM learning of the GMM statistical parameters, adequate initialization assists in reducing the overall run time of the algorithm. We adopt the use of k-means [32, Chapter 11.4] to acquire parameter initialization, which provides preliminary clustering and state labelling of the associated GM components. Let us denote the support set of impulses as \( \mathcal{F} \) and the support set of AWGN components as \( \mathcal{N} \). We implement 3-class k-means clustering to the absolute value of the input noise data \( w \). For our application, the 3-class k-means implementation, with one cluster referring to the impulses and the remaining two clusters referring to the AWGN, captures a more complete picture of the sparsity rate and variances compared to utilizing 2-class k-means clustering, thus yielding improved initialization of the
parameters. The \( k \)-means clustering algorithm outputs the corresponding state labels and centroids at each discrete index of \(|\mathbf{w}|\). We construct \( \mathcal{I} \) as the set of indices which correspond to the largest centroid cluster and \( \mathcal{N} \) as the set of indices corresponding to two remaining lesser centroids. Using the support sets \( \mathcal{I} \) and \( \mathcal{N} \), the parameter initializations are determined as:

\[
\sigma_i' = \frac{1}{2M_i} \sum_{j \in \mathcal{I}} \mathbf{w}_j \mathbf{w}_j^* \tag{2.14}
\]

\[
\sigma_n = \frac{1}{2M_n} \sum_{j \in \mathcal{N}} \mathbf{w}_j \mathbf{w}_j^* \tag{2.15}
\]

where \( M_i = |\mathcal{I}|, M_n = |\mathcal{N}| \), and \( \mathbf{w}_j^* \) the complex conjugate of \( \mathbf{w}_j \). Likewise, the accompanying impulse interference sparsity rate \( \rho \) is initialized as:

\[
\rho = \frac{M_i}{M_n + M_i} \tag{2.16}
\]

the quantity of impulse component labels over the total length of the signal.

### 2.3.5 Noise Characterization Results

Figure 2.2 shows the impulse sparsity rate and accompanying impulse variance and AWGN variance learned via the EM algorithm. It is evident that the EM algorithm captures the sparse occurrences of impulse noise as well as the increased variance compared to the AWGN. For the given set of ships analysed, although with varying sparsity, the impulse noise variance is consistently 15 dB greater than the AWGN variance, for all 48 ships. This can be utilized as an identifier of impulsive behaviour.

To evaluate the statistical viability of the two-component GMM distribution for modelling shipping noise, we analyse quantile-quantile (QQ) plots of empirical data quantiles versus the GMM generated quantiles based on the EM learned parameters. Figure 2.3 illustrates the QQ plot for one shipping noise acoustic recording and shows an almost linear match to the 45 degree line.\(^2\) The QQ plots for the other 47 acoustic recordings are similar to the plot shown in Figure 2.3. Overall,

\(^2\)The 45 degree line is used as a reference in order to visualize whether the empirical and theoretical quantiles match, i.e. indicating whether the data points are drawn from a common distribution.
Figure 2.2: EM learned statistical parameters of the two-term GMM at the 12 kHz center-frequency system (see Table 2.1). (a) sparsity rate, (b) impulse component and AWGN variances.

The QQ plots provide a promising validation to the EM learned GMM parameters for modelling HF ship-radiated noise. At lower frequencies (see Table 2.1), ship-radiated noise carries correlative structure that is difficult to approximate via a two component GMM, thus QQ plots do not serve as a sound metric for evaluation at a setting outside of the HF band. We present a thorough statistical investigation of ship-radiated noise in Chapter 5, where we consider both the probabilistic behaviour and correlative structure of shipping noise for HF and LF bands.
2.4 Conclusions on Statistical Characterization of Ship-radiated Noise

In this chapter, we introduced the OFDM system formulation that serves as the underlying framework for the statistical analysis of ship-radiated noise. Additionally, we defined the CS-based approach for impulse noise estimation and cancellation in OFDM systems and present the two component GMM. The empirical evaluation of the GMM characterized ONC ship-radiated noise data suggests that:

- Based on the observation of various QQ plots, the GMM is a reasonable match for ship-radiated noise in the HF band (from 8 to 16 kHz).

- The GMM parameters for ship-radiated noise vary per shipping noise record-
ing as the UA channel conditions change. This is seen in Figure 2.2. This result aids in the implementation of an empirical Bayesian algorithm for ship-radiated noise estimation and cancellation later described in Chapter 3.

• The GMM does not capture existing correlative structure that may be present within the noise signals, thus further work is necessary to find a probabilistic model that well approximates the correlative behaviour of ship-radiated noise, specifically at lower frequencies.
Chapter 3

Sparsity-based Ship-radiated Noise Estimation and Cancellation

In this chapter, we introduce the sparsity-based approaches for ship-radiated noise estimation and cancellation. First, we present the relevant background, motivation, and implementation behind the Gaussian mixture generalized approximate message passing (GM-GAMP) algorithm for estimating and cancelling the perturbing effects of ship-radiated noise. Next, the procedure for the estimation and cancellation of shipping noise via a sparse coded basis is outlined. We then compare the mitigation performance of these methods against each other and a benchmark approach in terms of per-ship-radiated noise signal cancellation capability. Finally, we provide concluding remarks and discuss the numerical results.

3.1 Message Passing for Compressed Sensing Estimation

Approximate message passing (AMP) is one of many iterative approaches for the CS recovery problem. Since its inception, AMP has gained significant traction in the field of communications in applications such as channel estimation and decoding [41], detection for multiple-input multiple-output OFDM systems [42], and handling impulse noise perturbations [43]. Of the latter, impulse noise mitigation
in OFDM systems under a CS framework is of particular interest. In addition, we
wish to utilize prior statistical knowledge regarding the distribution of the interfer-
ing ship-radiated noise to enhance the impulse noise estimation accuracy, which is
made possible with the AMP algorithm. An approach of this manner that embeds
EM updates within the AMP framework has been proposed in [44] and has shown
success in impulse noise cancellation for UA OFDM systems [45]. Therefore,
we take advantage of the AMP algorithm to estimate and cancel the ship-radiated
noise interference for UA OFDM systems. Below we outline the mathematical
framework of the AMP algorithm and introduce our GM-GAMP approach for
ship-radiated noise estimation and cancellation.

3.1.1 Generalized Approximate Message Passing

The estimation of sparse signals as defined by the CS problem in (P2) can be posed
under a graphical model framework [46] [47]. Under this framework, sum-product
belief propagation [48] is used to derive the AMP solver for the CS reconstruction
problem. We first show the AMP update steps for the Lasso CS recovery problem
posed in (P2), then define the generalized approximate message passing (GAMP)
algorithm.

Given the linear system \( \mathbf{v} = \mathbf{A}s + \mathbf{n} \) as defined in equation (2.1), let us consider
the problem of reconstructing \( s \) exploiting only the knowledge that \( s \) is sparse. The
aim is to estimate \( s \) from the set of noisy random linear measurements \( v \). From the
graphical model framework\(^1\) the AMP algorithm is derived and the vector update
terms for the \( t^{th} \) iteration reduce to:

\[
\eta'(\eta(s' + 1 + \mathbf{A}^H r'; \lambda + \gamma))
\]

\[
r^{t+1} = \mathbf{v} - \mathbf{A} s' + \frac{1}{\delta} r' \langle \eta'(s' - 1 + \mathbf{A}^H r' - 1) \rangle
\]

where \( \lambda \) is the regularization term as defined in (P2), \( \eta(\cdot) \) and \( \eta'(\cdot) \) is the soft
thresholding function and its respective first derivative, \( \gamma \) is the threshold level,

\(^1\)For a more detailed description regarding the expression of the CS recovery problem in terms
of a graphical model and the mathematical derivation procedure for the vector update terms of the
AMP algorithm, we direct the reader to the works of [46] and [47].
\[ \delta = k/L, \] and \( \langle \cdot \rangle \) denotes the average of a vector. The threshold level \( \gamma \) is also computed iteratively:

\[
\gamma^{t+1} = \frac{\gamma^t + \lambda}{\delta} \langle \eta'(s^t + A^H r^t; \lambda + \gamma^t) \rangle \tag{3.3}
\]

and the soft thresholding function is defined as:

\[
\eta(y; \tau) = \begin{cases} 
    y - \tau & \text{if } y > \tau, \\
    0 & \text{if } -\tau \leq y \leq \tau, \\
    y + \tau & \text{if } y < -\tau 
\end{cases} \tag{3.4}
\]

Equations (3.1), (3.2), and (3.3) define the general iterative AMP formulation for (P2). However, this implementation does not take advantage of any additional statistical information regarding the distribution of \( s \). Consequently, AMP can be implemented such that the soft threshold function \( \eta(y; \tau) \) in equations (3.1), (3.2), and (3.3) is replaced with a conditional expectation [46], ultimately leading to recovery improvements.

The above AMP iterative methodology has been extended to include arbitrary distributions at the input and output of the linear transform from equation (2.1) [49], known as GAMP. In this form, we can easily exploit additional statistical information on \( s \) to produce a more accurate estimate. Algorithm 1 outlines the iterative procedure of the GAMP algorithm. \( E, V \) define the expected value and variance operations respectively and \( A_{ij}^* \) denotes the complex conjugate of the \( i^{th} \) row and \( j^{th} \) column entry of the measurement matrix \( A \).

It is visible from Algorithm 1 that the prior distribution \( p(s_j) \) on the signal of interest is utilized to achieve an accurate estimate of \( s \). Therefore, with some assumption on the the distribution \( p(s_j) \), one can learn the statistical parameters that define \( p(s_j) \), then use the estimated prior to recover the signal of interest \( s \). The algorithm proposed in [44] has shown promising results in estimating the distribution parameters of \( p(s_j) \) via EM, assuming \( p(s_j) \) follows a GMM distribution, from the measurement vector \( v \) within the update steps of the GAMP algorithm. However, since this approach estimates \( p(s_j) \) from the measurement vector \( v \), the learned distributions parameters may be inaccurate compared to using examples of the true signal \( s \). Thus, an approach that uses true signal instances that approximate
distribution, as defined in equation 2.6, and employ the EM algorithm to learn the interfering ship-radiated impulse noise follows a two component CSC GMM distribution. We assume the distribution parameters of the ship-radiated noise impulse interference, then feed the estimated prior into the GAMP algorithm to achieve recovery. We assume the varying statistical behaviour of ship-radiated noise, as determined in Section 2.3 and visible from Figure 2.2, prompts for adaptive tracking of the shipping noise statistics. We propose an on-line learning-based approach to estimate the Algorithm 1: The implementation of the GAMP algorithm [49]

Inputs: $A$, $p(s_j)$, $p(v_i|z_i)$, $T$

Definitions: $v = As + n$, $z = As$, $n$ is AWGN

$p(z_i|v, \hat{p}, \mu^p) = \frac{p(v_i|z_i)\mathcal{N}(z_i; \hat{p}, \mu^p)}{\int_{\hat{p}} p(v_i|z_i)\mathcal{N}(z_i; \hat{p}, \mu^p)}$

$p(s_j|v, \hat{r}, \mu^r) = \frac{p(s_j)\mathcal{N}(s_j; \hat{r}, \mu^r)}{\int_{\hat{r}} p(s_j)\mathcal{N}(s_j; \hat{r}, \mu^r)}$

Initialize:

∀ $j : \hat{s}_j(1) = \int s_j p(s_j)$
∀ $j : \hat{\mu}^j_0(1) = \int s_j - \hat{s}_j(1)^2 p(s_j)$
∀ $j : \hat{q}_j(0) = 0$

For: $t = 1 : T$

∀ $i : \hat{\mu}^i_0(t) = \sum_{j=1}^L |A_{ij}|^2 \hat{\mu}^j_0(t)$
∀ $i : \hat{\mu}^i_0(t) = \sum_{j=1}^L A_{ij} \hat{s}_j(t) - \hat{\mu}^0_0(t) \hat{q}_i(t - 1)$
∀ $i : \hat{\mu}^i_0(t) = \mathcal{N}(z_i|\hat{v}_i(t), \mu^0_0(t))$
∀ $i : \hat{\mu}^i_0(t) = \mathbb{E}\{z_i|v, \hat{v}_i(t), \mu^0_0(t)\}$
∀ $i : \hat{\mu}^i_0(t) = (1 - \hat{\mu}^i_0(t)/\mu^0_0(t)) \mu^0_0(t)$
∀ $i : \hat{\mu}^i_0(t) = (\sum_{j=1}^k |A_{ij}|^2 \hat{\mu}^j_0(t))^{-1}$
∀ $i : \hat{\mu}^i_0(t+1) = \mathbb{E}\{s_j|v, \hat{r}_j, \mu^0_j(t)\}$
∀ $i : \hat{\mu}^i_0(t+1) = \mathcal{N}(s_j|\hat{v}_i(t+1), \mu^0_0(t+1))$
∀ $i : \hat{\mu}^i_0(t+1) = \mathbb{E}\{s_j|v, \hat{r}_j, \mu^0_j(t)\}$

End

Outputs: $\{\hat{z}(T), \mu^0_0(T)\}$, $\{\hat{r}_j(T), \mu^0_j(T)\}$, $\{\hat{s}_j(T), \mu^0_j(T)\}$

$s$ would be beneficial in producing a more accurate estimate for $p(s_j)$.

3.1.2 GM-GAMP for Ship-radiated Noise Estimation and Cancellation

The varying statistical behaviour of ship-radiated noise, as determined in Section 2.3 and visible from Figure 2.2, prompts for adaptive tracking of the shipping noise statistics. We propose an on-line learning-based approach to estimate the distribution parameters of the ship-radiated noise impulse interference, then feed the estimated prior into the GAMP algorithm to achieve recovery. We assume the interfering ship-radiated impulse noise follows a two component CSC GMM distribution, as defined in equation 2.6 and employ the EM algorithm to learn the
parameter set $\theta = [\rho, \sigma_n^2, \tilde{\sigma}_i^2]$. The estimated GMM distribution is then used in the GAMP procedure, thus labelling the approach as GM-GAMP, i.e. estimation via GAMP with a Gaussian mixture prior.

Figure 3.1 summarizes the procedure for the ship-radiated noise distribution parameter estimation via EM and the GM-GAMP based recovery. Once an estimate for the impulse noise is achieved, we subtract the perturbing interference from the original noise signal. In terms of performance metrics, we consider the estimation of independent ship-radiated noise signals $\tilde{w}$, then report the mitigated noise signal $\tilde{w} = w - i_{est}$.

3.2 Estimation via Sparse Coded Basis

Sparse coding is a learning-based method that models given input data as a sparse linear combination of its key elements. The procedure of determining a sparse linear representation of the input data is formally known as dictionary learning (DIL). In general, sparse representations of input data can be achieved by utilizing existing bases, such as the wavelet transform basis which typically yields sparse representations for images, or through learning a dictionary that sparsely represents the input data [50]. DIL has been fairly well studied such that there are a variety of available DIL algorithms to choose from [51]. We propose the use of the K-singular value decomposition (K-SVD) algorithm [52] for sparse representation learning of the set of ship-radiated noise signals, an efficient and less computationally demanding algorithm compared to its counterpart approaches [50]. The basic principles behind DIL and the K-SVD algorithm are outlined below. We then show how the learned sparse representation via K-SVD can be used for estimation and cancellation of ship-radiated noise.

3.2.1 K-SVD for Dictionary Learning

Given a matrix of $N$ data examples $Y \in \mathbb{R}^{n \times N}$, the goal of DIL is to learn an overcomplete dictionary matrix $D \in \mathbb{R}^{n \times K}$ that can sparsely represent the data elements $\{y_i\}_{i=1}^N$ as a linear combination of the dictionary elements $\{d_j\}_{j=1}^K$. Following from
Figure 3.1: EM learning and GM-GAMP estimation procedure of impulse noise with CSC GMM statistical prior and k-means initialization of parameters $\theta$ for specified noise window of fixed duration.
the above notation, the DIL objective can be defined as:

$$\begin{align*}
\text{minimize} \quad & \|Y - DX\|_F^2 \\
\text{subject to} \quad & \forall i, \|x_i\|_0 \leq \kappa
\end{align*}$$

(P5)

where $X$ denotes the sparse representation coefficients and $\kappa$ controls number of non-zero coefficients in $X$, i.e. a smaller $\kappa$ will yield to a more sparse solution. The selection of $\kappa$ can directly affect the estimation of the desired signal when using the learned dictionary $D$ in CS recovery, thus selecting an adequate $\kappa$ can lead to better reconstruction accuracy at the later stage. We select $\kappa$ through empirical observation of the CS reconstruction results. It is clear from (P5) that the DIL objective is highly non-convex, thus iterative solutions are necessary to learn the dictionary matrix $D$.

The K-SVD algorithm comprises of two main stages: (1) the sparse coding stage, where given a fixed dictionary matrix $D$, the sparse coefficients $X$ are updated, and (2) the dictionary update stage, where $X$ and $D$ are assumed fixed, then the individual rows and columns, $x_i^T$ (denoting the $k$th row of $X$) and $d_k$ respectively, are updated [52]. In the sparse coding stage, we fix $D$, thus we can decompose (P5) such that the objective becomes solving $N$ independent problems:

$$\begin{align*}
\text{minimize} \quad & \|y_i - Dx_i\|_2^2 \\
\text{subject to} \quad & \forall i, \|x_i\|_0 \leq \kappa
\end{align*}$$

(P6)

Unlike (P5), the optimization problem defined by (P6) is solvable using iterative pursuit algorithms.

The dictionary update stage requires the computation of the representation error of the objective function in (P5):

$$\|Y - DX\|_F^2 = \left\| \left( Y - \sum_{j \neq k}^K d_j x_j^T \right) - d_k x_k^T \right\|^2_F ,$$  (3.5)

where the representation error term for all $N$ examples with the $k$th entry removed
is

\[ E_k = \left( Y - \sum_{j \neq k}^K d_j x_j^T \right) \tag{3.6} \]

Then, a selection matrix \( \Omega_k \) is defined that selects the non-zero entries of \( x_j^T \). We construct \( \Omega_k \) from the set of indices

\[ \omega_k = \{ i \mid 0 \leq i \leq K, x_j^T(i) \neq 0 \} \tag{3.7} \]

for the \( i^{th} \) data example \( \{ y_i \} \). Therefore, \( \Omega_k \) is an \( N \times |\omega_k| \) matrix consisting of ones at the \( \omega_k(i)^{th} \) rows and \( i^{th} \) columns, and zeros elsewhere. Using the selection matrix \( \Omega_k \), the terms in equation (3.5) can be redefined as

\[ \left\| \left( Y - \sum_{j \neq k}^K d_j x_j^T \right) \Omega_k - d_k x_k^T \Omega_k \right\|_F^2 = \left\| E_k^R - d_k x_k^R \right\|_F^2, \tag{3.8} \]

where \( E_k^R \) is a matrix of selected columns from the error matrix \( E_k \) and \( x_k^R \) is a row vector of selected non-zero entries from the identified index set \( \omega_k \). The key attribute of K-SVD is the use of SVD in the dictionary element update stage, which is repeated \( K \) times for each element \( \{ d_i \}_{i=1}^K \) [52]. Thus, SVD is used to minimize the final expression in equation (3.8), decomposing \( E_k^R = USV^T \). The approximate solution for \( d_k \) and the sparse coefficient vector \( x_k^R \) is the first column of \( U \) and the first column of \( V \) multiplied by the singular value \( S(1,1) \), respectively.

The K-SVD algorithm iterates between the sparse coding stage, which is iteratively determined using matching pursuit based algorithms, and the dictionary update stage, which is solved via SVD and repeated \( K \) times. This procedure is iterated until some convergence criteria is met, such as a set max iteration limit or break once the representation error is reduced to below some small target value.

### 3.2.2 CS Estimation of Ship-radiated Noise via Sparse Coded Dictionary

In this approach, we take advantage of the large data set of acoustic shipping noise recordings at hand to learn an \( n \times K \) basis \( D \), with \( n < K \), where the shipping noise can be adequately represented from few column elements of \( D \). We utilize the K-
SVD algorithm [52], defined in the previous section, to learn the basis $D$ that can sparsely represent the class of shipping noise signals in their respective complex baseband representations.

Let us denote $w = Dc$, where $c$ is the vector of sparse coefficients. Then the received signal in (2.5) becomes

$$ r_n = F_n w = F_n Dc $$

where $F_n d = 0$ still holds as we probe only the sub-carriers which carry no data. Knowing $c$ is sparse by design, we may now formulate the CS reconstruction problem

$$ \min_{c} \|c\|_1 \quad \text{subject to} \quad r_n = F_n Dc \quad (P7) $$

From the estimate $\hat{c}$ obtained from $(P7)$, we determine the estimated noise signal

$$ i_{est} = D \hat{c}. \quad (3.10) $$

This method is advantageous in contrast to GM-GAMP as it does not require constant learning of the statistical noise parameters to achieve noise estimation. Rather, we are able to learn a sparse representative basis off-line from the large quantity of acoustic recordings, and thus realizing an estimate $i_{est}$ using the learned basis. We use basis pursuit (BP) to recover the sparse coefficients $\hat{c}$, hence namely label the method as dictionary learning and basis pursuit (DIL-BP) for the remainder of this paper. Identical to the noise cancellation stage in Section 3.1.2, we report the mitigated noise signal as $\tilde{w} = w - i_{est}$.

3.3 Numerical Results

In this section, we present the numerical results on the performance of ship-radiated noise cancellation via GM-GAMP, DIL-BP, and BPDN on the ONC shipping noise data. First, we describe the performance evaluation procedure as well as the parameter and implementation characteristics for the DIL-BP and GM-GAMP methods. Then, the numerical results regarding the performance evaluation of the
select ship-radiated noise mitigation methods are discussed. Here, we only consider the ONC data for the performance evaluation to determine which sparsity-based ship-radiated noise cancellation method performs best. Later in section 4.4.3, the best performing sparsity-based cancellation method is evaluated on experimentally acquired ship-radiated noise data to observe how the method generalizes to new instances of shipping noise interference signals.

### 3.3.1 Method Set-ups and Performance Evaluation Framework

For the DIL-based approach, we learn dictionaries for each of the three frequency bands of consideration, see Table 2.1. We set the dictionary sizes to $64 \times 10000$ for the HF and LF bands, and $64 \times 6000$ for the VLF band. We wish to capture instances of individual impulses, therefore the data is segmented into columns of 64 discrete entries rather than 1024. Reconstruction is then achieved by estimating the smaller segments and concatenating them to obtain the full noise estimate for each OFDM symbol. The K-SVD algorithm [52] also takes the quantity of sparse representative coefficients to use as input, which we set as 4 for each dictionary, and the amount of iterations used for training, which we set to 40. The acoustic recordings are equally partitioned into a training set and test set. We use the training set to learn the respective dictionaries. We train the dictionaries on a training set and leave out a portion of the shipping noise data for performance evaluation that comprise the test set.

We evaluate the performance of BPDN, GM-GAMP, and DIL-BP methods by considering the noise variance $\sigma^2$ per OFDM signal after noise mitigation for the acoustic recordings on the test set. In case of GM-GAMP, the EM algorithm learns the statistical prior using 10 OFDM symbols for the HF and LF band testing data sets and 1 OFDM symbol for the VLF testing data set. The mitigation performance evaluation is accomplished over a duration of 20 OFDM symbols for HF and LF bands, and 3 OFDM symbols for the VLF band. The difference is due to the fact that the OFDM symbol duration is much larger for VLF band when using $N = 1024$ sub-carriers, and hence there are fewer symbols over the same time duration than for the HF and LF band systems. We utilize the SPG-L1 solver [53] for BPDN and BP implementations.
3.3.2 Ship-radiated Noise Cancellation: Results and Discussion

Figure 3.2 illustrates the mitigation capabilities when using GM-GAMP and DIL-BP for an acoustic shipping noise signal in the HF band system. It can be seen from this result that the Bayesian-based estimation algorithm yields improved mitigation capabilities relative to DIL-BP, specifically when observing the impulsive components of the signal. Figure 3.3 and 3.4 show the empirical cumulative distribution functions (CDFs) of the noise variance per OFDM symbol after mitigation for the HF and LF band systems, respectively, considering all acoustic recordings in the test set. It is clear that GM-GAMP provides the greatest noise mitigation for the HF and LF band systems. The DIL-BP method achieves improved results compared to BPDN and measurable cancellation results compared to GM-GAMP in the LF system where the noise is less sparse and less well represented by the GMM.

We define the relative cancellation gain as the difference between the noise variance per OFDM symbol of the mitigated and the original noise signal. Tables 3.1 and 3.2 report the relative cancellations gains at specified probabilities $P(X > \sigma^2)$ of 0.1 and 0.01 for the three frequency band systems using 25% and 12.5% OFDM sub-carrier sampling. We observe that estimation via GM-GAMP outperforms both the traditional CS estimation method BPDN and the DIL-BP method in almost all scenarios. BPDN yields relatively poor results in the LF and VLF band systems as the shipping noise signal is less sparse in time compared to the HF band system. Although shipping noise is less well characterized as a GMM in the LF and VLF bands, the GM-GAMP based approach still produces promising mitigation results compared to its competitors due to utilizing additional information regarding the prior distribution of the interference. However, it is evident that the DIL-BP method yields measurable cancellation results compared to GM-GAMP in the LF band system. This result creates inclination that ship-radiated noise consists of increased correlative structure in lower frequencies, thus other learning-based approaches could be inherited for estimating ship-radiate noise in this setting. Following this logic, we should observe that the DIL-BP method achieves similar cancellation results to GM-GAMP in the VLF system, but due the lack of VLF shipping noise data, the K-SVD algorithm learns a dic-
tionary that under-fits the training data. Therefore, the learned dictionary does not well represent the test ship-radiated noise data, leading to poor cancellation results.

3.4 Conclusions on Sparsity-based Ship-radiated Noise Cancellation

In this chapter, we introduced the mathematical formulation of sparsity-based ship-radiated noise estimation and cancellation methods. Then, we evaluated the performance of the ship-radiated noise cancellation methods in terms of per OFDM symbol noise variance, i.e. the lower the cancelled noise variance, the better the performance of the mitigation technique. The empirical performance evaluation of the GM-GAMP, DIL-BP, and BPDN methods for the mitigation of ship-radiated noise...
Figure 3.3: Empirical CDF of the noise variance per OFDM symbol after noise mitigation using 25% sub-carrier sampling in the HF band system.

noise suggests that:

- GM-GAMP outperforms the benchmark BPDN and the DIL-BP approaches for ship-radiated noise cancellation in the HF and VLF band systems and achieves measurable cancellation results in the LF band system. This is likely due to the additional statistical information exploited by GM-GAMP algorithm.

- The DIL-BP method for ship-radiated noise cancellation yields improved mitigation results for ship-radiated noise in the LF band system. This is due to the increased correlative structure that exists in LF ship-radiated noise, thus the learned dictionaries can better represent the class of shipping noise signals.
Figure 3.4: Empirical CDF of the noise variance per OFDM symbol after noise mitigation using 25 % sub-carrier sampling in LF band system.

- The success of the DIL-BP method in the LF system prompts for further analysis into learning-based approaches for ship-radiated noise cancellation that exploit the inherit correlative structure that exists in the presence of such interference.
Table 3.1: Relative cancellation gain of ship-radiated noise with 25 % null sub-carrier sampling via sparsity-based estimation algorithms.

<table>
<thead>
<tr>
<th></th>
<th>BPDN</th>
<th>DIL-BP</th>
<th>GM-GAMP</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P(X &gt; \sigma^2)$</td>
<td>0.1</td>
<td>0.87 dB</td>
<td>0.88 dB</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>1.89 dB</td>
<td>0.79 dB</td>
</tr>
<tr>
<td>Low Frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P(X &gt; \sigma^2)$</td>
<td>0.1</td>
<td>0.13 dB</td>
<td>1.00 dB</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>0.44 dB</td>
<td><strong>1.01 dB</strong></td>
</tr>
<tr>
<td>Very Low Frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P(X &gt; \sigma^2)$</td>
<td>0.1</td>
<td>0.00 dB</td>
<td>0.74 dB</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>0.16 dB</td>
<td>0.96 dB</td>
</tr>
</tbody>
</table>

Table 3.2: Relative cancellation gain of ship-radiated noise with 12.5 % null sub-carrier sampling via sparsity-based estimation algorithms.

<table>
<thead>
<tr>
<th></th>
<th>BPDN</th>
<th>DIL-BP</th>
<th>GM-GAMP</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P(X &gt; \sigma^2)$</td>
<td>0.1</td>
<td>0.25 dB</td>
<td>0.27 dB</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>0.63 dB</td>
<td>0.22 dB</td>
</tr>
<tr>
<td>Low Frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P(X &gt; \sigma^2)$</td>
<td>0.1</td>
<td>−0.39 dB</td>
<td>0.48 dB</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>0.31 dB</td>
<td>0.48 dB</td>
</tr>
<tr>
<td>Very Low Frequency</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$P(X &gt; \sigma^2)$</td>
<td>0.1</td>
<td>−0.38 dB</td>
<td>0.09 dB</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>−1.33 dB</td>
<td>0.68 dB</td>
</tr>
</tbody>
</table>
Chapter 4

Deep Learning-based
Ship-radiated Noise Estimation
and Cancellation

In this chapter, we introduce the DL based methods for the estimation and cancellation of ship-radiated noise. First, a general overview of current DL applications in UAC and the motivations behind the DL approaches for ship-radiated noise cancellation is presented. Next, we introduce the mathematical framework for the construction of fully connected and convolutional deep neural networks (DNNs). Then, the application of DNNs for CS estimation is introduced and existing DL approaches are outlined. We then present and discuss the numerical results for ship-radiated noise cancellation via the DL approaches in terms of noise mitigation capability and compare them to the GM-GAMP and BPDN methods. We provide ship-radiated noise cancellation results for the ONC data and the experimentally acquired data. Finally, we discuss and draw conclusions that adhere from the numerical results.

4.1 Background

Inspired by the biological neural connections within the human brain, DL is a subfield of machine learning that utilizes artificial neural network (ANN) structures
for classification, regression, and probabilistic modelling problems [54]. Thanks to the rapid progression of computing technologies over the past two decades, DL-based methods have become viable and powerful solutions to many problems in engineering and science. In the context of communication systems, DL-based solutions have demonstrated measurable and advantageous results to traditional analytical approaches for physical layer transmitter and receiver design [55], channel estimation and signal detection [56], and communication networks [57]. In general, DL-based solutions accept slow off-line run-time during the training process to obtain significantly faster on-line application speeds compared to their respective counterpart approaches, thus desirable in many communication systems applications.

The applications of DL in wireless communications have quickly extended into UAC to handle the various non-linear distortions present in the UA channel. For instance, [58] offers a DL-based receiver for on-line channel estimation and equalization for single carrier UAC systems. Likewise, channel estimation techniques via DL in multi-carrier UA OFDM systems have received significant research attention [59–61]. While [59] and [60] offer DL-based solution for channel estimation for UA OFDM systems, [61] is one of very few research works that suggest a DL-based method for handling impulse noise perturbations in the UA channel. To the best of our knowledge, no research studies have investigated the applicability of DL-based approaches for suppressing or cancelling the interfering effects if ship-radiated noise. However, various studies have suggested and shown the success of DL methods for ship classification and detection via acoustic signatures [62, 63]. This signifies that ship-radiated noise carries correlative structure that can be captured by DL models.

Recently, DL-based approaches for structured signal recovery from linearly and non-linearly sampled measurement have received attention in the domain of image processing [2] [3] and have shown competitive recovery results to the counterpart CS methods. In [2], a linear stacked de-noising autoencoder (L-SDA) is employed to recover sets of original signals from their linearly sampled measurements. Moreover, the authors propose a non-linear stacked de-noising autoencoder (NL-SDA), which simultaneously learns a non-linear sampling procedure alongside the recovery stage, improving the overall recovery results. The use of convolu-
tional neural networks (CNNs) in the setting of structured signal recovery presents similar recovery results also measurable to state-of-the-art CS methods [3]. The two key advantages of the DL recovery methods in contrast to the counterpart CS solvers are: (1) they do not rely on the sparsity of the signal of interest through linear transformation as do the CS methods, and (2) they trade off slow off-line run-time during the model training process for superior on-line run-time.

Motivated by the fact that ship-radiated noise carries correlative structure and due to the recent success and advantages of DL methods for structured signal recovery, we propose the use the existing DL models in the application of suppressing ship-radiated noise for UA OFDM systems. In the same manner as Chapter 3, we conduct a data driven study utilizing the ONC database in terms of ship-radiated noise cancellation capability. In addition, we include experimentally acquired data to show the off-line trained DL models can scale to new never before “seen” sets of ship-radiated noise signals.

4.2 Deep Neural Networks

In the most fundamental terms, a DNN is defined as an ANN which consists of two or more hidden layers [54]. In this section, we introduce the mathematical framework behind fully connected and convolutional DNN models. Additionally, since our goal is to achieve cancellation of ship-radiated noise interference in the complex baseband, we require complex operations for the linear and non-linear transformations present in DNN models. Thus, we also introduce the mathematical framework for DNN complex number operations.

4.2.1 Fully Connected DNNs

Figure 4.1 (a) and Figure 4.1 (b) illustrate an example of a simple two layer fully connected DNN and the structure of an individual neuron which comprises of linear and non-linear transformations, respectively. Each neuron accepts a set of inputs that are multiplied by the weights and scaled by a bias term before being transformed by a non-linear activation function. Let \( \mathbf{x} = \{x_1, x_2, \ldots, x_N\} \) denote the inputs, \( \mathbf{w} = \{w_1, w_2, \ldots, w_N\} \) the weights, \( b \) the bias term, and \( h(z) \) the non-linear...
Figure 4.1: Simple DNN model: (a) a two layer fully connected DNN, (b) an example of an individual neuron and its input-output relationship.

activation function. Then, the output of each neuron can be expressed as:

\[ y = h \left( \sum_{i=1}^{N} x_i w_{ij} + b \right) \quad (4.1) \]

This simple relationship at the level of an individual neuron serves as the foundation for creating various DNN models.

Following from equation (4.1), we can formulate the per-layer output expressions in vector notation. Let \( l \) denote one of \( M \) layers in a respective DNN model. Then, for connecting the \( j^{th} \) neuron in the \( (l-1)^{th} \) layer to the \( i^{th} \) neuron in the \( l^{th} \) layer, \( w_{ij}^l \) denotes the respective weight term, \( b_i^l \) denotes the respective bias term, and \( y_j^{l-1} \) denotes the respective output. The output at the \( l^{th} \) can then be expressed as

\[ y_i^l = h \left( \sum_j w_{ij}^l y_j^{l-1} + b_i^l \right) \quad (4.2) \]

where \( W^l \) is the weight matrix of the \( l^{th} \) layer containing the weight terms \( w_{ij}^l \) at the \( i^{th} \) rows and \( j^{th} \) columns. The relationship in equation (4.2) is propagated through all \( M \) layers until the output layer \( y^M \), where the outputs are then compared to some target value via a loss or objective function. In most cases the aim is to minimize this objective function, which is iteratively accomplished via back-propagation [64], easily derived from the cascades of equation (4.2) over each of
Table 4.1: Activation functions for transformations in DNNs.

<table>
<thead>
<tr>
<th>Activation Name</th>
<th>Abbreviation</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identity</td>
<td>–</td>
<td>$h(z) = z$</td>
</tr>
<tr>
<td>Rectified linear unit</td>
<td>ReLU$(z)$</td>
<td>$h(z) = \begin{cases} 0 &amp; \text{for } z \leq 0, \ z &amp; \text{for } z &gt; 0 \end{cases}$ (4.4)</td>
</tr>
</tbody>
</table>
| Leaky rectified linear unit       | LReLU$(z)$     | $h(z) = \begin{cases} \alpha z & \text{for } z \leq 0, \\ z & \text{for } z > 0 \end{cases}$ (4.5)  
where $\alpha < 1$ (default value: $\alpha = 0.01$) |
| Sigmoid function                  | $\sigma(z)$   | $h(z) = \frac{1}{1 + e^{-z}}$ (4.6)                                      |
| Hyperbolic tangent function       | tanh$(z)$     | $h(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$ (4.7)                          |

the $M$ layers.

In order for the back-propagation procedure to iteratively update the weights and bias terms, the activation functions $h(z)$ at each layer need to be differentiable. The activation function is key in providing non-linearities in the DNN that enables the DNN to push beyond simple linear models and thus capture and model arbitrary non-linear effects. Table 4.1 denotes some of the commonly used activation functions for DNNs.

### 4.2.2 Convolutional Neural Networks

Motivated by the natural operational phenomena that occur in the visual cortex of the human brain, CNNs have been extensively used in the domain of image processing and image classification/segmentation [54]. Convolutional DNNs follow a similar structure as introduced in Section 4.2.1 but with the addition of the convolution operation. Given the discrete-time functions $p[.]$ and $q[.]$, the convolution
operation in discrete form is

\[ (p \ast q)[n] \triangleq \sum_{m=-\infty}^{\infty} p[m]q[n-m]. \] (4.8)

Equation 4.8 serves as the building block for the convolutional layer in CNNs.

At each layer, CNNs comprise of several feature maps\(^1\) where all neurons share the same weight and bias terms [54]. Due to this, CNNs typically have a significant reduction in the number of trainable parameters compared to DNNs. In addition, CNNs are translationally invariant, i.e. fully connected DNNs memorize certain configurations of the training data in the provided locations, while CNNs learn the recognition of patterns within the data through the convolution operation [54]. Following the notation from section 4.2.1, we can express the three dimensional output of the \(l^{th}\) convolutional layer for the \(k^{th}\) two dimensional feature map as

\[ y_{ijk}^l = h \left( \sum_{u} \sum_{v} \sum_{k} w_{uvk}^l x_{ijk}^{l-1} + b_k \right), \] (4.9)

where \(i' = us_u + f_u - 1\) and \(j' = vs_v + f_v - 1\). Here, \(s_u\) and \(s_v\) define the vertical and horizontal strides\(^2\) of the convolution operation and \(f_u\) and \(f_v\) denote the respective height and width of the feature maps in the \(l^{th}\) layer. We denote \(x_{ijk}^{l-1}\) as the neuron in the \(i^{th}\) row and \(j^{th}\) column of the \(k^{th}\) feature map from the \((l-1)^{th}\) layer. Likewise, \(w_{uvk}^l\) denotes the weight that connects the outputs of the \((l-1)^{th}\) layer from feature map \(k'\) to the \(k^{th}\) feature map in layer \(l\). Finally, \(b_k\) is the bias term of the \(k^{th}\) feature map.

### 4.2.3 Complex Number Operations for DNNs

Since we are dealing with complex signals, we need to account for the dependancies between the real and imaginary components. Given a vector \(z = a + jb\), a typical approach is to split the real and imaginary components \(a\) and \(b\) and concatenate them together to form a new vector that is twice the length. This approach works in

\(^1\)A feature map is the result of applying a convolutional filter to the output of the previous layer.

\(^2\)The stride denotes the step of each discrete convolution index taken in the operation defined in equation (4.8).
the setting of fully connected DNNs as every neuron in the \((l - 1)^{th}\) is connected to every neuron in the \(l^{th}\) layer, thus the dependences between the real and imaginary components are learned. However, in application for CNNs, the concatenation of the real and imaginary components does not necessarily lead to adequate capturing of the dependency between the components. In addition, applying the convolution operation at the boundary between the real and imaginary vector components does not portray intuitive sense. Therefore, we propose the use of deep complex networks, which in essence train two DNNs in parallel, one for the real components and the second for the imaginary components, while simultaneously accounting for the complex number relationships between the two networks [65].

Deep complex networks are proposed by [65] to accommodate the absence of complex operations in DNNs, where only real number operations are utilized. We introduce the complex convolution operation for CNN layers. Let us denote \(W = W_R + jW_I\) as the two-dimensional complex filter matrix and \(v = v_R + jv_I\) as a complex vector. Then, using the distributive property of the convolution operator, the real number output of the complex convolution operation between the complex filter matrix \(W\) and complex vector \(v\) can be defined as

\[
W * v = (W_R * v_R - W_I * v_I) + j(W_I * v_R + W_R * v_I),
\]

which can be expressed in matrix notation in terms of only real numbers as

\[
\begin{bmatrix}
\text{Re}\{W * v\} \\
\text{Im}\{W * v\}
\end{bmatrix} = \begin{bmatrix}
W_R & -W_I \\
W_I & W_R
\end{bmatrix} * \begin{bmatrix}
v_R \\
v_I
\end{bmatrix}.
\]

Under a similar manner of the above formulation, complex operations for fully connected layers, activation layers, batch normalization layers, and more can be derived.

### 4.3 DNN-based Structured Signal Estimation

We aim to utilize existing DL models, with the addition of complex DNN operations and some augmentation to the model parameters, to realize ship-radiated noise estimation and cancellation. In particular, our primary goal is to learn a non-
linear mapping to solve problem \((P3)\) using the ONC shipping noise dataset.

We consider three DL models for the structured signal recovery of ship-radiated noise in UA OFDM systems:


The L-SDA and the CNN methods use the reduced DFT linearly sampled measurements (see section 2.1.2 equation (2.5)) to estimate the original noise signal, while the NL-SDA learns a non-linear sampling procedure alongside the recovery process. In practical implementations, OFDM systems are constrained to sampling the noise via the reduced DFT matrix, thus the learned sampling procedure of the NL-SDA is not usable in this application. Therefore, the NL-SDA serves as an empirical performance upper bound on the L-SDA in the case a learned sampling procedure can be utilized. We use this result to comment on the performance of the L-SDA.

In terms of the estimation and cancellation of ship-radiated noise, in addition to estimating the impulsive agitations, the DNN-based approaches also recover the correlative structures of shipping noise interference. Thus, following from section 2.1.2, we are able to achieve some degree of estimate for the entire shipping noise signal \(w\) in addition to the impulsive components \(i\). The outputs of the L-SDA, NL-SDA, and the CNN models for structure signal recovery will yield an estimate \(\hat{w}\), and therefore the mitigated ship-radiated noise signal is reported as \(\tilde{w} = w - \hat{w}\).

To handle the complex ship-radiated noise signals, we use the complex DNN operations [65] as described in section 4.2.3. For the remainder of this section, we introduce and describe the L-SDA, NL-SDA, and CNN models for the structured signal recovery of ship-radiated noise in terms of a single real number network. However, the DNN models consist of two identical networks that are trained and evaluated in parallel that capture the mathematical dependencies between the real and imaginary components of the ship-radiated noise data.
4.3.1 Stacked De-noising Autoencoder for Structured Signal Estimation

Let us denote \( \mathbf{x} \) as the \( 1024 \times 1 \) complex input vector, \( \mathbf{y} \) the \( m \times 1 \) sampled measurement vector, and \( \Phi \) as the \( m \times 1024 \) complex measurement matrix. The quantity of measurement points is denoted by \( m \), where \( m < 1024 \). The goal is to achieve an estimate \( \hat{\mathbf{x}} \) from the sampled measurement vector \( \mathbf{y} \) by training a stacked de-noising autoencoder (SDA) that learns a non-linear mapping that is analogous to the CS recovery problem. An example of the general structure of a SDA is illustrated in Figure 4.2. Below we describe the individual implementations of the L-SDA and NL-SDA.

1. **L-SDA**: In this implementation, the measurement matrix \( \Phi \) is fixed. In our case, \( \Phi = F_n \), where \( F_n \) is the reduced DFT sampling matrix as defined in section 2.1.2. As the data is normalized between \([-1, 1]\) (the structure of the training and testing data is described later in section ??), we use the hyperbolic tangent function defined in equation (4.7) (See Table 4.1) at the hidden layers, \( L_1 \) and \( L_2 \), as well as the output layer. The L-SDA learns a non-linear mapping from \( \mathbf{y} = F_n \mathbf{x} \) and produces an estimate \( \hat{\mathbf{x}} \).

2. **NL-SDA**: Different from the L-SDA, this implementation learns the measurement paradigm via the matrix \( \Phi \) while simultaneously learning a non-linear mapping to estimate \( \hat{\mathbf{x}} \). This is advantageous to the L-SDA as the learned measurement procedure enables more efficient encoding of the input examples \( \mathbf{x} \) compared to the reduced DFT sampling matrix. Similar to the L-SDA, the data is normalized between \([-1, 1]\), and the hyperbolic tangent activation function is used at the hidden layers, \( L_1 \) and \( L_2 \), the output layer, and additionally at the sampling layer, i.e. \( \tanh(\mathbf{y}) = \tanh(\Phi \mathbf{x}) \). Because the NL-SDA learns a new optimized sampling procedure that is not the reduce DFT matrix, it does not serve as a realizable implementation for OFDM systems. Therefore, we use the NL-SDA as a upper benchmark on the performance of the L-SDA with the reduce DFT measurement matrix.

To aid and accelerate the training procedure, we also include the use of batch normalization layers, placed after the fully connected layers, but prior to the ac-
Figure 4.2: Stacked de-noising autoencoder for structured signal recovery [2].

Batch normalization layers allow for less focused network initializations, higher learning rates, and in general are found to aid in the convergence of DNN model training [66], thus valuable in the application training a SDA for structured signal recovery.

4.3.2 CNN for Structured Signal Estimation

Different from the SDA implementations, the CNN for structured signal recovery uses convolutional layers to reduce the overall quantity of parameters for training while taking advantage of the natural structures of the input signals in order to achieve an accurate estimate $\hat{x}$. Figure 4.3 illustrates our CNN model architecture that stems from the Deep Inverse model proposed by [3]. Different from Deep
Inverse, our model operates in one dimension and uses less feature maps at each hidden layer, however the principle of first achieving a pseudo-estimate $\tilde{x} = \Phi^H y$ from the linearly samples vector $y$ remains the same.

Alike the SDA implementations, the input and output data are normalized between $[-1, 1]$, thus we utilize the hyperbolic tangent activation function at the output of hidden layers $L_1, L_2,$ and $L_3$, as well as at the output layer. Batch normalization layers are also included between the outputs of each hidden layer and the activation layer to facilitate for a fast and robust training phase. Each of the hidden layers $L_1, L_2,$ and $L_3$ use a $16 \times 1$ convolutional filter and preserve the input size of the previous layers.

### 4.4 Numerical Results

In this section, we present the numerical results on the cancellation performance of the L-SDA, NL-SDA, and CNN methods for the structured signal recovery of ship-radiated noise. We compare the aforementioned approaches to the benchmark approach BPDN and an idealistic implementation of GM-GAMP. To evaluate the performance of the proposed DL structured signal recovery models:
1. We plot the empirical CDFs of the per-OFDM symbol noise variance and report the difference between the suppressed and original signals.

2. We evaluate the trained DL models on experimentally acquired data and report the mean squared error (MSE) between the original ship noise signals and the recovered ship noise for each method.

First, we outline the preparation and partition of the training and testing data sets using the ONC ship-radiated noise data. Then, the results for ship-radiated noise cancellation via the proposed DL approaches on the ONC shipping noise data are presented and discussed. Finally, we demonstrate the scalability of our proposed DL approaches to never before seen ship-radiated noise signals acquired from our experimental procedure.

4.4.1 Training and Testing Data

We use the ONC ship-radiated noise data to train and test the DNN models for structured signal recovery. Then, we apply the ONC trained DNN models to experimentally acquired shipping noise data and report the cancellation results. Here we describe the ONC data preparation for our proposed DL approaches.

To aid in the training procedure, each input data example vector and output data label vector is normalized between $[-1, 1]$, thus after the estimation step we must re-normalize the estimate $\hat{x}$ to have a generalized framework for estimating any ship-radiated noise signal via the DNN models. Let $X'$ denote the $C \times n$ complex example matrix of ship-radiated noise signals and $Y'$ the $C \times m$ sampled example matrix of ship-radiated noise signals, where $C$ is the number of shipping noise signal examples, $n = 1024$ the number of OFDM system sub-carriers and the ship-radiated noise vector length, and $m$ the quantity of null sub-carrier sampling points. Then, for example $i$, the per signal data normalizations are defined as

$$X_i = \frac{1}{\sqrt{2} \max \{|X_i^\prime|\}} \quad X_i^\prime$$

$$Y_i = \frac{1}{\sqrt{2} \max \{|Y_i^\prime|\}} \quad Y_i^\prime.$$
After the estimation stage of the DNN models, re-normalization of the output is required to conserve the original amplitudes of the ship-radiated noise signals. For the NL-SDA, this is trivial as we reverse the process of equation (4.12) given the idealistic scenario modelled by the NL-SDA. However, for the L-SDA and CNN methods, we use the the sampled ship-radiated noise vectors to re-normalize the estimated output. Denoting the \( C \times n \) complex estimate matrix of ship-radiated noise signals as \( \hat{X} \), the re-normalization of estimated output vector \( i \) is defined as

\[
\hat{X}_i' = \hat{X}_i \frac{2\sqrt{2}}{E[|Y_i'|]} = \hat{X}_i K.
\]  

(4.14)

The matrix \( Y' \) consists of the DFT sampled examples of \( X' \), i.e. \( Y' \) is a matrix containing the Fourier transformed ship-radiated noise signals at the null sub-carrier indices. Therefore, we use the spectral magnitude information provided from \( Y' \) of the sampled ship-radiated noise signals to estimate a re-normalization factor \( K \) that re-normalizes \( \hat{X}_i \) to \( \hat{X}_i' \).

The L-SDA, NL-SDA, and CNN models utilize different variants of training and testing sets. Let us denote \( D_{\text{train}} = \{ \text{train data examples}, \text{train data labels} \} \) and \( D_{\text{test}} = \{ \text{test data examples}, \text{test data labels} \} \) as the training and testing sets, respectively. Then, for each DNN model, we can define the individual training and testing sets:

1. **L-SDA**: \( D_{\text{train}} = \{ Y_{\text{train}}, X_{\text{train}} \} \) and \( D_{\text{test}} = \{ Y_{\text{test}}, X_{\text{test}} \} \).

2. **NL-SDA**: \( D_{\text{train}} = \{ X_{\text{train}}, X_{\text{train}} \} \) and \( D_{\text{test}} = \{ X_{\text{test}}, X_{\text{test}} \} \).

3. **CNN**: \( D_{\text{train}} = \{ F_n H Y_{\text{train}}, X_{\text{train}} \} \) and \( D_{\text{test}} = \{ F_n H Y_{\text{test}}, X_{\text{test}} \} \).

We consider the OFDM systems with \( m = 256 \) and \( m = 128 \) null sub-carriers, corresponding to the sampling ratios \( m/n = 25\% \) and \( m/n = 12.5\% \), and train DNN models for each case, respectively.

All three models are trained using the momentum based RMSprop optimizer [67] and the MSE loss function. For the L-SDA and NL-SDA, the learning rate is set to 0.0001 and the models are trained over 200 epochs. For the CNN method, the learning rate is set to 0.001 and the model is trained over 50 epochs. The DNN
model weights for all cases are initialized with a standard normal. The overall HF train and test set sizes are 23040 and 5760, respectively. The LF data set is lesser in size compared to the HF data set, thus we include one dimensional translational augmented versions of the pre-processed shipping noise signals to increase the LF data set size by a factor of 4. The LF train and test set sizes are 51321 and 5703, respectively. The training procedure uses a mini-batch size of 128 examples and the training set examples are randomly permuted at the start of every epoch to aid the training procedure convergence of the DNN models.

Due to the low quantity of VLF ship-radiated noise examples and the band overlap with the LF band, we consider only the HF and LF band systems for the structured signal recovery of ship-radiated noise via the DL models.

4.4.2 ONC Data Noise Cancellation: Results and Discussion

We evaluate noise cancellation performance for the L-SDA, NL-SDA, and CNN methods by considering the per OFDM symbol ship-radiated noise variance $\sigma^2$ of the mitigated and original shipping noise signals from the test data set. We compare the cancellation capabilities of the DNN models to BPDN and an idealistic GM-GAMP implementation. In this setting, ideal-GM-GAMP estimates the GMM parameters from the true ship-radiated noise signals prior to the estimation phase. In realistic applications, the full noise signals are unknown, thus the aforementioned GM-GAMP implementation is an idealistic approach. We use Ideal GM-GAMP as an upper performance benchmark to comment on the ship-radiated noise cancellation effectiveness of the DNN approaches. Similar to section 3.3.2, we plot the CDFs for the HF and LF systems and report the relative noise cancellation gains for the 90% and 99% strongest noise. Since we utilize the ideal GM-GAMP implementation, we do not require to leave out test data for the estimation of the GMM parameters as in section 3.3.2, therefore the test data set in this analysis contains a greater number of ship-radiated noise examples.

Figure 4.4 and Figure 4.5 show the per OFDM symbol noise variance of the respective method mitigated and original ship-radiated noise signals for the HF and LF systems, respectively. From Figure 4.4 it is visible that the NL-SDA and CNN methods achieve measurable shipping noise cancellation to ideal GM-GAMP and
outperform the BPDN algorithm for HF ship-radiated noise. Likewise, Figure 4.5 illustrates that superior cancellation gains of the NL-SDA method in the LF band system. In addition, the L-SDA and the CNN methods outperform BPDN cancellation and closely match the mitigation performance of the ideal GM-GAMP algorithm in the LF band system.

Tables 4.2 and 4.3 present the relative cancellation gains for the 90% and 99% strongest noise for the cases of using 256 and 128 null sub-carriers of the total 1024 available sub-carriers, respectively. Tables 4.2 and 4.3 give a more precise presentation of ship-radiated noise cancellation capabilities of the respective approaches that are shown in Figures 4.4 and 4.5.

The results suggest that the CNN method achieves measurable cancellation gains to the ideal GM-GAMP algorithm, but with superior run-time performance.
Figure 4.5: Per-OFDM symbol noise variance of original and mitigated ship-radiated noise signals using 25% null sub-carriers sampling for LF-ONC test data set.

Table 4.2: Relative cancellation gain of ship-radiated noise with 25% null sub-carrier sampling via the DL-based estimation methods.

<table>
<thead>
<tr>
<th>$P(X &gt; \sigma^2)$</th>
<th>BPDN</th>
<th>GM-GAMP</th>
<th>L-SDA</th>
<th>NL-SDA</th>
<th>CNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>1.01 dB</td>
<td><strong>1.64 dB</strong></td>
<td>0.63 dB</td>
<td>1.37 dB</td>
<td>1.14 dB</td>
</tr>
<tr>
<td>0.01</td>
<td>0.97 dB</td>
<td><strong>1.70 dB</strong></td>
<td>0.66 dB</td>
<td>1.38 dB</td>
<td>1.16 dB</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$P(X &gt; \sigma^2)$</th>
<th>BPDN</th>
<th>GM-GAMP</th>
<th>L-SDA</th>
<th>NL-SDA</th>
<th>CNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.26 dB</td>
<td>1.40 dB</td>
<td>1.33 dB</td>
<td><strong>9.67 dB</strong></td>
<td>1.64 dB</td>
</tr>
<tr>
<td>0.01</td>
<td>0.13 dB</td>
<td>1.65 dB</td>
<td>0.98 dB</td>
<td><strong>6.05 dB</strong></td>
<td>0.73 dB</td>
</tr>
</tbody>
</table>
as no iterative solvers are required. In terms of real-time applications, the superior run-time performance of the CNN method for ship-radiated noise cancellation is a desirable trait. Therefore, in cases where high cancellation gains are desirable, GM-GAMP would serve as the algorithm of choice, but in cases where high run-time speed is required, the CNN cancellation method would be a better alternative.

The L-SDA method for ship-radiated noise cancellation never achieves the upper performance bound determined by the NL-SDA. This indicates that the bottleneck for the DNN approaches for shipping noise cancellation in UA OFDM systems is the reduced DFT sampling matrix. In the case such as the NL-SDA, the learned sampling procedure leads to improved cancellation results compared to the L-SDA and CNN approaches in the HF systems where shipping noise is more sparse. However, in the LF band system where ship-radiated noise is highly correlated, the NL-SDA shows superior cancellation gains to all other approaches, including the L-SDA which is approximately $5 - 9$ dB short in cancellation capability to the NL-SDA. This result demonstrates the power of the DNN-based methods for ship-radiated noise estimation and cancellation, but standard OFDM systems that require the reduced DFT sampling matrix constrain the DNN-based approaches.

From Tables 4.2 and 4.3, it is also visible that the sparsity-based approaches, BPDN and ideal GM-GAMP, achieve higher cancellation gains for the 99% strongest noise relative to the 90% strongest noise. This is consistent to the sparsity-based

---

**Table 4.3:** Relative cancellation gain of ship-radiated noise with 12.5% null sub-carrier sampling via the DL-based estimation methods.

<table>
<thead>
<tr>
<th>$P(X &gt; \sigma^2)$</th>
<th>BPDN</th>
<th>GM-GAMP</th>
<th>L-SDA</th>
<th>NL-SDA</th>
<th>CNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>0.20 dB</td>
<td><strong>0.72 dB</strong></td>
<td>0.19 dB</td>
<td>0.54 dB</td>
<td>0.53 dB</td>
</tr>
<tr>
<td>0.01</td>
<td>0.22 dB</td>
<td><strong>0.87 dB</strong></td>
<td>0.26 dB</td>
<td>0.61 dB</td>
<td>0.63 dB</td>
</tr>
</tbody>
</table>

High Frequency

<table>
<thead>
<tr>
<th>$P(X &gt; \sigma^2)$</th>
<th>BPDN</th>
<th>GM-GAMP</th>
<th>L-SDA</th>
<th>NL-SDA</th>
<th>CNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>$-0.48$ dB</td>
<td>$-0.08$ dB</td>
<td>0.50 dB</td>
<td><strong>7.50 dB</strong></td>
<td>0.28 dB</td>
</tr>
<tr>
<td>0.01</td>
<td>$-0.09$ dB</td>
<td>$-0.05$ dB</td>
<td>0.41 dB</td>
<td><strong>5.74 dB</strong></td>
<td>0.14 dB</td>
</tr>
</tbody>
</table>

Low Frequency
foundations of the algorithms, as the 99% strongest noise pertains to more impulsive noise contributions. Moreover, we see the DNN-based approaches yield improved cancellation gains for the 90% strongest noise compared to the 99% strongest noise. This is also consistent with our expectations as the 90% strongest noise is less impulsive and carries increased correlative structure relative to the 99% strongest noise. This result suggest that some form of a hybrid approach that utilizes an iterative sparsity-based estimator and a DNN model in conjunction could achieve improved cancellation capabilities.

4.4.3 Experimental Data Noise Cancellation: Results and Discussion

After acquiring various experimental ship-radiated noise recordings via the procedure outlined in section 2.2.2, we identify the acoustic hydrophone recordings with the most prominent shipping noise and no interference from other noise sources present during the sea trials. Two experimental recordings, both approximately one minute in length, are identified and considered for analysis:

- **Acoustic recording 1**: Date: May 20th, Time: 15:52 – Label: EXP1
- **Acoustic recording 2**: Date: May 20th, Time: 15:53 – Label: EXP2

Prior to analysis, the experimental acoustic recordings are pre-processed identical to the ONC shipping noise data.

Table 4.4 shows the MSE results between the estimated and the actual experimental shipping noise signals using the BPDN algorithm, the ideal GM-GAMP implementation, and the three DNN models trained via the ONC data set. It is visible from Table 4.4 that the CNN model for ship-radiated noise estimation outperforms all other methods on the experimental data in both HF and LF systems. This result suggests that the experimental ship-radiated noise signals contain increased correlative structure compared to the ONC shipping noise data that is well captured by the convolutional filters of the CNN model. Thus, the CNN model is able to recover the experimental ship-radiated signals with better accuracy compared to BPDN and the ideal GM-GAMP implementation.

Overall the results indicate that the CNN method for ship-radiated noise cancellation scales best to new shipping noise instances that adhere from a source
Table 4.4: MSE between estimated and original experimental ship-radiated noise signals using 25% null sub-carrier sampling.

<table>
<thead>
<tr>
<th>Ship Noise Data</th>
<th>Estimation Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BPDN</td>
</tr>
<tr>
<td>HF-EXP1</td>
<td>2.1E−6</td>
</tr>
<tr>
<td>HF-EXP2</td>
<td>3.0E−6</td>
</tr>
<tr>
<td>LF-EXP1</td>
<td>6.6E−5</td>
</tr>
<tr>
<td>LF-EXP2</td>
<td>6.9E−5</td>
</tr>
</tbody>
</table>

different from the ships that generate the noise signals that comprise the ONC data set. This further confirms the shipping noise cancellation capabilities of the CNN method compared to ideal GM-GAMP, with the key advantage of superior run-time speed for noise cancellation.

4.5 Conclusions on Deep Learning-based Ship-radiated Noise Cancellation

In this chapter, we introduced the DL-based approaches for ship-radiated noise cancellation in UA OFDM systems formulated under the CS noise estimation framework. The DL methods were evaluated in terms the per OFDM symbol noise variance shipping noise cancellation gains. The empirical results for the noise cancellation capabilities of the DNN-based approaches for ship-radiated noise suggest:

- The CNN method serves as a more suitable choice compared to ideal GM-GAMP for the cases of increased correlative structure of ship-radiated noise. This is particularly the case in the LF band system where ship-radiated noise exhibits increased correlative structure compared to the HF band system.

- The non-linear sampling procedure learned by the NL-SDA leads to superior ship-radiated cancellation results. This also indicates that the bottleneck for achieving higher cancellation gains with the DNN-based methods is constrained by the reduced DFT sampling procedure. This is visible from the...
empirical results of the L-SDA which do not achieve cancellation gains to that of the NL-SDA for both the HF and LF band systems.

- A hybrid approach consisting of a DNN-based model and a sparsity-based iterative estimator for the cancellation of ship-radiated noise could yield improved mitigation gains. This is motivated by the performance of the respective cancellation algorithms at the 90% and 99% strongest shipping noise, i.e. the DNN methods perform better on the 90% strongest noise which carries increased correlative structure compared to the 99% strongest noise which consist of more impulsive attributes. The sparsity-based approaches exemplify the reverse relative to the DNN methods.

- The CNN method for ship-radiated noise cancellation scales best to newly never before seen shipping noise signals. This is visible from the experimental results, where the CNN-based approach outperforms all other cancellation methods.
Chapter 5

Stochastic Ship-radiated Noise Modelling via Generative Models

In chapter 4, we demonstrated the use of supervised learning for training DNNs to achieve estimation and cancellation of ship-radiated noise interference. The DL models introduced in chapter 4 are examples of high dimensional discriminative networks. Contrary to the goal of cancelling the perturbing effects of ship-radiated noise via discriminative DNNs, in this chapter we focus on the objective of generating new realistic instances of ship-radiated noise signals via generative DNNs trained using unsupervised learning methods. In addition, we reassess the GMM as a probabilistic generative model for ship-radiated noise, introduced in section 2.3.1.

First, a general overview of GAN based generative models and the motivation behind using unsupervised learning techniques for training probabilistic ship-radiated noise models is presented. Next, we introduce the mathematical framework behind the GAN [35], the GAN training procedure, and present the deep convolutional generative adversarial network (DCGAN) [4] for ship-radiated noise modelling. Then, the numerical results for the DCGAN and the GMM for probabilistically modelling the stochastic characteristics of ship-radiated noise are presented. Finally, we discuss and draw relevant conclusion regarding the numerical results of the generative ship-radiated noise models.
5.1 Background

Given a set of training data examples $\mathbf{X}$ and a set of training data labels $\mathbf{Y}$, generative models are concerned with the task of capturing the joint probability $P(\mathbf{Y}, \mathbf{X})$, or $P(\mathbf{X})$ in the case that the training labels $\mathbf{Y}$ are unavailable. In this chapter, we are concerned with the unsupervised learning task of training a generative model that well approximates the prior distribution $P(\mathbf{X})$. Introduced in section 2.3.1, the GMM is a well known generative model that is extensively used for modelling impulse noise in the UA channel and evaluating the performance of UA communication systems in the presence of such additive interference [18]. The GMM serves well in modelling some of the probabilistic and impulsive properties of HF ship-radiated noise, but does not capture existing correlative structure, as in the case of LF noise. Therefore, producing a probabilistic model that can fully capture the variational properties and structure of ship-radiated noise remains a challenge.

GANs are another popular generative modelling approach. Different from the GMM, which is trained via the EM algorithm (see section 2.3.2), GANs train a generative model through a min-max two player game [35]. Since their original introduction, extensive research interest in probabilistic generative modeling via GANs has led to numerous variants of the GAN model. For instance, the DCGAN [4], the conditional GAN [68], and the stacked GAN [69] are some examples of GAN model variants derived from the original adversarial training framework of the GAN model. The success of GANs has sparked motivation in the field of communications for use in stochastic channel modelling. For instance, the authors in [70] propose an end-to-end learning communication system framework using a conditional GAN to model the stochastic channel effects, where the gradients of the end-to-end training procedure are propagated through the GAN. Likewise, [71] suggests the use of variational GANs for modelling a wide variety of stochastic channel effects learned from observed data. To this end, there is reason to believe that GANs can capture the stochastic behaviour and statistical characteristics of ship-radiated noise.

Recently, UA applications of GAN models have been proposed for acoustic signal identification [72] [73] and sonar imaging [74] [75]. However, to the best of our knowledge there have been no appearances in recent research that propose
GAN based channel modelling approaches for UAC systems. Therefore, in this chapter we address the aforementioned research gap.

Stimulated by the above research gap and the lack of an adequate temporal stochastic model for shipping noise, we propose the use of the DCGAN [4] to capture the correlative structure of LF ship-radiated noise, while investigating the suitability of GMMs for modelling HF ship-radiated noise. Similar to the previous chapters in this thesis, we conduct a data driven study utilizing the ONC publicly available database of long term acoustic recordings of shipping noise [1], to train a DCGAN that can generate new realistic realizations of ship-radiated noise. Likewise, we use the learned GMM parameters presented in section 2.3 to construct a GMM that provides a stochastic model for ship-radiated noise. We then evaluate the suitability of the GMM and the DCGAN in producing stochastic time-domain models of ship-radiated noise in the HF and LF band systems.

5.2 Generative Adversarial Networks for Ship-radiated Noise Modelling

GANs directly learn the prior distribution $P(X)$ without any assumption or definition on the probability distribution function (PDF) [35]. In contrast, the GMM first assumes the data $X$ follows a Gaussian mixture PDF, then fits the model parameters via the EM algorithm. Therefore, the GAN is desirable in the case where it is difficult to first assume the PDF on the data $X$. For instance, the case of LF ship-radiated noise, which is found to be less well characterized by the GMM (see section 2.3.5). In this section, we first present the general GAN model framework and introduce the iterative min-max GAN training process. Then, we present the DCGAN model for stochastic ship-radiated noise modelling.

5.2.1 GAN Model Framework and Training Procedure

During training, GANs play a min-max two player game between the generator network $G$, which aims to generate new realistic and artificial instances of the training data, and a discriminator network $D$, which attempts to differentiate be-
between real and fake\(^1\) data examples \([35]\). The generator network tries to learn an approximate distribution over the training data examples \(\mathbf{x}\) by mapping a randomly generated low-dimensional latent space \(\mathbf{z}\), drawn from some prior distribution \(p(\mathbf{z})\), i.e. \(\tilde{\mathbf{x}} = G(\mathbf{z})\). We sample the latent space \(\mathbf{z}\) from a standard normal distribution, i.e. \(\mathbf{z} \sim \mathcal{N}(\mu, \sigma^2)\), where \(\mu = 0\) and \(\sigma^2 = 1\). The discriminator network takes the real training data examples and the newly generated fake data examples as input and attempts to determine whether a certain example is drawn from the training set or generated from \(G\). We illustrate this process in Figure 5.1. The two stages of the min-max training objective can be summarized:

- Train \(D\) such that the probability \(D(\mathbf{x})\) of classifying the real and fake data examples is maximized.

- Train \(G\) such that the cost function \(\log(1 - D(G(\mathbf{z})))\) is minimized.

Likewise, following from the two objectives listed above, we can denote the GAN objective function as

\[
\min_G \max_D \{ \mathbb{E}_x [\log D(\mathbf{x})] + \mathbb{E}_z [\log (1 - D(G(\mathbf{z})))] \}. \tag{5.1}
\]

The training procedure iterates between maximizing \(D(\mathbf{x})\) by fixing \(G\), then minimizing \(\log(1 - D(G(\mathbf{z})))\) by fixing \(D\), until some convergence is achieved.

### 5.2.2 A Deep Convolutional GAN Ship-radiated Noise Model

The DCGAN has shown success in generating sharp and realistic two dimensional images for various image datasets by embedding the architecture of CNNs within the GAN model framework \([4]\). Due to the success of the DCGAN in probabilistically generating new realizations of images, we adopt the DCGAN for the task of stochastic ship-radiated noise modelling under a image processing framework. However, unlike typical implementations of the DCGAN for two dimensional images, we devise an alternate implementation for generating one dimensional vectors of ship-radiated noise signals. Identical to section 4.3 we utilize the complex number operations for DNNs (see section 4.2.3) to train two real number networks

---

\(^1\)In this setting, the real and fake data examples correspond to the data examples from a given dataset and newly generated data examples via the generative model, respectively.
in parallel that capture the relationship between the real and imaginary components. Figure 5.2 (a) and Figure 5.2 (b) illustrate the respective single real number generator and discriminator networks of the DCGAN for ship-radiated noise modelling. Below we denote the structures of the generator and discriminator networks.

- **Generator network:** The general structure of the generator network is shown in Figure 5.2 (a). Let us denote \( z \) as the complex standard normal generated latent space vector. We use a latent space size of 64, thus the latent space layer of the DCGAN model is \( 64 \times 1 \). The generator network consists of the four transposed convolutional hidden layers \( L_1, L_2, L_3, \) and \( L_4 \), which map the randomly generated \( 64 \times 1 \) latent space vector \( z \) to a \( 1024 \times 1 \) output vector \( \tilde{x} \). The dimensions of each layer are defined as \( (n \times 1 \times k) \), where \( n \times 1 \) is the feature map size (the length of the one dimensional vectors) and \( k \) is the number of feature maps. The output vector \( \tilde{x} \) is the newly generated ship-radiated noise signal that probabilistically mimics the training data examples. The filter size of each transposed convolutional layer is \( 4 \times 1 \). Unlike the CNN for structured signal recovery introduced in section 4.3.2

\[ \text{Figure 5.1: General GAN structure.} \]
which preserves the input vector size through each hidden layer, the generator network of the DCGAN needs to increase the input size of the latent space \( z \) to the output size of \( \tilde{x} \). Therefore, we use a stride of 2 and zero padding\(^3\) of 1 at each transposed convolutional layer. The ReLU activation function (see table 4.1) is placed after the outputs of hidden layers \( L_1, L_2, \) and \( L_3 \) and the hyperbolic tangent activation function is used at the output layer \( L_4 \). Batch normalization layers are utilized at each hidden layer to aid in the convergence of the training process.

- **Discriminator network:** The general structure of the discriminator network is shown in Figure 5.2 (b). The discriminator network comprises five convolutional hidden layers that provide a mapping for determining whether a 1024 \( \times \) 1 input vector is a real ship-radiated noise example or a fake example generated by the generator network. The five convolutional hidden layers \( L_1, L_2, L_3, L_4, \) and \( L_5 \) map the input vector to a single probability \( D(x) \). Opposite to the generator network, the discriminator network maps a higher input size, to a lower sized single output variable. This is achieved using convolutional layers rather than transposed convolutional layers. For the discriminator network, we use a filter sizes of 4 \( \times \) 1, a stride of 4, and zero padding of 1 at each convolutional hidden layer. The LReLU activation function (see table 4.1) with the default \( \alpha \) value is utilized at layers \( L_1, L_2, L_3, \) and \( L_4 \) and the sigmoid activation function is used at the output layer \( L_5 \). Identical to the generator network, we use batch normalization layers at each hidden layer to help in the convergence of the training process.

### 5.3 Numerical Results

In this section, we present the numerical results of the DCGAN and GMM based stochastic models for HF and LF ship-radiated noise. We consider three methods of evaluation to determine the suitability of the respective generative models for modelling the time-domain stochastic behaviour of shipping noise:

\(^3\)Zero padding appends zeros to both sides of the feature map outputs, which is accounted for in the size of each feature map.
Figure 5.2: DCGAN [4] for stochastic modelling of ship-radiated noise with (a) the generator network $G$, and (b) the discriminator network $D$.

1. The 1-nearest neighbour (1-NN) two sample test, reporting the leave-one-out (LOO) accuracy in classifying the real and fake data examples [76].

2. Noise estimation and cancellation analysis via GM-GAMP, as in Chapter 3 on the ONC shipping noise data, GMM generated shipping noise,
and DCGAN generated shipping noise.

3. Empirical symbol error rate (SER) versus signal to noise ratio (SNR) analysis of a quadrature phase shift keying (QPSK) OFDM system without noise cancellation, imposing ship-radiated noise vectors from the ONC shipping noise data, DCGAN generated shipping noise, and GMM generated shipping noise.

First, we describe the partition of the testing and training data sets utilized for the training and testing evaluation of the GMM and DCGAN generative models. Then, the 1-NN LOO accuracy results of the HF and LF DCGAN models on the ONC and experimental test data sets and DCGAN generated shipping noise data are presented and discussed. Next, we present the numerical results of the noise estimation and cancellation analysis via the GM-GAMP algorithm on the ONC, DCGAN generated, and GMM generated ship-radiated noise data. Finally, we show and discuss the QPSK-OFDM system simulation numerical results with imposed noise from the ONC, DCGAN generated, and GMM generated ship-radiated noise data.

5.3.1 Training Data

We use the ONC ship-radiated noise data to train DCGAN models and GMMs for both the HF and LF band systems. The HF and LF ONC data sets are partitioned and normalized between $[-1, 1]$ in the same manner as presented in section 4.4.1. However, unlike the training procedures for the DNNs in Chapter 4, the DCGAN model and GMM require no training labels as the training procedures of the respective models are unsupervised.

Both the HF and LF DCGAN models are trained using the Adam optimizer [77] with a mini-batch size of 128 training examples over a training period of 100 epochs with the HF and LF ONC training data sets, respectively. Because the learning stages of the DCGAN model alternate between convolutional filter weights updates for the generator and discriminator networks individually, we must define learning rates for each network separately. In this case, we use a learning rate of 0.0001 for both the generator and discriminator networks.
To fit the HF and LF GMMs, we first estimate the respective GMM parameters via the EM algorithm for each shipping noise vector from the respective HF and LF training sets. Then, we take the medians of the respective EM estimated GMM component parameters of the shipping noise signals. This produces a HF and LF GMM with fixed parameters that approximates the distribution of the ship-radiated noise training data as a single two component Gaussian mixture for the HF and LF ONC data sets, respectively.

Examples of LF real ship-radiated noise signals and fake generated ship-radiated noise signals via the DCGAN model are shown in Figure 5.3 (a) and Figure 5.3 (b), respectively. Likewise, Figure 5.4 (a) and Figure 5.4 (b) present the HF real ship-radiated noise signals and the fake GMM generated ship-radiated noise signals, respectively. From initial observation of the generated shipping noise signals shown in Figure 5.3 and Figure 5.4, it is visible that the LF DCGAN model is able to capture some of the correlative structure present in LF ship-radiated noise while the HF GMM serves well in approximating the impulsive behaviour of HF ship-radiated noise.

Identical to chapter 4, we do not consider the VLF ONC data set due to the lack of training examples and the band overlap with the LF ONC shipping noise data. Likewise, the LF ONC shipping noise data set is translationally augmented in the same manner as introduced in section 4.4.1 in order to increase the size of the data set.

5.3.2 The 1-Nearest Neighbour Two Sample Test

The 1-NN test is a type of two sample test, used to assess whether or not two distributions match. The 1-NN two sample test has been found to be an effective evaluation metric for GAN models [76]. For the purpose of our evaluation, we take advantage of the 1-NN test to provide initial observations and comments regarding the trained DCGAN models and to observe how the DCGAN models generalize to experimental shipping noise data. We report the LOO of the 1-NN test on the separated HF and LF ONC test data set and on the experimentally acquired data. Below, we denote and outline the general structure of the 1-NN two sample test.

We define $\mathbf{X}_{\text{test}}$ and $\mathbf{X}_{\text{gen}}$ as $K \times n$ matrices containing $K$ real ship-radiated
noise examples from the test set and generated ship-radiated noise examples, respectivley. Here, $K$ denotes the number of generated and real ship-radiated noise examples and $n$ denotes the size of each example. $X_{data} = [X_{test}^T | X_{gen}^T]^T$ is the $2K \times n$ real and generated concatenated shipping noise example matrix. Likewise,
we denote $Y_{data}$ as the $2K \times 1$ label matrix, labelling the real ship-radiated noise signals as 1 and the fake ship-radiated noise signals as $-1$. We shuffle the rows of $X_{data}$ and $Y_{data}$ synchronously. Then, we fit a 1-NN classifier using all, except for one, examples and respective labels from $X_{data}$ and $Y_{data}$. The single left
out example, and respective label, is used in the testing stage of the previously fit 1-NN classifier. We record predicted label of the 1-NN test via the single left out example from \( \mathbf{X}_{data} \) and the corresponding true label from \( \mathbf{Y}_{data} \). This process is then repeated until a 1-NN classifier is fit and predicted for all \( 2K \) examples in \( \mathbf{X}_{data} \). Finally, the LOO accuracy is calculated using the subsequent predicted and true labels from the \( 2K \) 1-NN classifiers. In this test, a LOO accuracy of 50% indicates that the 1-NN classifier cannot distinguish whether a certain example is real or fake, suggesting that the generative model well approximates the real data distribution.

We implement the 1-NN two sample test on the individual complex discrete sample points of the ship-radiated noise signals. On the ONC test data set, the \( \mathbf{X}_{test} \) matrix is \( 10240 \times 2 \), containing the real and imaginary components of the 10 randomly selected and concatenated actual ship-radiated noise signals. Likewise, \( \mathbf{X}_{gen} \) is a \( 10240 \times 2 \) matrix, containing the real and imaginary components of 10 generated and concatenated fake ship-radiated noise signals. Because the experimental data sets are significantly smaller than the ONC test data sets, we use 5 randomly selected, and 5 generated, ship-radiated noise signals for the 1-NN evaluation on the experimental data. Table 5.1 reports the LOO accuracies of the 1-NN two samples tests on the HF and LF ONC and experimental shipping noise data. From Table 5.1 it is clear that the LF DCGAN model generates samples closer to the distribution of the real data compared to the HF DCGAN model, for both the ONC and experimental shipping noise signals. Likewise, both DCGAN models produce LOO results relatively close to 50%, suggesting the generated DCGAN samples to some degree follow the structure of the real ship-radiated noise. However, apart from initial observations regarding the ability of the DCGAN model to approximate the distribution of the ship-radiated noise data, the 1-NN test does not serve as an absolute evaluation metric. Thus, in the next two sections we provide evaluations in terms of the OFDM system framework for the HF and LF bands.

### 5.3.3 Noise Estimation and Cancellation Analysis

We perform noise estimation and cancellation analysis using actual ship-radiated noise signals and fake GMM and DCGAN generated ship-radiated noise signals
Table 5.1: Per-complex-discrete sample LOO Accuracy of 1-NN Classifier For Classification of Real and Fake Data Examples on ONC test data and Experimental Data

<table>
<thead>
<tr>
<th>Ship Noise Data set</th>
<th>DCGAN Real</th>
<th>DCGAN Fake</th>
</tr>
</thead>
<tbody>
<tr>
<td>HF-ONC</td>
<td>0.609</td>
<td>0.612</td>
</tr>
<tr>
<td>LF-ONC</td>
<td>0.531</td>
<td>0.527</td>
</tr>
<tr>
<td>HF-EXP1</td>
<td>0.624</td>
<td>0.625</td>
</tr>
<tr>
<td>HF-EXP2</td>
<td>0.623</td>
<td>0.620</td>
</tr>
<tr>
<td>LF-EXP1</td>
<td>0.523</td>
<td>0.524</td>
</tr>
<tr>
<td>LF-EXP2</td>
<td>0.529</td>
<td>0.527</td>
</tr>
</tbody>
</table>

for the HF and LF band systems. This follows from the performance evaluations presented in Chapter 3 and Chapter 4 where we plot the empirical CDFs of the per-OFDM symbol noise variance of the original and mitigated ship-radiated noise signals. The ideal GM-GAMP algorithm (see section 4.4.2) for the estimation and cancellation of the real and generated ship-radiated noise signals is considered for the extent of this evaluation. For both the HF and LF band systems, we randomly select 8000 real shipping noise signals from the respective ONC training sets and generated 8000 fake shipping noise signals via the GMM and DCGAN. Then, we apply the ideal GM-GAMP algorithm to estimate and cancel the respective HF and LF actual and model generated ship-radiated noise signals.

Figure 5.5 (a) and Figure 5.5 (b) show the empirical CDF plots of the original and mitigated per-OFDM symbol shipping noise signal variances for the ONC shipping noise data, GMM generated shipping noise data, and DCGAN generated shipping noise data. With reference to Figure 5.5, it is clear that the GMM model provides more accurate approximation of the per-OFDM symbol ship-radiated noise variance compared to the DCGAN for the HF band system. In contrast, the DCGAN yields more realistic approximation of the per-OFDM symbol ship-radiated noise variance compared to the GMM for the LF band system. This result is consistent with our expectation that the LF ship-radiated noise carries increased correlative structure that is arguably well captured by the convolutional layers of
5.3.4 OFDM System Simulation with Model Generated Noise

To evaluate the effectiveness of the GMM and DCGAN in generating realistic realizations of ship-radiated noise for HF and LF OFDM systems, we report the SER versus SNR under a QPSK-OFDM system simulation framework. The closer the match between the SER curves pertaining to the QPSK-OFDM system simulation using the actual versus generated shipping noise interference, the more suitable the respective generative model in approximating the ship-radiated noise. We use ship-radiated noise samples from the ONC training set in order to observe how well the respective generative models approximate the probabilistic distributions of the training data.

We simulate a QPSK-OFDM system in the complex baseband, as introduced in section 2.1.2, and consider the case where all 1024 OFDM sub-carrier are utilized for data transmission. Likewise, we consider a simple OFDM system with no
cyclic pre-fix and no channel estimation and equalization as we aim to only explore the additive interfering effects of ship-radiated noise. The complex QPSK modulated symbols are randomly generated from the set of points defined in \{±1, ±1\} and placed at the 1024 OFDM data sub-carriers. Following the IDFT of the OFDM sub-carriers, as defined in equation (2.2), we impose the respective ship-radiated noise signals to the time-domain OFDM signal. Then, we perform the reception process via the DFT of the time-domain OFDM signal, now containing the additive ship-radiated noise interference. We then evaluate the SER of the QPSK symbols. This process is performed and repeated over 8000 OFDM transmissions at various SNRs for the HF and LF band systems (outlined in Table 2.1).

Figure 5.6 (a) and Figure 5.6 (b) present the SER versus SNR curves for the HF and LF OFDM systems, respectively. With reference to Figure 5.6 (a), it is clearly visible that the GMM serves as a more suitable time-domain stochastic model for HF ship-radiated noise in the SNR range between −5 dB to 15 dB, relative to the DCGAN. Likewise, from Figure 5.6 (b), we observe the DCGAN serves as a more suitable time-domain stochastic model for LF ship-radiated noise in the SNR range between −5 dB to 20 dB, compared to the GMM. Overall, these results are consistent with our expectations and indicate that the DCGAN well captures the correlative structure present in LF ship-radiated noise while the GMM is better suited in modelling the impulsive agitations which occur in the presence of HF ship-radiated noise.

5.4 Conclusions on Stochastic Ship-radiated Noise Modelling

In this chapter, we introduced the DCGAN model for modelling the time-domain stochastic behaviour of ship-radiated noise. In particular, we took advantage of convolutional layers of the DCGAN model to capture the correlative structure of LF ship-radiated noise. The GMM was further evaluated as a the time-domain stochastic model for HF ship-radiated noise. The 1-NN two sample test was used to provide initial evaluation metrics and observations for the trained DCGAN models. We evaluated the suitability of the GMM and DCGAN in generating realistic time-domain realization of ship-radiated noise through noise estimation and can-
Figure 5.6: SER v.s. SNR for QPSK-OFDM system in (a) HF ship-radiated channel noise (b) LF ship-radiated channel noise.

cellation analysis and a QPSK-OFDM system simulation framework. The numerical results for the stochastic modelling of ship-radiated noise suggest:

- The DCGAN model serves as a more suitable choice for modelling the time-domain stochastic behaviour of LF ship-radiated noise. This is expected as the convolutional layers of the DCGAN model are able to capture the increased correlative structure present in LF ship-radiated noise.

- The GMM serves as a more suitable choice for modelling the time-domain stochastic behaviour of HF ship-radiated noise. This is further confirmation from the initially provided evaluations performed in section 2.4.

- The DCGAN may be over-designed for modelling the HF ship-radiated noise statistics, as the DCGAN fails to capture the impulsive agitations present in HF ship-radiated noise. Rather, a fully connected GAN may better approximate the impulsive characteristics of HF ship-radiated noise.
Chapter 6

Conclusions

To conclude this thesis, we provide a summary and discussion of the main results on the modelling and cancellation of ship-radiated noise for UAC systems and suggest future research directions.

6.1 Conclusions and Remarks

In this thesis, we investigated and modelled the time-domain statistical characteristics of ship-radiated noise and proposed ship-radiated noise cancellation techniques for UA OFDM systems. First, we introduced and evaluated the two-component GMM for characterizing the statistical attributes of ship-radiated noise. Next, under a CS framework, we proposed and investigated sparsity-based ship-radiated noise cancellation methods for UA OFDM systems. Following the same CS framework, DL-based approaches for ship-radiated noise cancellation for UA OFDM systems were introduced and evaluated. Finally, we proposed the use of DCGANs to model the stochastic and correlative properties of ship-radiated noise. The DCGAN model was evaluated alongside the GMM in producing a time-domain stochastic model for ship-radiated noise.

The main conclusions drawn from the work in this thesis suggest:

• Evident from observation and statistical analysis, ship-radiated noise exhibits impulsive characteristics that can be detrimental to UA OFDM systems. Under a CS framework, we offer sparsity-based solutions that esti-
mate and cancel these impulsive interfering effects of ship-radiated noise. The GM-GAMP algorithm serves as the best estimation and cancellation method of ship-radiated noise for UA OFDM systems.

- DL-based methods for the estimation and cancellation of ship-radiated noise for UA OFDM produce measurable mitigation results to the GM-GAMP algorithm. Advantageous to GM-GAMP, the DL approaches do not require the ship-radiated noise to be sparse in order to achieve accurate estimation and cancellation. Rather, the DL methods capture existence correlative structure also present in ship-radiated noise interference. In conjunction to the competitive cancellation results, the key advantage of the DL-based cancellation methods is their superior on-line run-time performance in contrast to the slow iterative GM-GAMP and similar CS based solutions. Therefore, the DL-based methods are more suitable in real-time applications of ship-radiated noise cancellation for UA OFDM systems.

- The GMM serves as the most suitable time-domain stochastic model for HF ship-radiated noise, while the DCGAN model better approximates the time-domain stochastic behaviour of LF ship-radiated noise for UA OFDM systems. Therefore, when evaluating the performance of UA OFDM systems in the presence of ship-radiated noise, the GMM and DCGAN model produce relatively accurate approximation of simulated ship-radiated noise for HF and LF band systems, respectively.

In manifesting the above conclusions, this thesis has provided novel contributions in the domains of temporal stochastic ship-radiated noise modelling and ship-radiated noise cancellation under a machine learning inspired framework for UA OFDM systems.

6.2 Future Work

The following future research directions could provide additive performance benefits to the existing methods introduced in this thesis:

1. The research work conducted in [78] proposes an iterative CNN channel noise decoder. The proposed approach first produces an initial channel noise
estimate, then subtracts the noise contributions from the received encoded data before estimating the received data symbols. In the next stage, the estimated data symbols are subtracted and a new estimate of the channel noise is achieved. Then, a CNN further improves the noise estimate prior to subtracting the estimated noise contributions from the initially received data symbols. This process is iterated until some desired criteria are met. We propose, in the same iterative manner as the proposed algorithm in [78], an iterative process that first estimates and cancels the ship-radiated noise contributions in an OFDM system before detecting the data symbols. Then, follow the iterative procedure proposed in [78] via a CNN to further improve the ship-radiated noise estimate. Such an implementation could facilitate for further improved ship-radiated noise cancellation for UA OFDM systems.

2. In section 4.4.2 we demonstrated the power of a non-linear CS measurement paradigm learned within the embedded estimation process of a DL-based method for ship-radiated noise cancellation, i.e. the NL-SDA. However, for OFDM systems the aforementioned measurement paradigm is constrained by the DFT sampling procedure. To address this constraint, and following from the previous point above, we propose to embed DNN models, such as the NL-SDA, within the iterative structure of the iterative noise estimation and cancellation process. Although this suggested solution is not identical to the procedure of the NL-SDA, it is a step in the direction of utilizing the full power of the NL-SDA and other DL models alike.

3. Fully connected GANs have shown success in modelling simple channel effects, such as the cases of AWGN or Rayleigh channel fading [70] [71]. This suggests that simple fully connected GAN models may be able to capture the impulsive characteristics of HF ship-radiated noise, compared to the potentially over-designed DCGAN model proposed in Chapter 5. Likewise, a fully connected convolutional GAN [79], that uses both fully connected and convolutional layers, may both capture the impulsive agitations and the existing correlative structure of HF ship-radiated noise. Therefore, we propose a more thorough investigation that considers fully connected and fully connected convolutional GAN based models for producing a stochastic
time-domain model of ship-radiated noise.
Bibliography


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