Cross-correlation based Acoustic Signal Processing Technique and its Implementation on Marine Ecology

By

S. M. Asif Hossain

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Khulna University of Engineering & Technology
Khulna 9203, Bangladesh

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Declaration

This is to certify that the thesis work entitled "*Cross-correlation based Acoustic Signal Processing Technique and its Implementation on Marine Ecology*" has been carried out by *S. M. Asif Hossain* in the Department of Electronics and Communication Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh. I declare that this thesis has been composed solely by myself and that it has not been submitted, in whole or in part, in any previous application for the award of any degree or diploma. Except, where states otherwise by reference or acknowledgment, the work presented is entirely my own.

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Asif Hossain

Signature of Candidate

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This is to certify that the thesis work submitted by *S. M. Asif Hossain* entitled "*Cross-correlation based Acoustic Signal Processing Technique and Its Implementation on Marine Ecology*" has been approved by the board of examiners for the partial fulfillment of the requirements for the Degree of *M.Sc. Engineering* in the Department of *Electronics and Communication Engineering*, Khulna University of Engineering & Technology, Khulna, Bangladesh in December 2018.

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Abstract

As a scientific study of marine-life habitation, populations, and interactions among organisms and surrounding environment, marine ecology includes numerous fish and mammals as part and parcel. Marine fish and mammals have an enormous impact on marine ecosystems. Not only for their ecological values, but also for commercial purposes, a proper estimation of their population size is necessary. Besides, an efficient monitoring of populations and communities is the precondition of ecosystem-based management in marine areas. Most conventional techniques for estimating fish population are visual sampling techniques, environmental DNA (eDNA) technique, minnow traps, removal method of population estimation, echo integration techniques, etc., which are sometimes complex, costly, require human interaction, and harmful for inhabitation of marine species. In order to overcome these difficulties, an acoustic signal processing technique is proposed in this thesis. The method is based on a novel statistical signal processing technique called "cross-correlation" and different types of acoustic signals produced by diverse species of marine fish and mammals, like chirps, grunts, growls, clicks, etc. Our goal was to build a framework so that the technique can be implemented in practice. Therefore, we have investigated different tasks, which are crucial during its practical implementation like estimation with respect to different fish acoustics, different number of sensors and different distributions of fish and mammals. Similarly, we have carried an investigation to select the optimum estimation parameter for the technique. We have also analyzed different impacts, i.e., underwater bandwidth, SNR, etc., which have significant effects on practical estimation of this technique. From this research, we have found that chirp signals can produce better estimation results among the three fish acoustics, i.e., chirps, grunts, and growls signals. Among the three fish distributions, i.e., Exponential, Normal, and Rayleigh, Exponential distribution of fish and mammals produce better results. An increasing number of acoustic sensors provide better results in this technique. However, limited bandwidth of underwater channel poses a barrier during acquisition of fish signals, which has infinite bandwidth. To overcome this problem, a proper scaling is a mandatory task. We find that scaling factor 0.59512 for chirp signal and 0.55245 for grunt signal at 5 kHz underwater bandwidth. Similarly, a low signal to noise ratio (SNR) is also an impediment to obtain an accurate fish population. We have found that estimation with minimum SNR of 20 can perform like the noiseless estimation. These findings will immensely help the future researchers during practical implementation of the technique.

Keywords: Fish population estimation, cross-correlation function, estimation parameter, acoustic sensors, underwater bandwidth, SNR.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AUV	Autonomous Underwater Vehicles
ASL	Acoustic Sensors in line shape
AST	Acoustic Sensors in triangular shape
BT	Broad Tendon
BW	Bandwidth
CCF	Cross-correlation Function
CPUE	Catch Per Unit Effort
DIDSON	Dual-Frequency Identification Sonar
DP	Dorsal Process
eDNA	Environmental Deoxyribo Nucleic Acid
ETs	Enhanced Pectoral Fin Tendons
FSA	Framed-Slotted ALOHA
GF	Green's Function
LTMP	Long-term Monitoring Program
PCA	Principal Component Analysis
PCR	polymerase Chain Reaction
PDF	Probability Density function
PPS	Pulse Per Second
PS	Pectoral Spine
PT	Pharyngeal Teeth
ROV	Remotely Operated Vehicles
RSKM	Rough Set k-Means
SCUBA	Self-Contained Underwater Breathing Apparatus
SG	Shoulder Girdle
SL	Swim Bladder Lobes
SM	Sonic Muscle
SMe	Extrinsic Sonic Muscles

SMi	Intrinsic Sonic Muscles
SNR	Signal to Noise Ration
SPL	Sound Pressure Level
TDGF	Time Domain Green's Function
TS	Target Strength
USV	Unmanned Surface Vessels
UWVS	Underwater Video Sequence
VC	Vertebral Column
2R	Second Rib

CHAPTER I

INTRODUCTION

This chapter is introduced with an aim to bring a discussion on different aspects of the proposed fish population estimation technique. The significance and objective of the research are also discussed precisely.

1.1 Introduction to Population Estimation of Fish and Mammals

Population size of fish and mammals is the key concern to the scientists, ecologists, and people engaged with commercial fishery managements. As the term is intimately related to ecological balance, a slight change to it can bring a disaster to our existence.

Some importance of fish and mammals are:

(a) Maintain the ecological balance and inter ecosystem interaction
(b) Provide us food and other necessities
(c) Refresh the environment by cleaning up water and marine areas
(d) Consider as ecological cardinality
(e) Every year, billions of dollar business is conducted with fish and mammal's commercial industry, etc.

Therefore, to cope up with it, numerous attempts to estimate their population have been conducted. In the past, such attempts were investigated using costly mechanical instruments, sometimes based on predictions and other human interactive ways. But the outcome of population estimation is suffered from accuracy. The recent fishery population estimation techniques emphasize on acoustic measures. Different acoustic techniques are proposing to estimate population size lately. In this thesis, our proposed technique is also an acoustic one. However, such acoustic methods have some limitations too. Some offers poor resolution, limited estimation area, and insecurity to the fish and mammals etc. Sometimes, some methods only discuss a trivial framework on their proposition. They lack most important impacts which could make the methods pragmatic. In our research, we have not only proposed a framework to estimate population size of fish and mammals but also analyze different aspects related to the estimation technique for practical implementation.

1.2 Vocalizing Nature in Marine Fish and Mammals

Researchers say the ocean is a noisy place. Millions of fish and mammals produce acoustics always. They do it to communicate with themselves, warn others to an impending jeopardy, express the paucity or availability of food etc.

1.2.1 Process of Sound Production

In some fish, the swim bladder is used as a sound-producing organ.

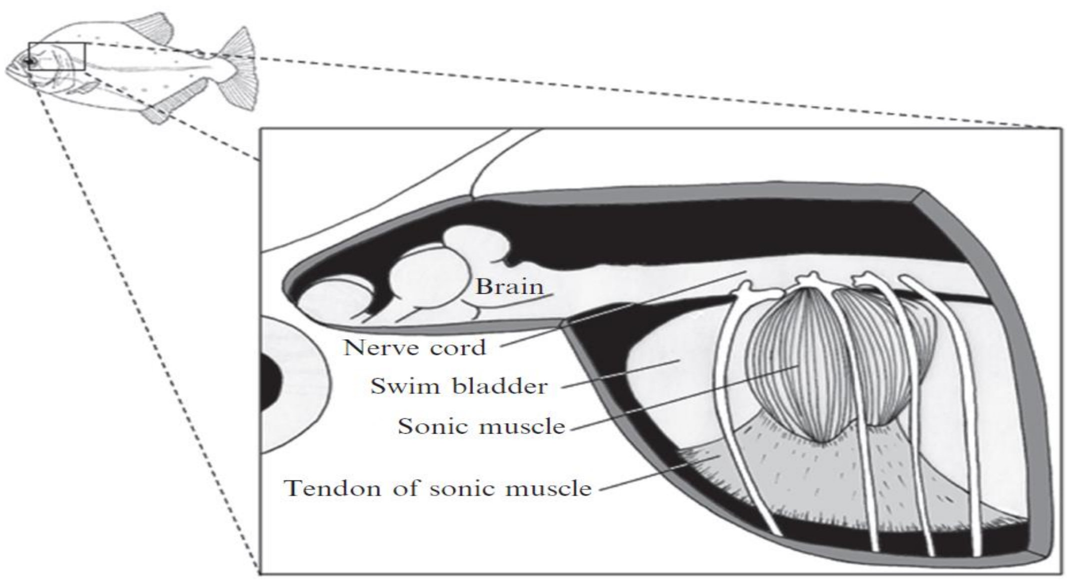

Fig. 1.1 Schematic *left* lateral view of the sound-producing mechanism (*black*) piranha (*Serrasalmus rhombeus*). Skull and vertebrae are not shown [1].

A muscle attached to the swim bladder (the sonic muscle) contracts and relaxes in a rapid sequence. This action causes the swim bladder to vibrate and produce a low-pitched drumming sound as shown in Fig. 1.1. The sonic muscle of the oyster toadfish is able to contract at a rate of

200 times a second. Another way in which fish may produce sounds is by stridulating; a process in which hard body parts like teeth or bones hit each other. Body movements that create water currents or splashes are also used to create sounds for communication. However, there are five basic mechanisms, i.e., muscular vibrations of a membrane or sac, stridulation, forced flow through a small orifice, muscular vibration of appendages, and Percussion on a substrate, for producing sounds, all of which are present in fishes.

1.2.2 Diversity of Sounds Among Fish and Mammals

The acoustics produced by different fish and mammals vary from several parameter. These acoustics have some own characteristics, which vary from species to species shown in Fig. 1.2.

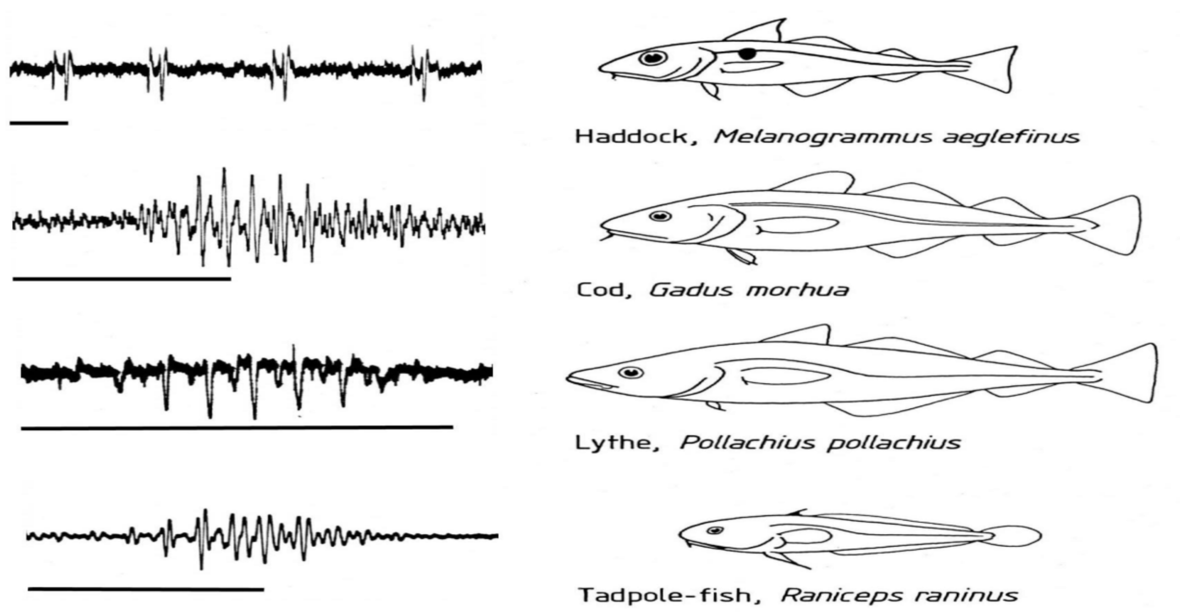

Fig. 1.2 Agonistic sounds produced by different members of the family Gadidae and the more distant related gadiform, the tadpole fish. Black bar represents the time scale of 100 ms for each fish. Haddock emits a series of knocks; cod, pollack and tadpole fish emit grunts; the shore rockling produces thump-like sounds [2].

Vocalizations of different species are different with respect to different parameters like, frequency, amplitude, etc. Different sound types are categorized in different names. Some of the common types of sounds are chirps, pops, grunts, growls, hoots, whistles, clicks, etc. However, a brief description on sound generation is discussed in chapter 3.

1.3 Acoustic Sensors

Researchers record fish vocalizations with the aid of an underwater microphone called acoustic sensors. This may be lowered into the water from a boat or carried by a scuba diver. Until now, divers were unaware of the wide varieties of fish vocalizations in the ocean because the sound of bubbles being released from scuba equipment masked the sounds produced by the fish. In addition, the bubbles often disturbed fish and caused them to swim away.

The researchers of fish sound are now using re-breathers instead of conventional scuba gear. A re-breather is a self-contained system in which the diver repeatedly breathes in his or her exhaled air, so no gas bubbles enter into the water. Carbon dioxide is removed from the exhaled air inside the re-breather. An oxygen sensor monitors the level of oxygen in the re-breathed air and a microprocessor controls the delivery of fresh oxygen into the air when it's needed.

1.4 Cross-correlation

In signal processing, cross-correlation is a measure of similarity of two series as a function of the displacement of one relative to the other. This is also known as a sliding dot product or sliding inner-product. In this research, total procedure is based on cross-correlation of different fish signals with a statistical procedure. However, the impulse response of a communication channel, i.e., the Green's function (GF) retrieval of cross-correlating the waves excited by randomly generated ambient noise sources recorded by sensors at two locations. There have been many investigations regarding the use of ambient noise cross-correlation to extract the time-domain GF in various environments and frequency ranges of interest, e.g., underwater acoustics [3-4], helio-seismology [5], and ultrasonic [6-9]. The procedural steps for determining the noise cross-correlation function (CCF) are similar for all the above-mentioned environments. In brief, the procedure is as follows: firstly, signals from a number of different noise sources are collected by two sensors separated by a certain distance in the region of interest; secondly, the received signals are summed at each of the two sensor locations; and finally, these two noise signals are cross-correlated. Most researchers have only tried to retrieve an estimate of the GF; for example, it has been shown theoretically that the GF can be obtained with ambient noise cross-correlation in the simple case of a homogeneous medium with attenuation [10]. Some researchers have given their attention to the emergence rate of the time-domain GF (TDGF) [6-7]. Moreover, ward [11] identities, means, and variances [12] have been performed in diffuse field-field correlations. However, none of these investigations indicate the estimation of the number of noise sources.

1.5 Statistical Signal Processing

Direct manipulation of the CCF is a complex problem. To make it simpler, in this research, the cross-correlation technique is reframed to a probability problem using the well-known occupancy problem which follows the binomial probability distribution from which a parameter is chosen to estimate the population of fish and mammals.

1.5.1 Occupancy Problem

Occupancy problems deal with the pairings of objects and have a wide range of applications in different fields containing probabilistic and statistical properties [13]. The basic occupancy problem is about placing m marbles into b bins [14]. If one threw some marbles randomly towards several bins, the bins would be randomly filled by the marbles, resulting in some bins being occupied by more than one marble, some by one while some may have none, Howlader reframed the framed slotted ALOHA protocol of the number of nodes estimation in terms of this occupancy problem [15]. He described the reframing process as follows:

(a) In FSA (Framed-Slotted ALOHA), N nodes transmit to F slots in a frame.

(b) Some slots will get no packet; some will one and others more than one.

Thus, by defining the slots with only one packet as singleton slots, those with more than one packet collision slots and those with no packet empty slots, Howlader used the classical occupancy problem to determine the probabilities of empty, singleton, and collision slots [15]. This helped him to determine the number of neighboring nodes in a communication network. However, in our research, similar approach is used to convert the CCF in to statistical problem.

1.6 Practical Issues Regarding Fish Population Estimation

Different issues are vital, which must be considered during practical fish population estimation. Such issues include fish distributions, bandwidth, SNR, multipath, etc.

1.6.1 Distribution of Fish and Mammals

Different fish distributions are practical phenomenon. If we want to estimate fish population size in a fishing area, the estimation performance varies for different distribution of fish and mammals [16]. In this research, we have considered three distribution cases, i.e., Exponential, Normal, and Raleigh, of fish and mammals. From simulation, we have found that the exponential distribution of fish and mammals can provide better results. However, for exponential distribution, the Probability density function (PDF) is $y = f(x|m) = 1/\mu \times e^{-x/m}$, where m is the mean parameter, for Rayleigh distribution, the PDF is $y = f(x|m) = x/\beta^2 \times e^{-x^2/2\beta^2}$, where β is the scale parameter, and for Normal distribution, the PDF is $y = f(x|m, s) = 1/\alpha \times \sqrt{2}e^{-(x-m)^2/2s^2}$, where s is the standard deviation. A description on different distribution of fish and mammals and their corresponding estimation performances is provided in chapter 4.

1.6.2 Underwater Bandwidth

In practical cases, underwater acoustic channels are band limited due to the frequency dependency of absorption loss. So, absorption loss becomes more significant with the increase of bandwidth, which limits the transmission range. Transmission range can be increased by limiting the bandwidth of signals. However, such limited bandwidth has an impact on the proposed fish population estimation technique. Typical bandwidths of the underwater acoustic channel for different ranges are shown in Table 1.1 [17].

Table 1.1 Available bandwidths for different ranges in underwater acoustic channel

Type	Range (km)	Bandwidth (kHz)
Very long	1000	<1
Long	10-100	2 – 5

Medium	1-10	≈ 10
Short	0.1-1	20-50
Very short	<0.1	>100

An analysis on impact of bandwidth on fish population estimation technique is discussed in chapter 5.

1.6.3 Signal to Noise Ratio (SNR)

Signal strength and quality varies from place to place in harsh underwater circumstance. Hence, it poses challenge to fish population estimation. By different sources, strong background noise is created in underwater environment [18]. Actually, underwater sound is generated by a variety of natural sources, such as breaking waves, rain, and marine lives. It is also generated by a variety of man-made sources, such as ships and military sonar. Some sounds are present more or less everywhere in the ocean all the time. In the ocean, the background sound is called ambient noise. The primary sources of ambient noise can be categorized by the frequency of sound. A table of different ranges of frequencies and their corresponding noises are given bellow:

Table 1.2 Noise creates by different ranges of frequencies in underwater acoustic channel

Frequency Band	Created Noise
(0.1-10 Hz)	Noise sources include earthquakes, volcanic eruptions, storms and turbulence in the ocean and natural environment.
(50-300 Hz)	Ship traffic noise.
(0.5-50 kHz)	The main sources of noise are the state of an ocean surface, the wind conditions, the breaking waves as well as integration of air
up to 100 kHz	Wind and rain are the chief sources of noise.
above 100 kHz	Thermal noise

However, an analysis on impact of SNR on fish population estimation is discussed in chapter 5.

1.6.4 Multipath

Impact of multipath on fish population estimation is a practical case. Underwater acoustic signal propagation has to be introduced with multipath. The multipath geometry depends to the link configuration. Vertical channels showcase little multipath, but horizontal channels can have extremely long multipath spreads. Typical multipath spreads in the commonly used radio channels are to the order of several symbol intervals, whereas in the horizontal underwater acoustic channels, they increase to several tens or a hundred of sign intervals for moderate to high details rates [19], which implies more intense effects of multipath on fish population estimation.

1.6.5 Propagation Speed of Acoustics

Many things can affect the speed of acoustics, including not only the nature of the medium, (gas, liquid or solid) but also its temperature and any other additive substances, such as salt in water. Basically, acoustics travel faster through denser and hotter materials. However, in this research, we have considered the propagation speed of acoustics is 1500 m/s.

Table 1.3 Different rate of propagation speed in different medium during propagation of acoustics

Medium	Temperature	Speed in m/s
Air	0	331.4
Air	20	343.6
Air	30	348.7
Fresh Water	Normal	1,493
Sea Water	Normal	1,533
Diamond	Normal	12,000

1.6.6 Other Practical Issues

Beside the issues above, other issues, i.e., path loss, Doppler Effect, capture effect, etc., can affect the propagation of acoustic signals from fish/mammal to acoustic sensor.

1.7 Importance of Fish Population Estimation

Population estimation of fish and mammals is a very important task. It's a mandatory task to the ecologists and commercial fishery managers. In ancient ages, fishermen made prediction of optimum area of fish and moved there to catch. However, some but not limited to importance of fish population estimation are given bellow [20]:

(a) To maintain ecological balance
(b) To continue ecological research
(c) To discover optimum fishing area
(d) To conduct research on diverse species of fish and mammals
(e) To identify a sudden variation of number of a particular specie
(f) To protect illicit fishing
(g) To help commercial or occasional fishery activities
(h) To benefit researchers in the field of ecology and acoustic signal processing technology
(i) To benefit ocean community

1.8 Simplified Block Diagram of Cross-correlation based Fish Population Estimation

A simplified block diagram representation of cross-correlation based fish population estimation technique is illustrated in Fig. 1.3. The acoustics from fish and mammals are recorded by acoustic sensors with time delays.

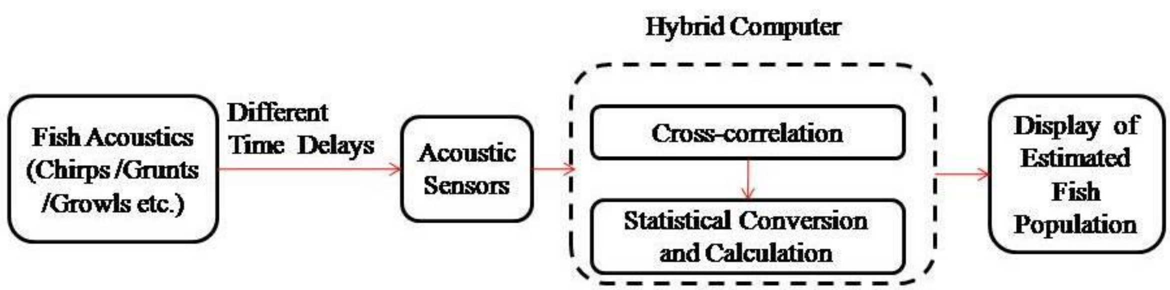

Fig. 1.3 Simplified block diagram of cross-correlation based fish population estimation technique.

These acoustics are then processed in a hybrid computer using cross-correlation technique and statistical conversion technique. Finally, the estimated population is displayed on a display system. However, a detail analysis of this technique is illustrated in this thesis.

1.9 Research Objective

The major objectives of this research work are given below:

(a) To provide a novel model for population size estimation of marine fish and mammals using an acoustic signal processing technique that can be performed in practical cases.

(b) To overcome the difficulties of conventional marine population estimation techniques like requirement of human interaction, protocol complexity, high cost, etc.

(c) To analysis the performance of the proposed estimation technique for different types of distributions, acoustic sensor numbers, acoustic sensor locations, etc.

(d) To implement different estimation parameters for performance evaluation and investigate different impacts, e.g., bandwidth, SNR, and Doppler effect, on the proposed technique.

(e) To benefit the researches and investigators in the field of acoustic signal processing, marine ecology, and commercial or occasional fishery management.

1.10 Research Motivation

Population estimation of fish and mammals is the most important task in marine ecological management and commercial fishery activities. Hence, from ancient ages, such estimations are continuing. But, several drawbacks affected the conventional estimation techniques. Our plan was to propose an effective method and investigate every aspect regarding its practical implementation. However, the research was started with an inspiration from a novel underwater node estimation technique proposed by Anower et. al [13]. There, the researchers have eradicated the barriers of protocol complexities and human interaction of conventional node estimation techniques. They used cross-correlation and statistical signal processing techniques. We have used that idea in our research. In that node estimation technique, the researches processed Gaussian signals to estimate underwater nodes in a communication network. But, in our research, we have processed different types of acoustics from fish and mammals with acoustic sensors to estimate their population size. Our goal was not only propose a method but also give proper directions to implement it in the practical cases. In this research, we have tried to build a complete framework to implement the proposed fish population estimation technique in practice.

1.11 Thesis Organization

The rest of the thesis is organized as follows:

Chapter 2 provides a literature review of various fish population estimation techniques and their limitations. This chapter is actually introduced to acknowledge the readers about the background of our research.

Chapter 3 illustrates a description on different types of fish acoustics. Generation of different fish acoustics from simulation, which are used in our research, is the key attraction of this chapter.

Chapter 4 presents our proposed fish population estimation technique which takes into account of different practical issues. We have analyzed the performance of estimation in various ways.

Chapter 5 represents different practical impacts on our proposed fish population estimation technique. Impact of bandwidth, SNR, and Doppler Effect are our key interest.

Chapter 6 concludes this thesis works and confers the directions for future works.

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CHAPTER II

LITERATURE REVIEW OF FISH POPULATION ESTIMATION

This chapter presents a precise description on different types of fish population estimation techniques of marine fish and mammals. Main features, advantages, and major limitations of those techniques are the main concentration of this chapter.

2.1 Introduction to Different Fish Population Estimation Techniques

The significance of population estimation techniques of fish and mammals can't be described in a single sentence. It is extremely related to our day to day life as well as echo-system. Hence, numerous investigations were carried out to estimate such population size. These investigations can be classified in to two types.

(a) Non-acoustic methods of fish population estimation
(b) Acoustic methods of fish population estimation

In the past, most of the techniques were based on the non-acoustic methods to estimate fish population. But lately, the researchers emphasize on acoustic methods and currently, copious researches are underway using acoustic methods for estimating fish population. However, the non-acoustics methods used mainly mechanicals ways to estimate fish population in a certain area. These processes are laborious, complex, and costly. Most of the time, they could not give accurate results. Hence, acoustic methods were introduced. Acoustic techniques of fish population estimation are classified in to two ways.

(a) Active acoustic measurement of fish population estimation and
(b) Passive acoustic measurement of fish population estimation

Active acoustics uses sound generated actively by transducers and the acoustic scattering properties of fish and mammals to image individual fish/mammals and population of fish and mammals [1]. Passive acoustics relies on listening to the sounds produced by fish/mammals with a hydrophone to assume their distribution and behavior [1]. For passive acoustics to be useful for a fish/mammal that must make a sound. Thus, this technique is limited to species that produce sounds with the times and places where they produce them. These techniques have typically been used independently, depending on the situation and goals of the study.

In this chapter, we describe different types of non-acoustic methods of fish population estimation firstly and then, we discuss briefly on different acoustic techniques of fish population estimation.

2.2 Non-acoustic Methods of Fish Population Estimation

Different types of non-acoustic methods were investigated in the past. Some of those are: visual sampling techniques, Raft, and Floating Radio Frequency Identification (RFID) tag systems, minnow traps, removal method of population estimation, environmental DNA technique, prediction-based macro ecological theory, etc. A discussion on major non-acoustic methods for fish population estimation is conducted bellow.

2.2.1 Fish Population Estimation with Visual Census Techniques

Visual census techniques are mainly used to estimate reef fish population. It easily collects the data without disturbing inherent that compare with other destructive sampling techniques [2]. Visual census consists of many techniques used to estimate reef fish population. Belt transect method was first described by Brock [3], has been adopted by the LTMP (Long Term Monitoring Program) to estimate reef fish population. In its simplest form, the belt transects method for visual census of fish population involves an observer, equipped with SCUBA gear, estimating the population of fish within a given area (the belt transect). A large number of factors, i.e., fish mobility, habitat complexity, etc., affected the estimation procedure. Further, errors in fish population estimations are likely to be introduced through observers' bias. As a result, any program using more than one observer might ensure that differences in bias between observers were minimized, to allow comparisons of data collected by different observers. The following protocol has been adopted by the LTMP as the standard methodology for undertaking visual census. Strict adherence to this protocol, combined with annual inter-observer training and standardization ensures that the resulting data are of high quality with maximal power to detect change over time. However, in this technique, at least three people are required for collection of visual census data. One person conducts the surveys, whereas, second person lies a tape measure along the centre line of each transects. The third person should stay in the boat to give surface support [2].

2.2.2 Environmental DNA (eDNA) Technique

It investigates the potential of using meta-bar-coding of environmental DNA (eDNA) obtained directly from seawater samples to account for marine fish biodiversity [4-6]. This eDNA approach has recently been used successfully in freshwater environments, but never in marine settings. Results from eDNA degradation experiment is illustrated in Fig. 2.1.

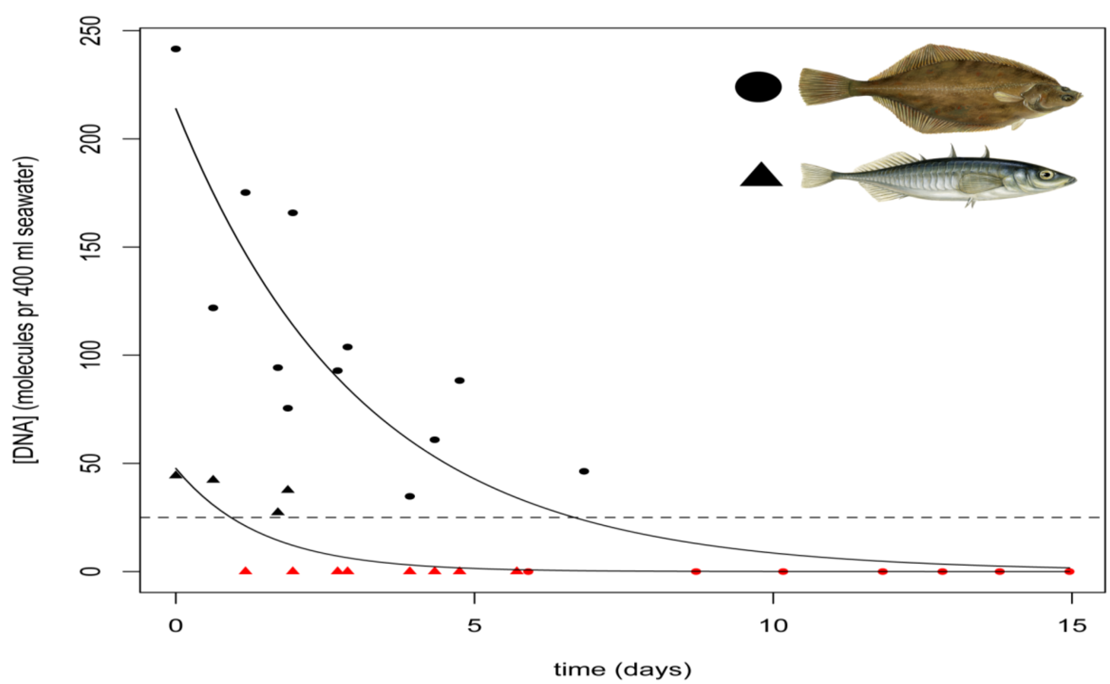


Fig. 2.1 Results from eDNA degradation experiment. eDNA concentration in seawater as a function of time for the two fish species; *Platichthys flesus* (circles) and *Gasterosteus aculeatus* (triangles), investigated in a 50 I aquarium [4].

It was performed by isolating eDNA from ½ litre seawater samples collected in a temperate marine ecosystem in Denmark. Using next-generation DNA sequencing of PCR amp icons, eDNA was obtained from 15 different fish species, including both important consumption species, as well as species rarely or never recorded by conventional monitoring. eDNA was also detected from a rare vagrant species in the area; European pilchard (*Sardina pilchardus*) [4]. To investigate the efficiency of eDNA approach, a comparison of its performance with 9 methods conventionally used in marine fish surveys.

Auspiciously, eDNA covered the fish diversity better than or equal to any of the applied conventional methods. Even small samples of seawater contain the eDNA from a wide range of local fish species [4-5]. Although, further studies are needed to validate the eDNA approach in varying environmental conditions, these findings provide a proof-of-concept with perspectives for future monitoring of marine biodiversity and resources [4-6]. However, this technique can ensure accuracy but suffers from oversensitivity, high-cost, and regulation complexities.

2.2.3 Estimation of Fish Population using Minnow Traps

The minnow trap is a popular practice to estimate fish population [7]. Minnow traps normally consist of two funnel-shaped entrances at either end of a mesh box or cylinder. Minnow traps are a type of passive sampling gear because they rely on fish to willingly encounter and enter the trap [8]. They can be used to sample freshwater fish in a wide range of environments including lakes, wetlands, rivers, and streams. The efficiency and selectivity of minnow traps are influenced by the probability that fish will encounter, enter, and be retained within the trap until it is retrieved [9]. The size of fish captured in minnow traps is limited by the size of the entrances, which are normally very small (20–30 mm). Minnow traps are regarded as efficient for capturing small freshwater seals when baited unlike gill nets. Most fish can be released alive after being captured in minnow traps and predation within the traps is probable to be less than with fyke nets. Because of their small size, minnow traps can also be set amongst complex habitat and in very small and shallow pools of water. The capture efficiency of minnow traps is primarily subjective to the diameter of the trap entrances and mesh size. Minnow traps can also be used to collect relative fish population data based on calculations of catch per unit effort (CPUE). Minnow trap CPUE, as with other passive netting methods, is usually expressed as number of fish caught per net per unit of time, e.g. hours or nights. The accuracy of CPUE as an index of fish population is primarily determined by whether catch efficiency or ability remains unaffected by other factors. Unvarying catch efficiency is one of the key assumptions made when assessing differences in relative fish population. In practice, a wide range of factors can influence catch efficiency when using minnow nets. It is important to take a cautious approach and consider potential differences in catch efficiency when comparing relative abundance data over time and space.

2.2.4 Fish Population Estimation from Underwater Video Sequences using Blob Counting and Shape Analysis

A method for fish population estimation from underwater video sequences (UWVS) using blob counting and shape analysis is described in [10]. f The system diagram of it is illustrated in Fig. 2.2, which is redrawn from Fabic et al. in [10]. The video sequences were obtained with a moving camera resulting in rapid viewpoint changes. This makes it difficult to employ motion detection schemes in extracting fish images from background.

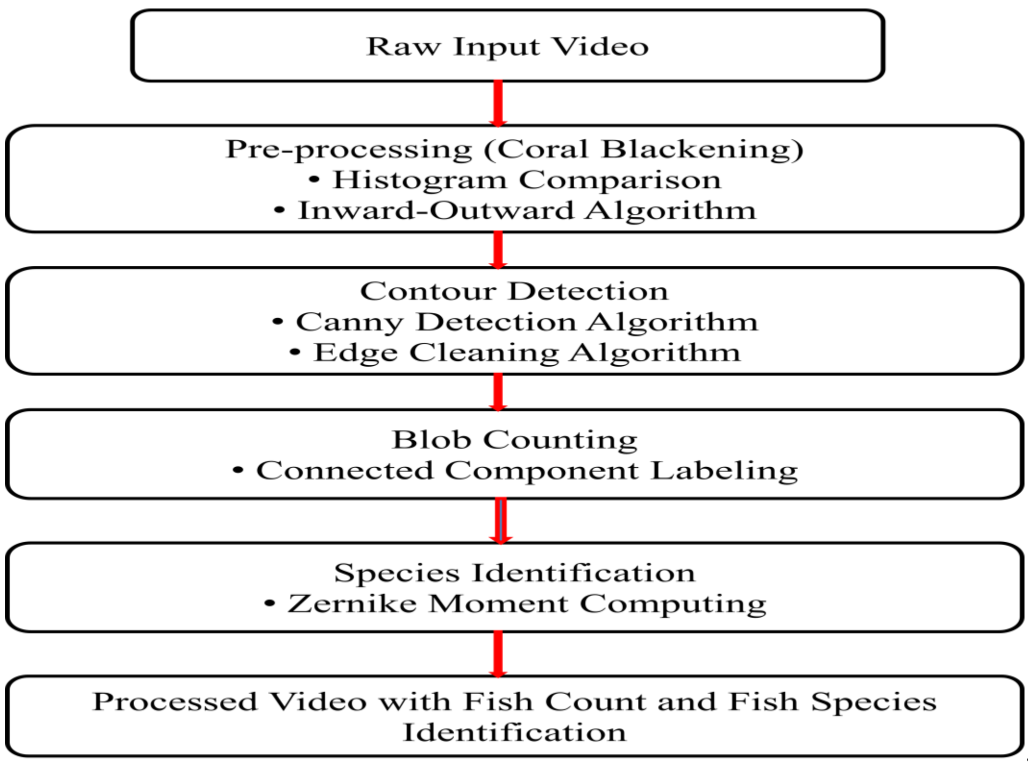


Fig. 2.2 System flowchart

Video preprocessing involved blackening out the corals from the underwater videos. This is done in order to effectively estimate fish population in the environment, though excluding those that are against a coral background. A histogram comparison to initially blacken out the occlusions using blue and non-blue templates obtained randomly from the UWVS is then applied. An erasure procedure to further aid in removing the coral background for fish detection is then introduced. However, canny edge detection was applied to extract fish contours. After the latter have been delineated, blob counting is then employed in order to compute the fish population.

Due to rapid frame changes, the average fish population per unit time is computed from the counts in each frame. For shape analysis, blob size is initially estimated and when a threshold is exceeded, Zernike moment-based shape analysis is performed on the blob for comparison with moment signatures of selected fish species stored in a database. The label of the best matching moments identifies the species of the fish blob. The shape-based classification algorithm is designed to identify the two most common species of fish found in the Tubbathaha reef in Sulu Sea, Philippines.

2.2.5 Mark–Recapture Techniques for Fish Population Estimation

Mark–recapture data to estimate the population of fish has evolved significantly since the adoption of the single-census method. Selecting a suitable model to ease optimal use of the available data is essential. Otis *et al.* [11] suggested that the suitable model for fish population estimation is the simplest one, which does not contain assumptions that are not met. The markand recapture method are generally favored over the depletion method and has been shown to be unbiased when more than 50% of a population is marked. The mark and recapture method require the following conditions: (a) Marked and unmarked fish have the same mortality rates; (b) Marked and unmarked fish are equally vulnerable to capture; (c) Marks are retained during the sampling period and all marks on recaptured fish are recognized; (d) Marked fish randomly mix with unmarked fish; (e) There is negligible immigration during the recapture period.
Petersen’s estimations were obtained using the unbiased estimator suggested previously (for sampling without replacement [12]:

$$N = \frac{(M+1)(C+1)}{(R+1)} - 1, \tag{2.1}$$

where, M is the number of individuals marked during the tagging period, C is the total number of individuals captured during the recapture period, and R is the number of marked individuals caught during the recapture period.

2.3 Acoustic Methods of Fish Population Estimation

The practice of using acoustics for fish population estimation is burgeoning. In very recent, the reliable methods for fish population estimation are acoustic ones. A generalized discussion on leading acoustic techniques for fish population estimation is discussed below.

2.3.1 A Generalized Description on Acoustic Measures for Fish Population Estimation

Acoustic surveys are used in the monitoring and management of many fish species, including herrings, anchovies, sardines, Atlantic cod, and walleye pollock. Fisheries scientists use active acoustics to estimate fish population; evaluate spatial and temporal distributions; and measure size distributions and fish population structure. In addition, these methods can also be used to characterize habitats and study behaviors such as migration, spawning, feeding, and schooling [13]. Scientific echo-sounders operate similarly to commercially available “fish finders” by producing a brief, focused pulse of sound and listening for echoes. When the sound encounters objects that are of different acoustic impedance than the surrounding water, such as fish or the seafloor, some of the sound energy is reflected back to the transducer and translated into a digital output on a monitor (echogram). An echogram can include images of both single objects and groups of objects [14].

Target strength is a measure of how much a fish, plankton, or other object in the water column scatters sound towards a transducer. In general, larger animals have larger target strengths, although other factors, such as the presence or absence of a gas-filled swim bladder in fishes, its size and shape, and a fish’s orientation and activity in the water column, also have an impact.

When individual targets are spaced far enough apart, the number of fish can be estimated by counting the number of individual targets. This is called echo-counting and is the historical way to estimate fish population. Sometimes, it is not possible to resolve individual targets, e.g., schooling fish or plankton layers, and the echo sounder is measuring the volume backscattering strength of the entire school. Echo-integration uses the total backscattered acoustic energy, divided by a previously determined volume backscattering coefficient [15]. This overall calculation is used to estimate fish population. Ground truthing acoustic data via fish trawls, video feeds from baited cameras, or looking to already-published data helps scientists authenticate acoustic estimations.

Problems in assessing fish population can arise from changes in the behavior of the fish. For example, lower levels of scattering coefficient were measured from a sprat population during the day, when the fish were aggregated into schools, than at night, when the fish were distributed throughout the water column [16]. The difference in scattering led to large differences in acoustic fish population estimates for daytime and night-time, with more than a doubling of the estimation at night.

Echo-sounders have progressed from single-beam systems developed after World War II to the multi-frequency, multi-beam systems in use today. Split-beam echo-sounders, operating in a frequency range of 12 to 200 kHz, are the standard equipment for hydro-acoustic fisheries assessments. Split-beam echo-sounders receive echoes in four quadrants on the transducer face, allowing the position of the target or the depth and range of a layer to be determined in three dimensions. Split-beam echo-sounders can sample to water depths of 100 m to greater than 500 m. Multi-beam echo-sounders, originally developed for mapping the seafloor, project a fan of narrow sound beams outward into the water and record echoes in each beam. This system covers a wide swath at high resolution. Broadband systems, which operate at a wider frequency band than traditional echo-sounders, allow for size classification of mixed assemblages of fish, something very important for diverse environments such as coral reefs [15, 17].

Most echo-sounders are mounted on a ship's hull. Transducers can also be deployed on a pole mount, or towed behind or alongside a vessel (e.g. "towfish"). Towed bodies are particularly useful for studies of deep-living species, which typically live below the range of an echo-sounder at the surface. Instruments can also be deployed on or towed behind remotely operated vehicles (ROVs), autonomous underwater vehicles (AUVs, such as gliders), and unmanned surface vessels (USVs) [18]. Fisheries assessments can also use transducers in fixed locations to provide continuous, high-resolution acoustic data to identify and count fish. Upward facing, split-beam echo-sounders are often used to quantify fish passage at hydroelectric dams. They can also be used to characterize schooling behavior in fish and investigate variability in schooling dynamics.

Acoustic cameras use higher frequencies and multiple beams to create high resolution, three-dimensional digital images of the water column. However, the higher frequencies used by these systems also limits their range.

2.3.2 Fish Population Estimation using Echo Integration

The theory of echo formation provides formulas relating echo energy to physical characteristics of the target. Single-target theory (applicable to counting isolated fish) is extended to the multiple-target case relevant to schooling fish. An echo-integrator equation relates fish population to echo energy integrated over a time gate corresponding to the depth channel of interest. Parameters include the equivalent beam angle, the expected backscattering cross section per fish, equipment sensitivity, and a time-varied-gain correction factor [19].

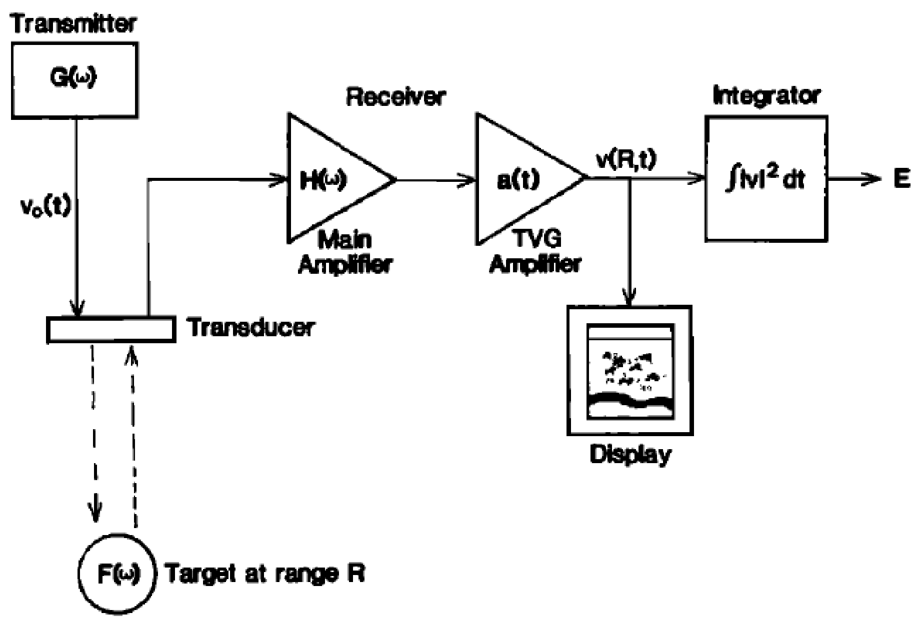
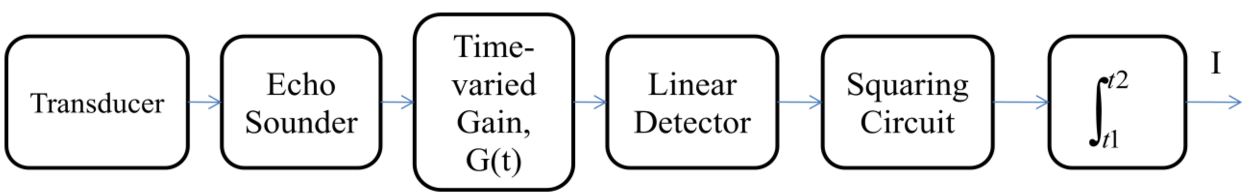


Fig. 2.3 Components of a sonar showing how the output signal due to a target at range R is formed where the transmitter pulse, $V_o(t)$ is the input that is successively modified by each component leading to the output signal $v(R, t)$ and the echo integral E [19].

Variation of environmental factors (sound speed and absorption) affects the parameter values. More important is the variation of biological factors (fish behavior and physiology) which affects back scattering cross-section and target strength. Sonar components are shown in Fig. 2.3. Verification of the echo-integrator equation, depending upon the linearity principle concerning the addition of signals from randomly distributed multiple targets, is discussed in [19]. The swim bladder is the leading sound reflector in fish having one. Therefore, fish targets may be classified as (a) bladder closed, (b) bladder open, or (c) no bladder. Within each category, fish of the same size have similar target strengths. Target strength has a variation with fish size, water depth, and time. Experimental target strengths are well scattered even for nominally similar fish. Nevertheless, useful information about fish population can be obtained through careful application of this acoustical technique.

2.3.3 Dual-Beam Transducer in Hydro Acoustic Fish Assessment Systems

The aspects of using a narrow wide-beam acoustic transducer in systems for estimating fish abundance are illustrated in [20]. In this technique, the acoustic pulse is transmitted with a narrow beam and the echo is received on both the narrow and wide beams. The signals received at the two transducers can be used to determine the acoustic scattering cross section of the fish. The mean value of the acoustic scattering cross section can be used to evaluate the scale factor needed by echo integrators to obtain absolute fish population estimation as in Fig. 2.4. The outputs of the two transducers can also be used to control the sampling volume in an echo counting system. However, two the main limitations of the system are it cannot provide both high resolution and good volume coverage.



(a).

Fig. 2.4 Block diagram of echo integrator.

2.3.4 Dual-Frequency Identification Sonar (DIDSON) Technique

Initially designed for military purposes, dual-frequency identification sonar (DIDSON) has been used in environmental management for a decade [21-22].

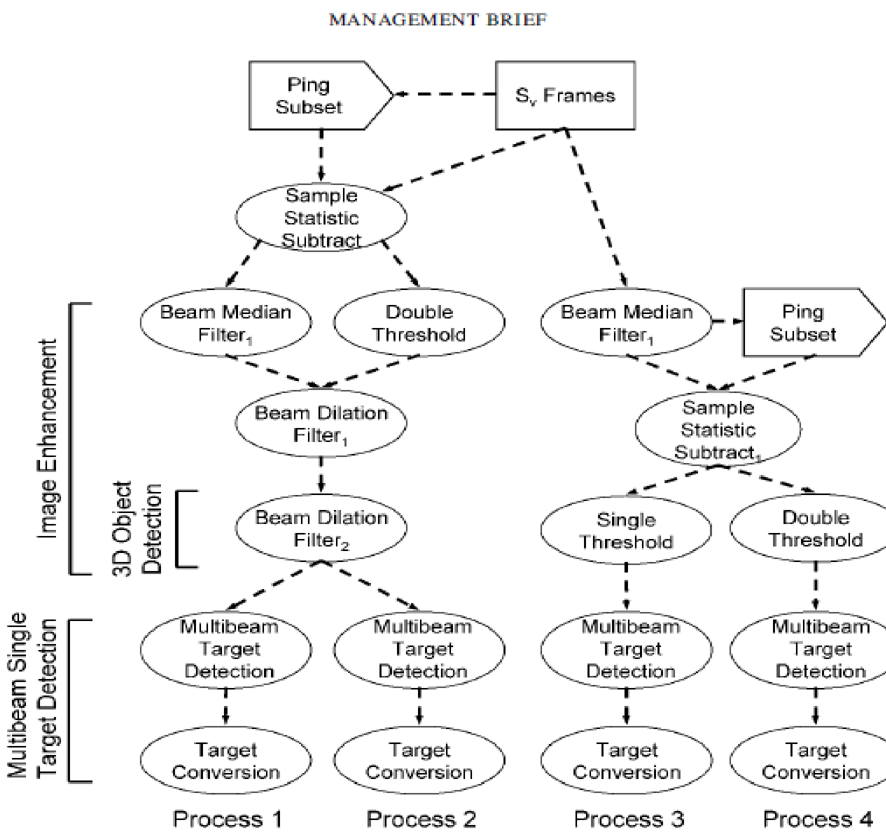


Fig. 2.5 Analysis pathways implemented in echo-view (version 4.1). Four parallel processes are presented that provide similar outcomes even though they are used to optimize analyses under various conditions [21].

This acoustic camera uses higher frequencies and more sub-beams than common hydro-acoustic tools, which improves image resolution and then enables observation of fish morphology and swimming behavior. The ability to subtract static echoes from echograms and directly measure fish length improve the species-identification process. An analysis of this technique stated in Fig. 2.5. However, some limits have been identified, such as automatic dataset recording and the low range of the detection beam, which decreases accuracy [22], but efficient tools are now being developed to improve the accuracy of data recording (morphology, species identification, direction and speed). The new technological properties of acoustic cameras, such as the video-like visualization of the data, have greatly improved monitoring of diadromous fish population, helping river and fisheries managers and researchers in making decisions [22].

2.3.5 Multiple Scattering in a Reflecting Cavity: A Fish Counting Technique

A pulse was transmitted in the tank using a single source; the echoes from the reverberations into the tank were recorded on receivers simultaneously. The recorded echoes have been reverberated by boundaries of the tank, and scattered by fish.

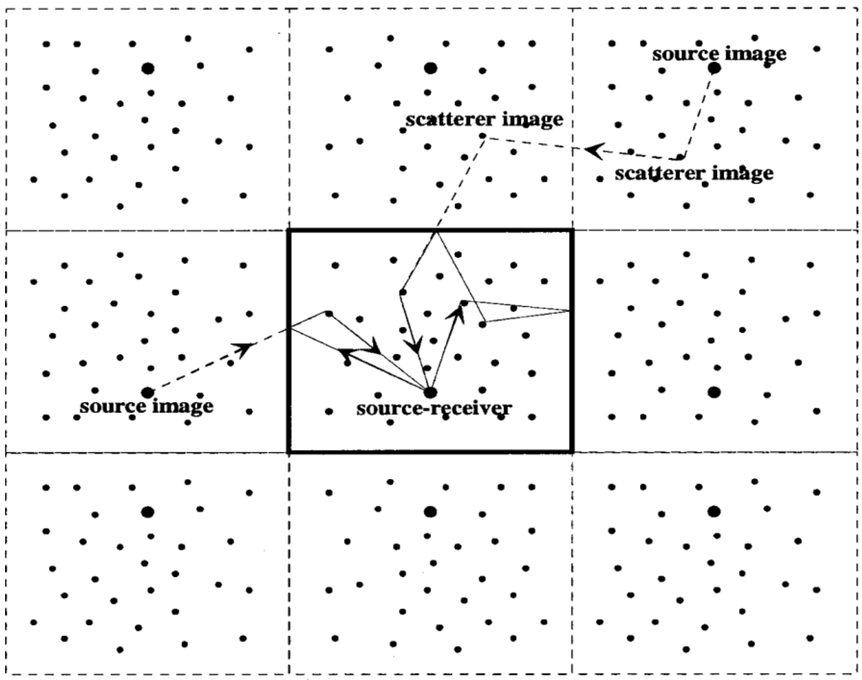


Fig. 2.6 Representation of two ray paths in square cavity (full lines) and their analog in a medium without interface (dashed lines) using the method of images [23].

M pulses were generated at a given rate, while the fish were swimming. For each of the pulses *k*, ranging from 1 to *M*, the positions of the fish is in the tank because they were swimming freely. Therefore, the echoes from the fish were different for each time series. And echoes from the fixed boundaries of the tank remained identical. Figure 2.6 represents two ray paths in square cavity (full lines) and their analog in a medium without interface (dashed lines) using the method of images.

For these experiments, the pulses consisted of 50 ms long chirps between 60 and 130 KHz, transmitted every other second. The process is explained in details in [23]. σ_t is estimated from the slope of $R(t)$ in logarithmic domain. From the exponential decay of $R(t)$, we easily found the number of fish abundance. This is defined as:

$$R(t) = e^{\frac{-N\sigma_t tc}{v}}, \tag{2.2}$$

where $R(t)$ is the total scattering cross section of one fish, N is the number of fish in the tank, V is the volume of the tank, c is the sound speed in water, and σ_t can be estimated from the exponential decay of the ratio of the measured coherent and incoherent intensities in the tank. However, these techniques need large number of fish to be captured, so these directly affects inhabits of the fish and mammals.

2.3.6 Multi-Frequency Fishery Sonar Surveys

Remote species classification using fisheries acoustic techniques in coral reef ecosystems remains one of the greatest hurdles in developing informative metrics and indicators required for ecosystem management. It was reviewed that long-term marine ecosystem acoustic surveys that have been carried out in the US Caribbean covering various coral reef habitat types and evaluated metrics that may be helpful in classifying multi-frequency acoustic signatures of fish aggregations to taxonomic groups. It was found that the energetic properties across frequencies, in particular the mean and the maximum volume backscattering coefficient, provided the majority of the discriminating power in separating schools and aggregations into distinct groups [24]. To a lesser extent, school shape and geometry helped isolate a distinctive group of reef fishes based on shoaling behavior. Schools and aggregations were clustered into five distinct groups. Cluster obtained from the RSKM plotted on a PCA bi-plot is illustrated in Fig. 2.7.

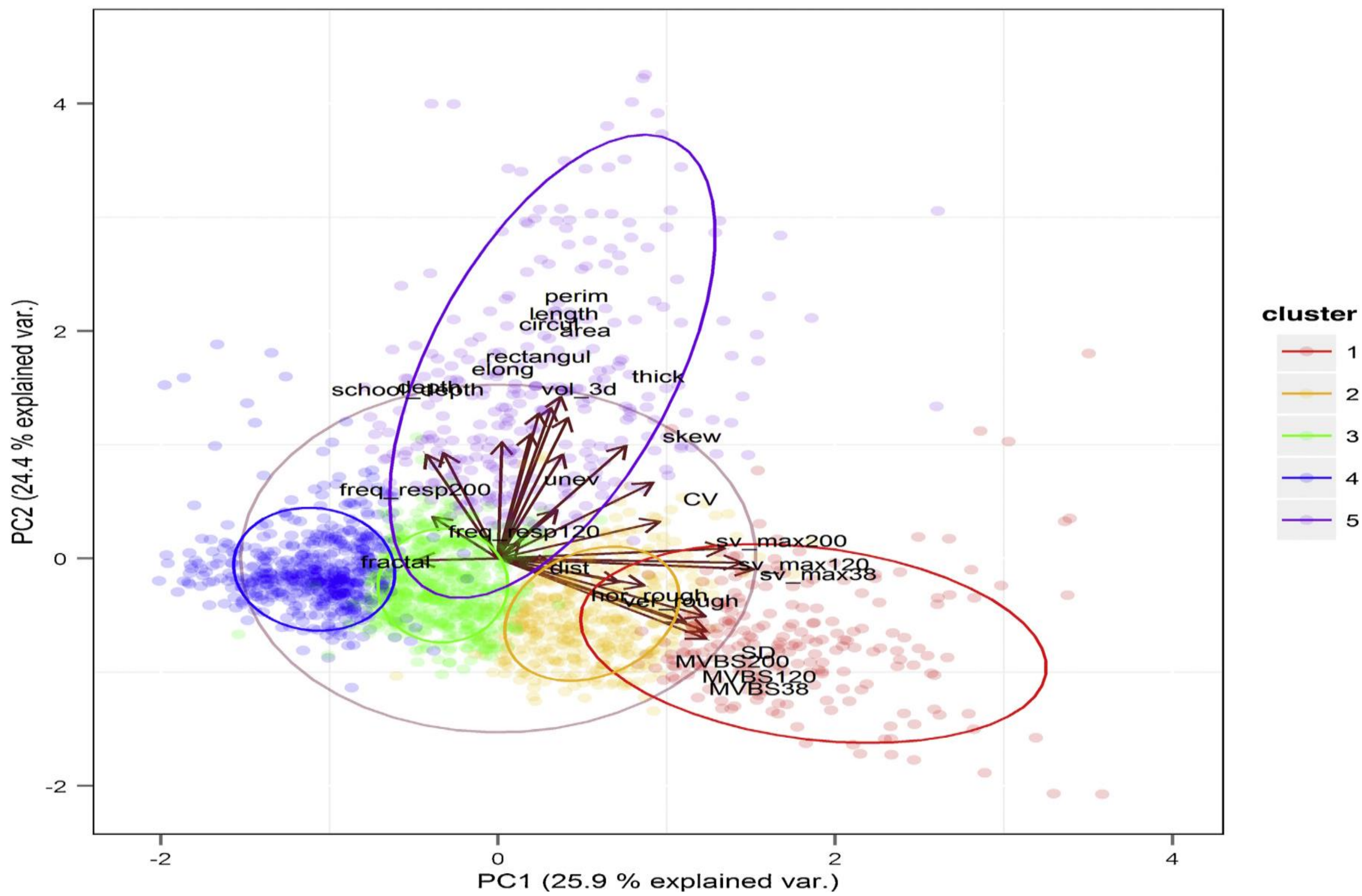


Fig. 2.7 Cluster obtained from the RSKM plotted on a PCA bi-plot. The ellipses surrounded the clusters show the 68 percent confidence intervals [24].

The use of underwater video surveys from a remote operating vehicle (ROV) conducted in the proximity of the acoustic observations allowed us to associate the clusters with broad categories of species groups such as large predators, including fishery important species to small forage fishes [24]. The remote classification methods described here are an important step toward improving marine ecosystem acoustics for the study and management of coral reef fish communities.

2.3.7 Fish Population Estimation Using Analysis of Echo Peak PDF from a Single-Transducer Sonar

Population size of fish was estimated in three Wisconsin lakes from echo peak probability density functions (PDFs) obtained at night with a single-transducer 70-kHz echo-sounder [25].

At night, cisco (*Coregonus artedii*) dominated the pelagic zone in all three lakes. The beam pattern effect was removed with a de-convolving filter technique. Fish size was estimated by fitting a combination of Rice PDFs to the de-convolved fish scattering PDF. Vertical density profiles and fish population estimation obtained acoustically corresponded to distributions and lengths of fish caught in vertical gill nets. The proportion of different size classes caught in gill nets agreed fairly well with the proportions determined acoustically.

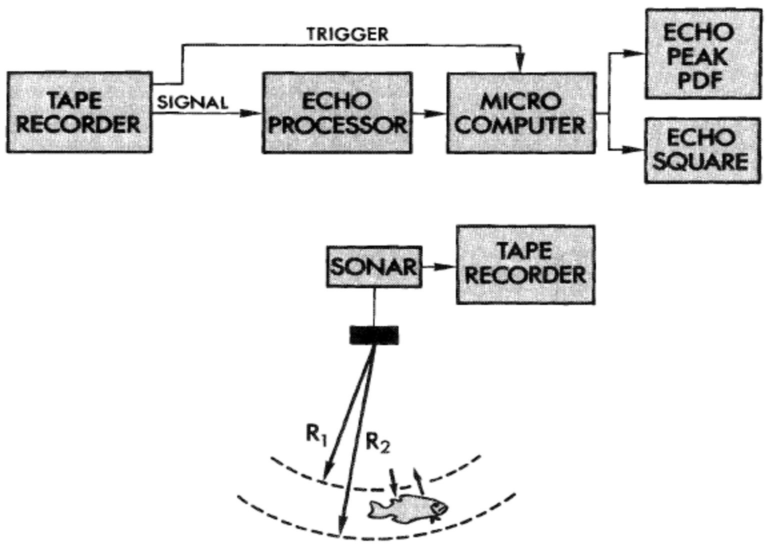


Fig. 2.8 Data collection and processing of the corresponding technique [25].

This analysis can be applied to signals from no calibrated sonar and can be used to calibrate simultaneously obtained echo squared integration values. With calibrated soars, target strength can be estimated in situ. For Cisco, $TS = 21log_{10}L - 67.2$, where, TS is target strength in (decibels) and L is fish length (centimeters) [25]. The average number of Cisco in the three lakes ranged from 89 to 1551 fish/ha, corresponding to a weight of 2-223 kg/ha. Maximum fish population ranges from 12 to 49 fish/1000 m^3 [25].

2.3.8 Statistical Signal Processing Approach of Fish Population Estimation

A statistical signal processing approach to estimate fish population was introduced in [26]. It was a passive acoustic technique and it can solve some major drawbacks of conventional approaches. Our proposed technique is quite similar to that. Though the technique has an immense significance, it avoids a number of practical effects, i.e., underwater bandwidth, SNR, Doppler Effect, multipath, and sensor locations, which will be arrived during practical implementation. It also considered only one fish signal to estimate population, where in practice, fish signals can be categorized in several types. Similarly, it used two sensors in estimation, where the increase of sensors can provide a better accuracy. The performance of different estimation parameters in this technique is also absent there. A consideration of uniform random distributions is executed throughout the literature [26]. But, in practical cases, the impact of different fish distributions is significant, which is absent in that literature. Though the process was based on different fish acoustics, a trivial discussion on only one signal was presented in that research. However, different acoustics patterns, frequency, and types are significant to define the technique. Taking into account of these limitations, we have continued our investigation to estimate the population of vocalizng fish and mammals, where the practical issues are properly analyzed. In this research, we have introduced a complete framework of cross-correlation based fish population estimation technique by overcoming the limitations of conventional techniques.

2.4 Discussions

Fish population estimation and classification of fish species have been an integral part of marine science and ecological research. These tasks are important for the assessment of fish abundance, distribution, and diversity in marine environments. With some particular advantages, most of the conventional non-acoustic fish population estimation techniques suffer from major drawbacks. Some common drawbacks are below:

(a) Time consuming
(b) Mostly human interaction
(c) Jeopardizing fish and mammals
(d) Poor accuracy
(e) Use of costly mechanical devices, etc.

To mitigate the limitations of conventional non-acoustic methods, lately, a great emphasize is put on acoustic techniques of fish population estimation. However, the conventional acoustic methods of fish population estimation described in sub-sections 2.3.2 - 2.3.7 suffer from several limitations like:

(a) Use of high frequency that harms the inhibitions of fish and mammals
(b) Requirement of large number of fish and mammals for proper estimation
(c) Low resolution and poor coverage area
(d) Requirement of costly electronic instruments and monitoring, etc.

To overcome all the major limitations, cross-correlation based fish population estimation technique is proposed. This technique is suitable because of its non-human interaction nature, requirement of low-cost instruments, being safe for fish inhabitations, and its well accuracy.

2.5 Chapter Summary

The main goal of this chapter is to show the background reason of our proposed technique. As a mandatory task, population estimation of fish and mammals carries a great significance. Several lacking of conventional techniques create a plot to propose a new one that can solve the major drawbacks. That was the cardinal reason of our research.

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CHAPTER III

GENERATION OF FISH ACOUSTICS

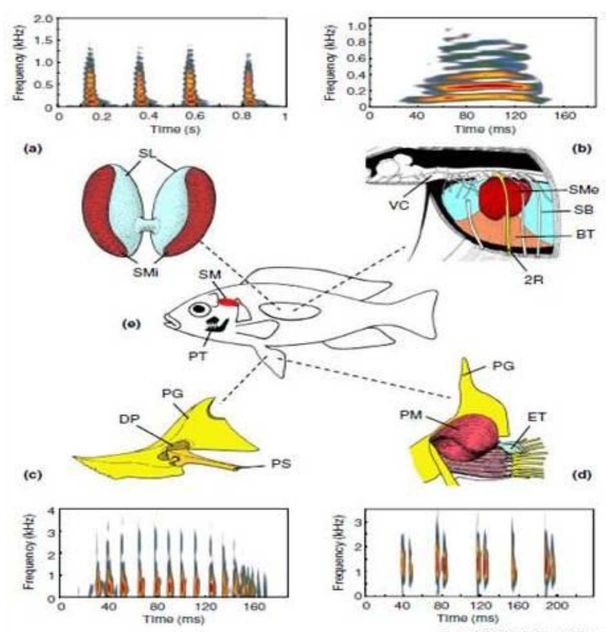
This chapter depicts a precise explanation on fish acoustics. Important aspects regarding fish acoustics, different mechanisms used in fish and mammals to generate acoustics and diverse types of fish acoustics are discussed here. However, generation of different fish acoustics from simulation is the key attraction of this chapter.

3.1 Introduction to Fish Acoustics

Vocalizing nature in fish and mammals are well known from thousands of years. Such nature is an important area of research from ancient age. Vocal fish produce sounds that commonly comprise low-frequency pulses that vary in duration, number, and repetition rate [1]. The diversity of sounds made by fish is not as remarkable as in other taxa, such as birds. Most fish show poor amplitude and frequency modulation in their sounds [2-3] and have relatively limited acoustical repertoires; few species of fish emit more than one or two distinct sound types [4-5]. Also, fish appear to produce fewer calls (under water) than insects, anurans or birds (air), which can produce thousands of calls per day, probably due to physiological constraints on sound production in water vs. air [6]. To understand the scope for acoustic communication in the variability of sounds emitted by different species of fish and in different social contexts, detailed comparisons between sound characteristics need to be made. Unluckily, various authors have adopted different ways of describing sounds, which creates confusion, such as in the labeling of sound types, the acoustic parameters measured, precision of data presented (including extremely small sample sizes and differences in descriptive statistics given), and filter bandwidth of sonograms selected. Also, studies that prove the function of sound variability (i.e. of certain sound types or specific acoustical characteristics) such as through playback experiments are lacking in the literature. Playback experiments have been useful in analyzing the role of advertisement calls such as those usually found in insects, anurans and birds, but have been largely unsuccessful with the typical close-range acoustic signals of fish, where additional stimuli are often needed [7]. In addition, technical limitations such as the inability of speakers to accurately propagate the low frequency and low amplitude sounds of many fish may be involved. Humans across different cultures have exploited sonic abilities of fish for centuries, often to these present days. Localizing fish by listening to species-specific acoustic signals is an art form that has been employed in conjunction with fisheries, e.g., Sciaenid and carangid fisheries in Malaya [8]. However, in this research, we use acoustic behaviors of fish and mammals to investigate a novel fish population estimation technique. Pre-knowledge about fish acoustics is one the prerequisite to implement this technique.

3.2 Mechanism of Fish Acoustics

Fish have evolved diverse mechanisms to generate sound as shown in Fig. 3.1. These include rubbing of bony elements against each other (stridulation), vibrating swim bladders or pectoral girdles via rapidly contracting muscles, and plucking enhanced tendons of pectoral fins. While stridulatory or plucking mechanisms produce wideband pulsed sounds with frequencies extending up to several kHz, vibration of the swim bladder results in low frequency (<1 kHz) tonal, often harmonic, and signals [9]. The major mechanisms of generating acoustics in fish and mammals are discussed below:



Acronym	Full Form
SMi	Intrinsic Sonic Muscles
SL	Swim Bladder Lobes
SMe	Extrinsic Sonic Muscles
2R	Second Rib
BT	Broad Tendon
DP	Dorsal Process
PS	Pectoral Spine
SG	Shoulder Girdle
ETs	Enhanced Pectoral Fin Tendons
PT	Pharyngeal Teeth
SM	Sonic Muscle
VC	Vertebral Column

Fig. 3.1 Diversity of sound generating mechanisms in fish and sonograms of sounds produced by these mechanisms (a) SMi attached to both SL in the Lusitanian toadfish *Halobatrachus didactylus,* (b) SMe originating at the 2R and inserting on a BT ventrally of the swim bladder in the black piranha *Serrasalmus rhombeus,* (c) in the stridulatory mechanism in catfish a ridged DP of the PS rubs in a groove of the SG, (d) ETs are plucked similar to guitar strings in the croaking gourami Trichopsisvittata, (e) PT stridulation in damselfish, sunfish, among others, and pectoral girdle vibration in sculpins by a SM originating at the skull and inserting at the dorsal part of the pectoral girdle. All sonagrams show sounds produced in agonistic contexts [10].

3.2.1 Stridulatory Mechanisms

Stridulatory mechanisms are found among species that rub pharyngeal teeth against each other in connection with non-feeding activities such as alarm reactions and defending territories. The best-known sound producers of this group are members of the family Haemulidae (grunts) [11]. Pharyngeal teeth stridulation is attributed to several additional fish families such as centrarchids or cichlids, which produce burst-like sounds, although the supporting evidence remains sparse [14]. Perhaps the best-studied stridulatory organs are those found in numerous catfish families; these organs consist primarily of enhanced pectoral spines with a series of ridges on their proximal end [13]. Rubbing the ridges, which are located on a dorsal process at the base of the spine or against a slightly concave groove within the fused pectoral girdle (cleithrum, coracoid), results in a series of short pulses [14-15]. A sound producing apparatus of the dorsal fin has been described in the sisorid catfish [16].

3.2.2 Swim Bladder Mechanisms

Inside the abdominal cavity of most types of fish is a gas-filled sac called a swim bladder. The fish uses the sac to control its buoyancy. When gas is added to the swim bladder, the fish is more buoyant and can swim higher in the water. When gas is removed, the fish sinks in the water. The swim bladder is filled in one of two ways. Some fish gulp air from the water surface. The air then passes through a duct connecting the esophagus to the swim bladder. Schematic view of the sound-producing mechanism in *Ophidion rochei* is shown in Fig. 3.2.

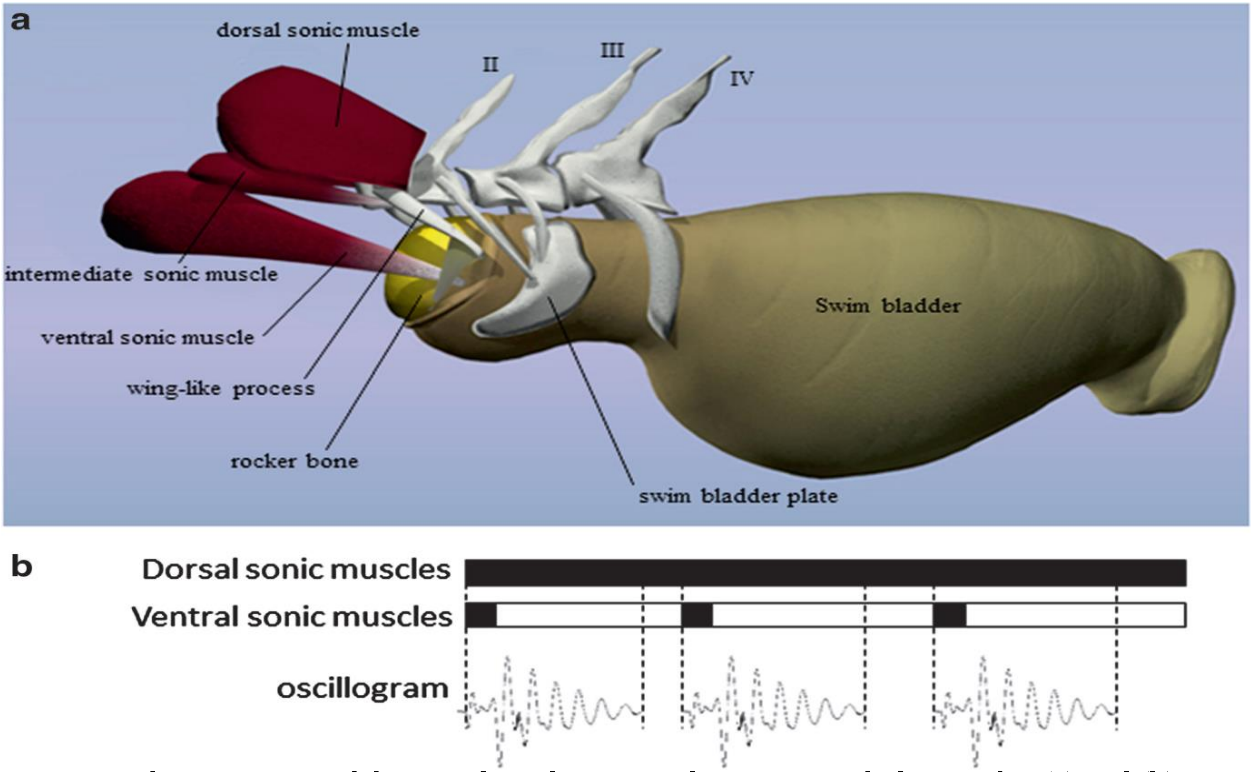


Fig. 3.2 Schematic view of the sound-producing mechanism in *Ophidion rochei* (a) and (b) schematicgraph showing the muscle activity during sound production and the related oscillograms of calls. Dark areas correspond to the muscle activity [17].

The esophagus is the passageway that connects the mouth to the stomach. Other fish have a gas gland. This extracts gas from the blood and sends it into the swim bladder. However, several swim bladder–based mechanisms result from evolutionary convergence and are constructed around the same basic principle: fish have to provoke the vibration of a gas-filled structure whose base functions include buoyancy and respiration [18]. Classically, the swim bladder has been modeled as a pulsating underwater bubble, an omni-directional and resonant monopole. Because of the compressibility of gas in the bladder compared with the surrounding water, an acoustic pressure wave is believed to excite the bladder into vibration that radiates particle motion to the ears [19]. Similarly, single muscle contractions would excite the swim bladder wall for sound production.

3.2.3 Cavitation Mechanisms

So-called cavitation sounds are produced during the feeding of the fish with a piece of food. Owing to the negative pressure inside of the mouth caused by its abrupt opening, aimed grabbing (suction) of the prey occurs. A rapid drop of the pressure inside of the oral cavity can lead to the appearance of small cavitation bubbles. Reducing of their volume occurs for a short time, and it is accompanied by a sound pulse [20]. The sounds produced in such a way belong to unspecialized sounds.

3.2.4 Hydrodynamic Mechanisms

Hydrodynamic sounds were discovered and identified before many other sounds during systematic investigations of underwater noises of biological origin. They appear during swimming of fishes. Some researchers suggest calling them swimming sounds because their origin is connected both with the movement of water against the external surface of the fish and with the movement of internal structures of the fish [21].

3.2.5 Respiratory Mechanisms

The sounds that appear during movements of the opercular plates in the process of breathing of fish are poorly investigated. Such sounds are similar to claps and knocks. Most of the cases, they belong to unspecialized sounds. However, the loud sounds of *Botiahorae* produced by opercular movements are registered during agonistic contacts. The blockage of the opercular movements by the fixation of the opercular plates leads to the loss of the capability for sound production [22].

3.3 Significant Aspects Regarding Fish Acoustics

Generally, fish acoustics have some characteristics, which may define its sources. The reason behind generation of acoustics in fish and mammals as well as different correlation between acoustic parameters is important topics in fish acoustics research. However, some significant aspects regarding fish acoustics are illustrated bellow.

3.3.1 Why are Sounds Produced in Some Taxa but not in others?

Although all fish possess the hearing sense and detect the acoustic scene [23], most fish species lack the ability to produce sounds, indicating that acoustic communication may be advantageous but is not a vital function as is swimming, feeding, breathing or eating. Interestingly, many of the structures used in these vital functions can be modified for sound production. Expatiation refers to a functional character previously shaped by natural selection for a particular function that is co-opted for a new use that enhances fitness [24]. The term expatiation has been used once in the fish sound-production literature [25] in regard to the jaw-snapping mechanism in damselfish. Recent descriptions of different mechanisms allow the suggestion that sound production mechanisms result from numerous and varied expatiations of existing structures. The parsimony principle states that a history involving a minimum number of changes in a set of sequences likely approximates the actual evolutionary history of the sequences. It is postulated that sound production appeared in fish taxa that were able to take advantage of their non-voluntary sounds. This hypothesis supports both observations of numerous unrelated mechanisms of sound production in fish and that many species do not produce sounds.

3.3.2 Reasons of Sound Production among Fish and Mammals

Although people have known for a long time that certain fish can vocalize, scientists have recently realized how widespread and intriguing this ability is. Like us, fish produce sound in two main ways, intentionally and unintentionally. Unintentional sounds are produced by fish all the time, mostly by swimming and feeding. However, they make a far greater variety of sound intentionally in their efforts to communicate with the other creatures living in their world.

Fish create sounds for several different reasons, to stay in touch with the shoal, to warn shoal-mates of danger, to attract, communicate with and stimulate mates, to scare intruders away from eggs and young and possibly even to echolocate in some deep-sea species [26]. Some fish are capable of making very loud sounds. One of the noisiest fish in the oceans is the Oyster

Toadfish, *Opsanus tau*. Because of their noisiness, Oyster Toadfishes were studied by the US Navy, they kept hearing them on their sonar, and it has been claimed that measured from a distance 60 cm the volume of sounds produced by the Oyster Toadfish can reach 100 decibels, which is equivalent to a piece of heavy machinery.

Of course, many fish try to take advantage of the sounds other species make. Thus, some sharks use sound to locate their prey while some smaller fish can detect the sounds larger predators make in their hunting. Recent research has shown that some Clupeid fish, (Herrings and Shads) can detect the ultrasonic echolocation sound produced by hunting dolphins from a distance of up to 187 meters.

3.3.3 Effect of Body Size on Acoustics Generation

Body size plays a significant impact on sound characteristics. A contrast between two damselfish was observed, where one is 4 mm larger than the other. The peak frequency of acoustics from the larger male was smaller than that of a smaller male damselfish [27]. An analysis on croaking sounds of female *T. vittata* revealed that sound characteristics are affected by different factors. While the factor body size explains some properties of sounds such as the dominant frequencies, it fails to affect others such as SPL in particular in adult fish [28]. However, some related terms regarding the impact of body size on acoustics generation are discussed below.

3.3.3.1 Dominant Frequency

The dominant frequency of sounds decreases with body size in female *T. vittata*, similar to males in all representatives of the genus *Trichopsis* [29] and many nonrelated species investigated so far. The correlation is strong for both size measures, namely weight and length. The relationships between size and dominant (peak) frequency of acoustic signals are mainly but not exclusively found in species generating short-pulsed sounds. Myrberg et al. argued that differences in the peak frequencies of chirp sounds produced by male bicolor damselfish are constrained by the volume of their swim bladder [30].

3.3.3.2 Sound Level

An increase in sound amplitudes with growth has been shown in several studies in non-related taxa such as tigerfish, *Therapon jarbua*, gouramis, toadfish and catfish. In contrast, a size-dependent increase in sound level has seldom been described in adult fish except in male *Cynoscion regalis*. In catfish species, it was demonstrated when both sexes and several species were pooled [31]. In both female and male seahorse *H. reidi*, such a relationship is lacking. Similarly, neither male nor female *T. vittata*s how a size-dependent change in sound level [29]. Interestingly, the current detailed analysis of female *T. vittata* revealed a decrease in the sound pressure level, SPL of acoustic signals produced later than at the beginning of agonistic interactions.

3.3.3.3 Temporal Characteristics

Temporal characteristics such as sound duration, number of pulses within sounds, pulse duration and pulse periods typically increased with growth or size in all species studied [32]. The few exceptions include the toadfish *H. didactylus*, in which the number of pulses within a sound and thus sound duration decreased as size increased during ontogeny [33]. It was showed that sound duration depended on the size of the sound-generating mechanisms, namely the length of the pectoral spine in 7 catfish species from 4 families [33]. There was no relationship between body size and temporal patterns of sounds such as pulse period in female *T. vittata* were found. A correlation between pulse period and size was also lacking in males [29].

3.4 Diversity of Acoustics in Fish and Mammals

According to the researchers, the world under the ocean is often noisy. Thousand types of fish and mammals, and perhaps many more, produce sounds. Such vocalizations have taken a spacious variety of forms, e.g., chirps, pops, hoots clicks, grunts, whistles, purrs, groans, growls, barks, hums, rattles, etc.

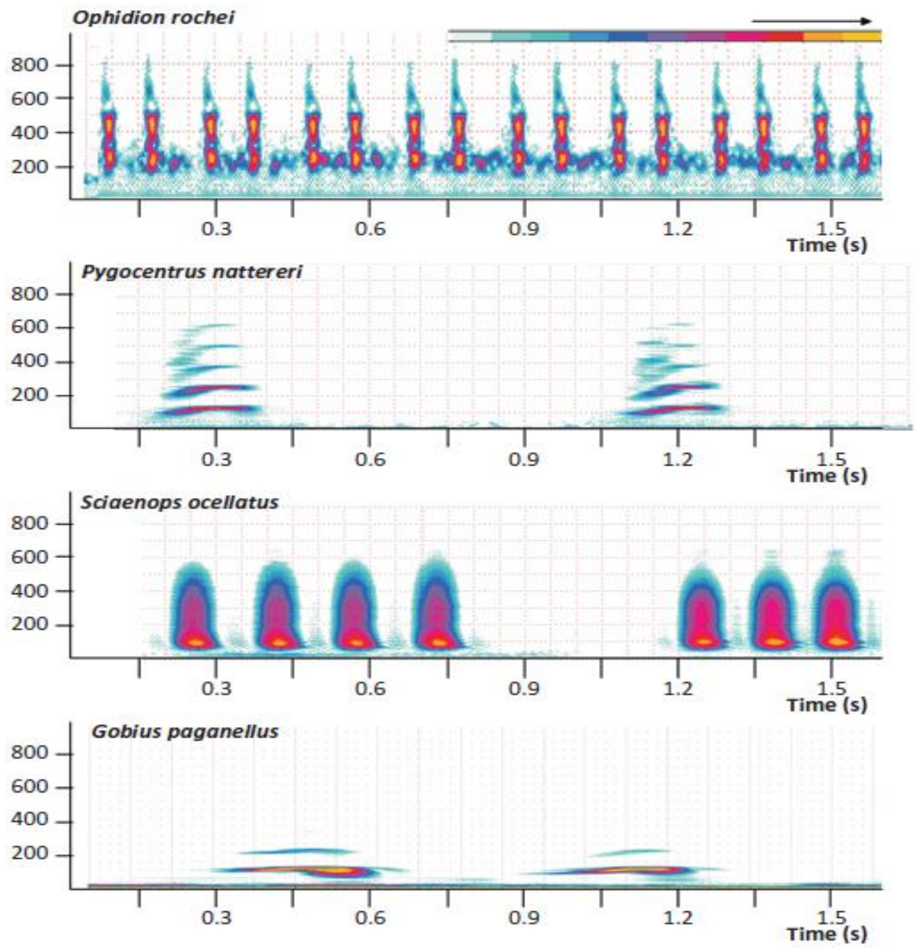


Fig. 3.3 Spectrogram of different fish sounds. Color scale: relative intensity [17].

Although numerous sonic fishes produce different sounds as shown in Fig. 3.3, sound production for social communication occurs in a restricted number of families. In some taxa, i.e., Doradidae, Bagridae, Pimelodidae, Batrachoididae, Gadidae, Sciaenidae, Holocentridae, Pomacentridae, and Carapidae, all, or almost all, species have the ability to call although mute species exist.

Many vocalizing fish from closely related species live sympatric ally [34] emit sounds to attract their mates to the spawning site [35]. However, a description of different types of fish acoustics is given below.

3.4.1 Chirp

Croaker is a kind of fish produce a sound, which is akin to a chirp signal. Likewise, some species of whale including humpback whales (*Megaptera novaeangliae*) [36], some dolphin species, including bottlenose dolphins [37], some mammals species like dugongs (*Dugong dugon*) [38] etc. can produce chirp like sound. From a sound analysis of *Plectroglyphidodon lacrymatus* and *Dascyllus aruanus* species of damselfishes, it was found that their generated chirps consisted of trains of 12–42 short pulses of three to six cycles, with a duration from 0·6 to 1·27 ms; and the peak frequency varied from 3400 Hz to 4100 Hz [39].

3.4.2 Clunk

Northern searobin (*Prionotus carolinus*), Southern striped searobin (*P. evolans*) [40-43], Black Sea gurnard [44], etc. can produce cluck like sound. The cluck, generated by Northern searobin (*Prionotus carolinus*) has a frequency range of 40Hz to 2400 Hz with duration of 100 ms [40-43].

3.4.3 Grunt

Japanese gurnard (*Chelidonichthys kumu*) [45], grey gurnard (*Eutrigla gurnardus*) [46], the oyster toadfish *Opsanus tau* [47-48], gulf toadfish *O. beta* [49-50], *Porichthys notatus* nesting males [51] etc. species can produce a grunt like sound. The haddocks emitted grunts lasted less than 75 ms and comprised 3–4 pulses, whereas the grunts produced by codfish had durations were typically smaller than 150 ms and consisted of around 9 pulses. Grunts are broadband (up to 3 kHz) pulsed sounds which have a lasting of 300 ms approximately.

3.4.4 Growl

Pollimyrus adspersus, *Cichlasoma centrarchu* [52] etc. produce a growl like sound. The growls are broadband (100 Hz – 2 kHz) pulsed sounds, variable in duration, and with the typical pulse repetition rate of 25 pps [53].

3.4.5 Hoot and Pop

Hoots and pops are sounds heard exclusively in aggressive interactions. Hoots are made by *P.Isidori* [54], *P. ballayi* [55], *P. adspersus* [56], etc. and are relatively short sounds (30 ms), with frequencies lower than 1 kHz, and made up of nearly sinusoidal waveforms. Pops are made by species of *Chromis chromis* [57], *Pollimyrus* [54, 56], *Gnathonemus petersii* [58], etc., and consist of a series of pulse emissions with focal energies up to 2–3 kHz.

3.4.6 Click

Cod (*Gadus morhua*) can produce click like sound with peak frequency 55.95 ± 2.22 kHz; peak-to-peak duration 50.70 ± 60.45 ms [59]. Beluga (*Delphinapterus leucas*), bottlenose dolphin (*Tursiops truncatus*) [60], Sperm whale [61], etc. fish and mammals can produce similar sound-signal.

3.4.7 Whistle

Whistle is common among the killer whale (*Orcinus orca*) [62], some species of dolphins like (*tursiops truncatus)* [63] and various species of mammals.

3.4.8 Knock

Three species of carapids from two genera (*Carapus* and *Encheliophis*) emitted sounds consisting of a series of knock and differed among species in timing and grouping of knocks [64]. Two species of *Carapus* differed in duration of sound sequence and knock period, one emitting long sounds (25–30 s) with fast knock repetition rate and the other producing brief sounds (3–5 s) with longer knock periods (2–4-fold larger than the former), while the *Encheliophis* species emitted single knocks or sequences of less than 1 s duration [64]. On average, Knocking sounds can vary from 1 s (short) to approximately 9 s (long). However, fish sound types are much more diverse. The discussion above just focuses on some of them which are primary types. Three types of acoustics and their generating species are illustrated in Fig. 3.4.

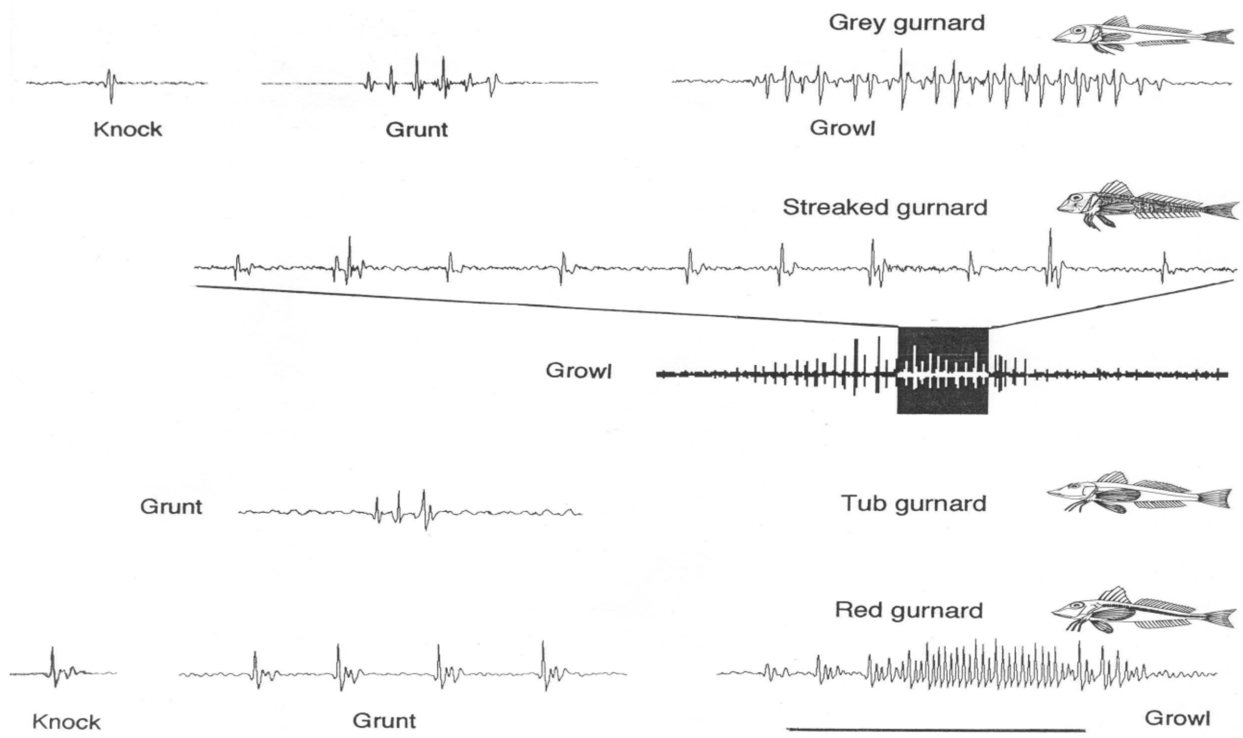


Fig. 3.4 Agonistic and disturbance sounds produced by the European grey, streaked tub and red gurnards can be classified into three types—knocks, grunts and growls. The differences among species in pulse number, pulse repetition rate and grouping of pulses within a sound is illustrated also. Similar time scales are considered for all ossiligrams, i.e., single bar = 100 ms; double bar = 1 s [64].

3.5 Generation of Fish Acoustics from Simulation

In our research, though we consider chirp signals and thus chirp generating species mainly, we take another two signals, i.e., grunt and growl, to show a relative performance analysis. We have used these signals which are categorized on frequency ranges. From section 3.4, we know that every type of signals has distinct characteristics, where the frequency range or dominant frequency plays the main role to define that signal. However, in this section, our main focus is on different types of fish acoustics generation from simulation based on frequency level. We used MATLAB as our simulation tool in this thesis.

3.5.1 Equation of Fish/Mammals Acoustics

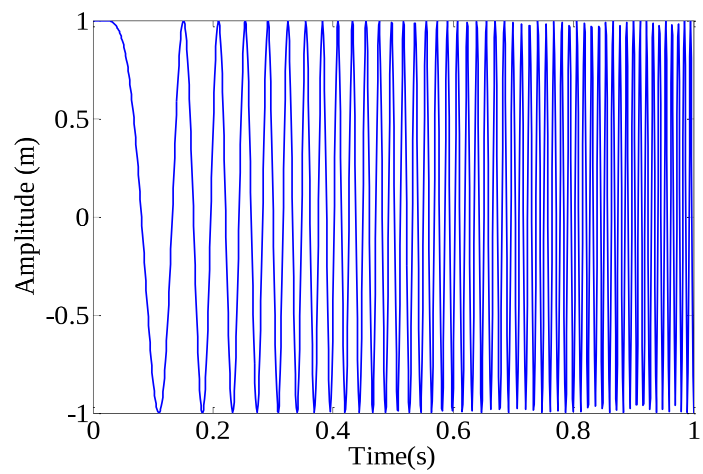
Typically, equation of acoustics from fish or mammals can be defined as follows [65-66]:

$$X(t) = A\cos\left[\left\{2\pi\left(\frac{(f_2 - f_1)t^2}{2d} + f_1 t\right)\right\} + P\right], \tag{3.1}$$

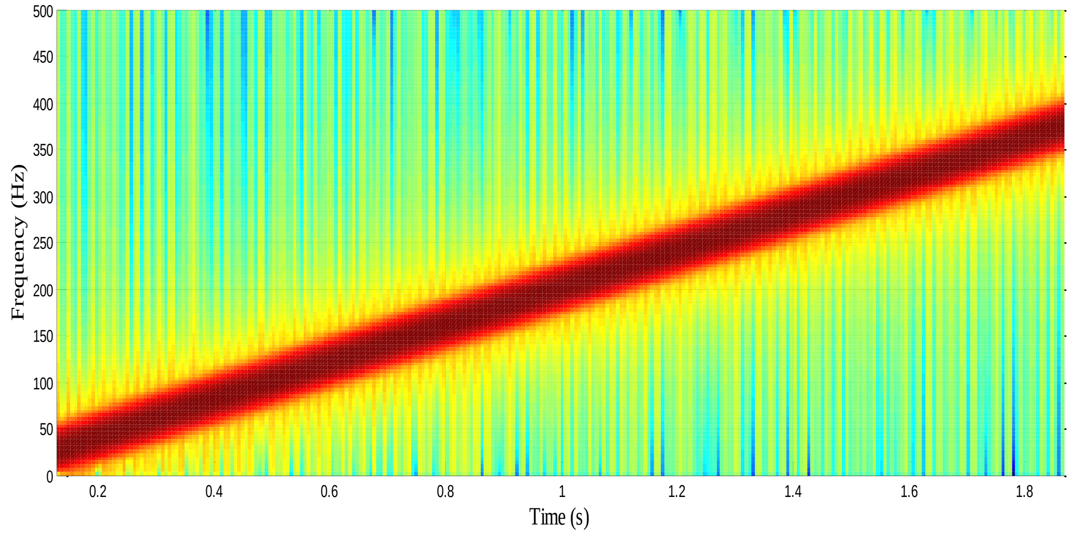
where, f_1 is the starting frequency in Hz, f_2 is the ending frequency in Hz, d is the duration in second, P is the starting phase, and A is the amplitude.

3.5.2 Generation of Fish Acoustics using MATLAB

Most fish signals consist of several pulses which generate a pulse train. In real-time surveys, researchers found fish acoustics as pulse train and sinusoidal form [66-68]. A pulse train can be periodic or non-periodic. In this thesis, we have worked with periodic pulse train to generate fish signals. We have generated fish acoustics considering different real-time parameters, i.e., frequency, time duration, bandwidth, etc., regarding fish signals. Similarly, fish signals can be represented as swift frequency wave. In addition to the sin and cos functions in MATLAB, the toolbox offers other functions that produce periodic signals such as sawtooth and square. The toolbox of MATLAB provides functions to generate swept-frequency waveforms such as the chirp function. Two optional parameters specify alternative sweep methods and initial phase in degrees. A simulated fish chirp is generated below:



(a)



(b)

Fig. 3.5 Chirp signal from simulation, (a) a simple simulated form and (b) spectrogram of chirp with linear instantaneous frequency deviation.

Figure 3.5 shows simulated form of chirp signal, where (a) represents a simple form of chirp with duration of 1s and (b) represents a chirp with linear instantaneous frequency deviation. Here, the chirp is sampled at 1 kHz for 2 seconds. The instantaneous frequency is 0 at t = 0 and crosses 200 Hz at t = 1 second.

In signal processing studies, chirp is a signal in which the frequency increases (up-chirp) or decreases (down-chirp) with time. In some sources, the term chirp is used interchangeably with sweep signal [69]. Chirps from fish and mammals are analogous to such sweep signal, where frequency is varied from species to species. However, a pulse train representation of fish signal is varied with different behaviors of fish and mammals, i.e., agnostic, courtship, etc. It also varies from species to species. Such signals with different frequencies are given below:

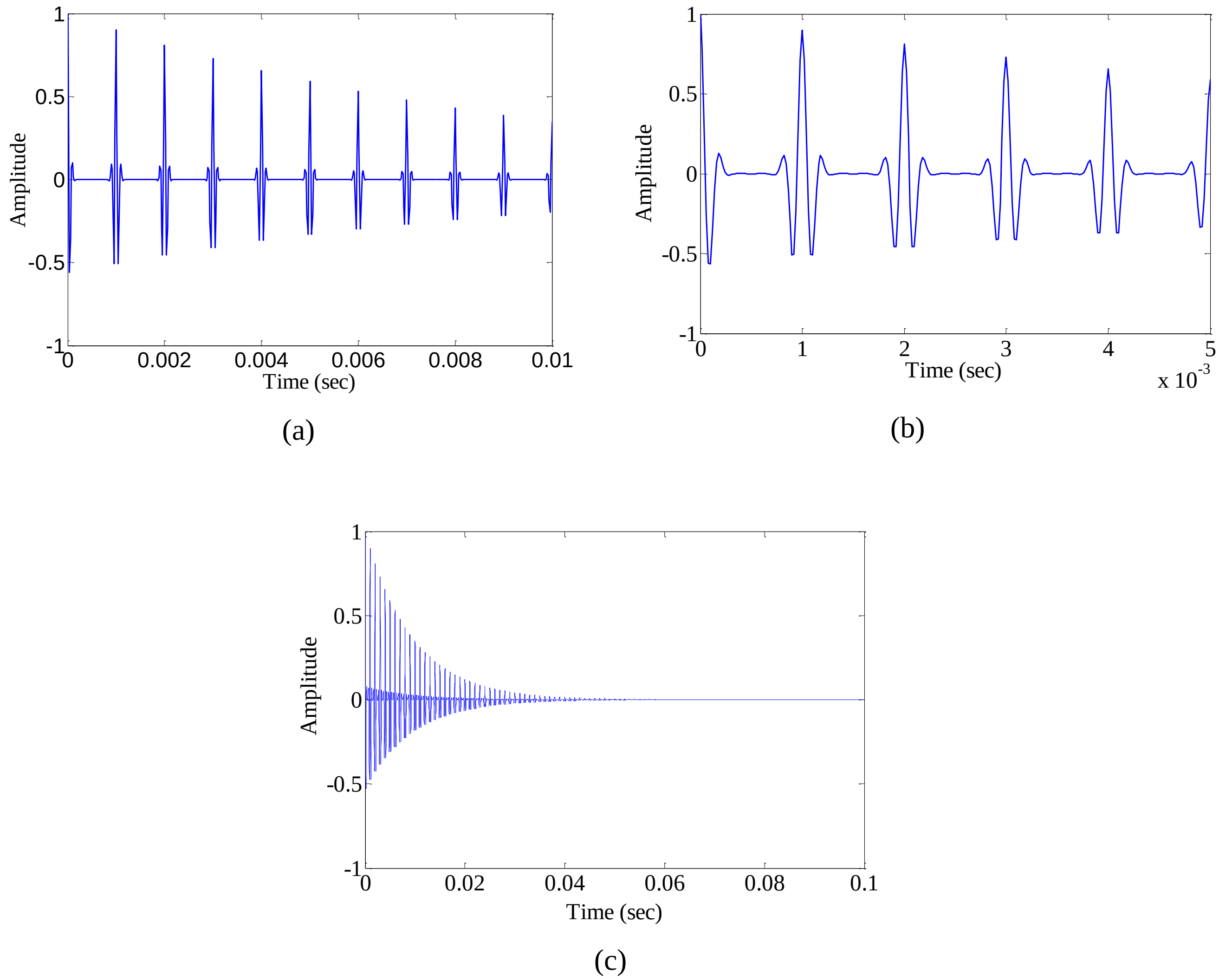


Fig. 3.6 Pulse train representation of acoustics of fish and mammals (a) 10 kHz fish signal with 10 ms duration, (b) 5 kHz fish signal with 5 ms duration, and (c) 3 kHz fish signal with 100 ms duration.

In Figs. 3.6(a), 3.6(b), and 3.6(c), the pulse repetition frequency is 1 kHz; sample rate is 50 kHz and the repetition amplitude should attenuate by 0.9 each time. Figures 3.6 (a) and 3.6(b) have 80% bandwidth and Fig. 3.6 (c) has 90% bandwidth. Figure 3.6 (c) represents a practical type of fish signal. It can be a 3 kHz grunt signal. However, to generate pulse trains, we use the pulstran function in MATLAB.

3.6 Chapter Summary

The time domain representation of fish acoustics can be in swift frequency wave or pulse train.

In practical situations, this acoustic signal can be affected by different factors to reach the recording tools. Consequently, it is a challenging task to receive a practical signal and continue estimation. However, the discussions on fish acoustics in this chapter carries a great importance to define the overall process of estimation and factors that affect the process of estimation.

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CHAPTER IV

CROSS-CORRELATION BASED FISH POPULATION ESTIMATION TECHNIQUE

This chapter describes the proposed population estimation technique of marine fish and mammals. Selection of optimum estimation parameter for estimation, use of different number of acoustic sensors to show a performance analysis, investigation of estimation with respect to different fish acoustics, and fish distributions, etc., are the main focus in this chapter. Basically, a theoretical and simulated form of estimation is conducted, where simulations are performed using MATLAB software.

4.1 Introduction to Fish Population Estimation

The ocean is a tremendous diversity and species-abundant place. It is the residence of myriad organisms dwelling in different ecosystems. Fish and mammals are key elements of marine ecology. For millennia mankind has had a close tie with them because they supply us food and numerous necessities. Millions of people rely on fishing or fish breeding for livelihood. Living with an amazing diversity of fish species, Marine mammals form a diverse group of 129 species that has depended on the ocean to survive [1-2]. Marine fish and mammals play a very important role in maintaining stability of marine ecosystems, mainly in the control of prey populations. Inauspiciously, people are slapdash to this natural resource. Over thousands of years, too many fish and mammals have been taken. Many fishing areas have been over-fished. Lack of early knowledge about the population and diversity of species as well as haphazardly fishing can make the ecosystem imbalanced. Therefore, a Proper estimation of marine population size is a mandatory task to maintain the ecological balance. An accurate estimation of marine population is also crucial because ecological research and managements largely depend on it. However, it is quite hard to estimate the exact population of fish and mammals in any particular area of the ocean. The dynamics of their population and harsh condition of the ocean represent the main difficulties in obtaining accurate data. Numerous studies have been performed to estimate the population of fish and mammals. Different drawbacks of conventional techniques motivate us to investigate the proposed cross-correlation based fish population estimation technique which can solve the major obstacles of conventional methods. In this chapter, an elaborate description on this statistical signal processing method of fish population estimation is illustrated.

4.2 A Brief Analysis on Cross-correlation Function

The CCF of time-delayed version of infinity in length, unity strength Gaussian signal is to be expressed by a delta function, whose amplitude relays on the attenuation. At the same time, its position will be the delay difference of signals from the center of the CCF.

Then, CCF for 1st signal source is:

$$C_1(\tau) = \alpha_{11}\alpha_{12}\delta\left(\tau\left[\frac{d_{11} - d_{12}}{S_p}\right]\right), \tag{4.1}$$

where d_{11} is the distance between 1st signal source and 1st receiver and d_{12} is the distance between 1st signal source and 2nd receiver.

Assuming the strength of source signal is high enough to overcome attenuations, so neglecting the attenuations CCF for 1st signal source become:

$$C_1(\tau) = \delta\left(\tau - \left[\frac{d_{11} - d_{12}}{S_p}\right]\right) \tag{4.2}$$

Likewise, CCF for the N^{th} signal source is:

$$C_N(\tau) = \delta\left(\tau - \left[\frac{d_{N1} - d_{N2}}{S_p}\right]\right) \tag{4.3}$$

Then, CCF for N number of signal sources

$$C(\tau) = \sum_{n=1}^{N} \delta\left(\tau - \left[\frac{d_{n1} - d_{n2}}{S_p}\right]\right) \tag{4.4}$$

It is innate that if N is larger than the number of bins b. Similarly, the bins are occupied by more than one delta due to the same delay differences. This increases the amplitude of the deltas of the bins, and thus the CCF is expressed in terms of bins as

$$C_i(\tau) = \sum_{m=1}^{b} p_i\delta_{i,} \tag{4.5}$$

where p_i is the amplitude of delta δ_i in the i^{th} bin.

The above analysis is verified by simulation shown in Fig. 4.1, where we have considered N is 32 and b is 19. Since, signal sources are larger than bins; there is possibility that some bins can be occupied by more than one source and some bins can be empty for time-delay difference. From Fig. 4.1, p_i values are: $p_1 = p_{19} = 4$, $p_4 = p_{10} = p_{13}=3$ and so on.

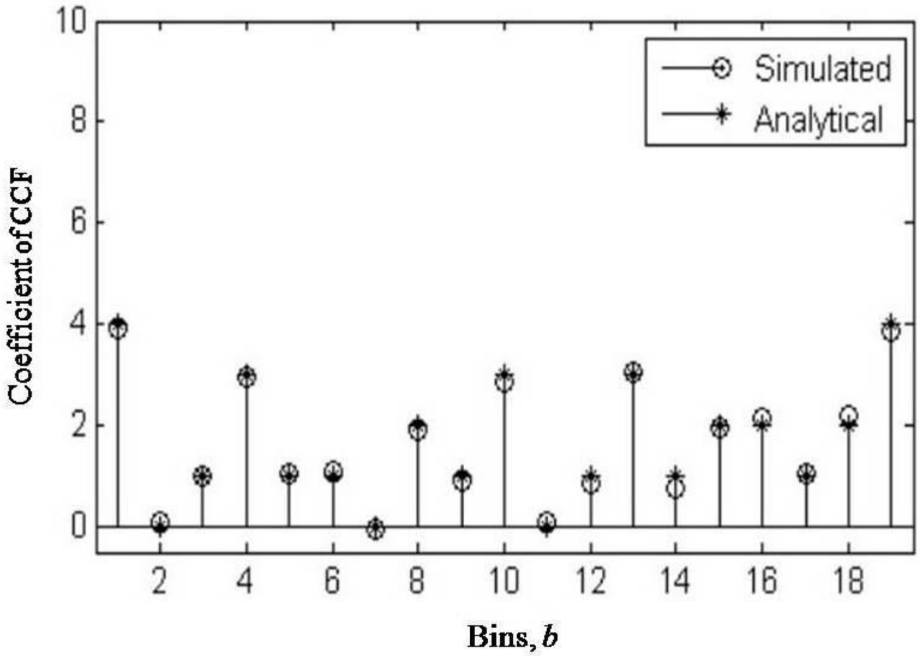


Fig. 4.1 Cross-correlation function (CCF) for 32 sources, and 19 bins.

Using moving average technique of cross-correlation [3-4], we can express the CCF generally by the expression bellow:

$$C(\tau) = \frac{1}{N_s - \tau}\sum_{i=1}^{N_s-\tau} x_i y_{i+\tau} - \left(\frac{1}{N_s}\sum_{i=1}^{N_s} x_i\right)\left(\frac{1}{N_s}\sum_{i=1}^{N_s} y_i\right), \tag{4.6}$$

where N_s is the signal length in terms of samples, τ is the time delay of cross correlated signals; x_i and y_i are i^{th} samples of the two sensor's signals. We assume Gaussian signal contains zero mean. So, the product of their mean is zero. Hence, the CCF:

$$C(\tau) = \frac{1}{N_s - \tau}\sum_{i=1}^{N_s-\tau} x_i y_{i+\tau} \tag{4.7}$$

This gives the peaks for the desired bins as follows:

$$\frac{1}{N_s+\tau}\sum_{i=1}^{N_s+\tau} x_i y_{i-\tau}\,, \dots \frac{1}{N_s+1}\sum_{i=1}^{N_s+1} x_i y_{i-1}\,, \frac{1}{N_s-0}\sum_{i=1}^{N_s-0} x_i y_{i+0},$$

$\frac{1}{N_s-1}\sum_{i=1}^{N_s-1} x_i y_{i+1}, \dots, \frac{1}{N_s-\tau}\sum_{i=1}^{N_s-\tau} x_i y_{i+\tau},$

where the peaks are the strengths of the deltas of (4.5), which are [5]:

$$P_1 = \frac{1}{N_s-\tau}\sum_{i=1}^{N_s+\tau} x_i y_{i-\tau}$$

$$P_2 = \frac{1}{N_s+(\tau-1)}\sum_{i=1}^{N_s+(\tau-1)} x_i y_{i-(\tau-1)}$$

$$\vdots$$

$$P_b = \frac{1}{N_s-\tau}\sum_{i=1}^{N_s-\tau} x_i y_{i+\tau} \tag{4.8}$$

Theoretical CCF is developed by putting these values in the equation (4.5) [3].

4.3 Formulation of CCF

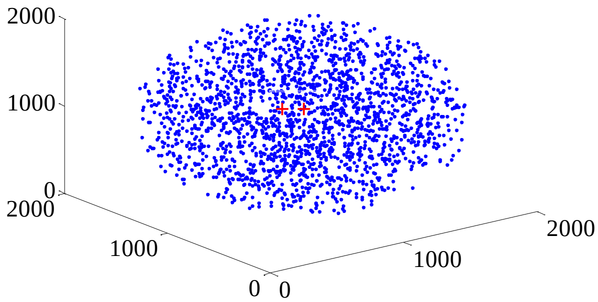
The formulation of cross-correlation of fish acoustics is analogous to the formulation of cross-correlation of Gaussian signal [5-7], which is the starting materials and method to estimate the population size of marine fish and mammals. All the transmitted signals are received by the acoustic sensor and recorded in the associated computer in which cross-correlation is executed. Transmission and reception of signals are performed for a time frame, called “signal length” throughout this thesis. At first, the CCF formulation process will be shown for two acoustic sensors and after that similar process will be performed for three acoustic sensors.

4.3.1 CCF Formulation for Two Acoustics Sensors

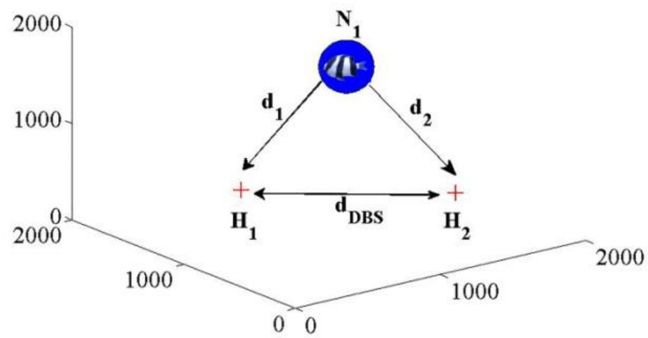
We assume *N* fish and mammals are distributed over the volume of a large sphere, the center of which lies halfway between acoustic sensors. A distribution of fish and mammals (simulation) is shown in Fig. 4.2(a).

A constant propagation velocity is considered, which is the sound velocity S_p in the medium. Two acoustic sensors H_1, H_2 and a fish/mammal (acoustics source) N_1 are taken, shown in Fig. 4.2(b). The acoustic sensors H_1, H_2 and the fish/mammal N_1 are located at (x_1, y_1, z_1), (x_2, y_2, z_2) and (a, b, c), respectively. If the distance between the two acoustic sensors is d_{DBS}

$$d_{DBS} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{4.9}$$



(a)



(b)

Fig. 4.2 (a) A distribution of fish and mammals where the two pluses (+) indicate the acoustic sensors and (b) from a distribution of fish and mammals in 3D spaces, we consider one fish/mammal N_1, where H_1 and H_2 are the acoustic sensors.

A signal coming from N_1 is $S_1(t)$, which is finite in length. As such, the signals received by H_1 and H_2 are correspondingly:

$$S_{r11}(t) = \alpha_{11} S_{11}(t - \tau_{11}), \tag{4.10}$$

$$S_{r12}(t) = \alpha_{12} S_{12}(t - \tau_{12}), \tag{4.11}$$

where $\tau_{11} = d_1/S_p$ and $\tau_{12} = d_2/S_p$ are the corresponding time delays for the signal to reach each acoustic sensor and α_{11} and α_{12} are the attenuations due to absorption.

Assuming τ_1 is the time shift in the cross-correlation and then the CCF is:

$$C_1(\tau) = \int_{-\infty}^{+\infty} S_{r11}(t) S_{r12}(t - \tau_1) d\tau \tag{4.12}$$

which takes the form of a delta function as it is across-correlation of two signals where one signal is fundamentally the delayed copy of another.

To find the CCF for N fish and mammals, we have to take the total signals received by the acoustic sensors from each of the fish/mammals and summing them. As such, the total signals $S_{r_{t1}}$ at acoustic sensor H_1

$$S_{r_{t1}} = \sum_{j=1}^{N} \alpha_{j1} S_j(t - \tau_{j1}) \tag{4.13}$$

While the total signals at acoustic sensor H_2 by $S_{r_{t2}}$ is:

$$S_{r_{t2}} = \sum_{j=1}^{N} \alpha_{j2} S_j(t - \tau_{j2}) \tag{4.14}$$

Assuming $\tau = d_{DBS} / S_p$ is the time shift in the cross-correlation. Hence, the final CCF between the signals at the acoustic sensors is:

$$C(\tau) = \int_{-\infty}^{+\infty} S_{rt1}(t) S_{rt2}(t - \tau)\, d\tau \tag{4.16}$$

This takes the form of series of delta functions, as it is a cross-correlation of two signals, which is the sum of several acoustic signals. Here, one signal is fundamentally a delayed copy of the other.

4.3.2 CCF Formulation for Three Acoustics Sensors

In the case of three sensors, two types of topologies are possible. One is acoustic sensors in a straight-line shape and another is acoustic sensors in a triangular shape. In this research, we have renamed acoustic sensors in straight line shape case as ASL case and acoustic sensors in a triangular shape case as AST case. Formulation of CCF with respect to these cases is described below:

4.3.2.1 CCF Formulation for Three Acoustic Sensors: ASL Case

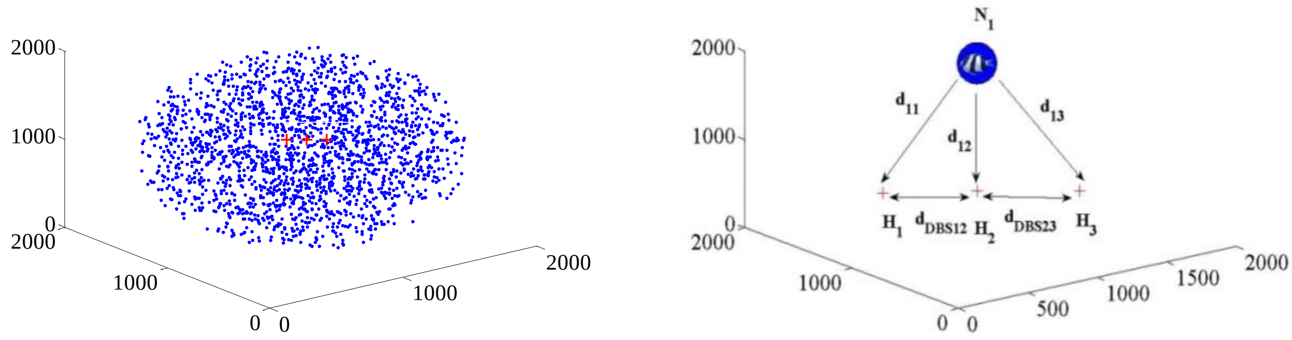
During the formulation of CCF for three acoustic sensors (ASL case), i.e., H_1, H_2, and H_3, and a fish/mammal, N_1 are located at (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), and (a, b, c).
Distance between acoustic sensors H_1 and H_2

$$d_{DBS_{12}} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{4.17}$$

Distance between acoustic sensors H_2, and H_3

$$d_{DBS_{23}} = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2 + (z_2 - z_3)^2} \tag{4.18}$$

We have considered, $d_{DBS_{12}} = d_{DBS_{23}} = d_{DBS}$, which implies that two CCFs are possible.



(a) (b)

Fig. 4.3 (a) A distribution of fish and mammals with three acoustic sensors (ASL case) and (b) a fish in 3D space with three acoustic sensors (ASL case).

Figure 4.3(a) shows a 3D space of a fish/mammal N_1 and three acoustic sensors H_1, H_2, and H_3. Here, we consider that the acoustic signal coming from N_1 is $S_1(t)$, which is finitely long. The signal received by acoustic sensors H_1, H_2, and H_3 are S_{r11}, S_{r12}, and S_{r13}, respectively:

$$S_{r11}(t) = \alpha_{11} S_{11}(t - \tau_{11}), \tag{4.19}$$

$$S_{r12}(t) = \alpha_{12} S_{12}(t - \tau_{12}), \tag{4.20}$$

$$S_{r13}(t) = \alpha_{13} S_{13}(t - \tau_{13}), \tag{4.21}$$

where α_{11}, α_{12}, and α_{13} are the attenuation due to absorption and dispersion in the medium, and τ_{11}, τ_{12}, and τ_{13} are the respective time delays for the acoustic signals to reach the acoustic sensors.

The CCFs for acoustic sensors in ASL case are:

$$C_1(\tau) = \int_{-\infty}^{+\infty} S_{11}(t) S_{12}(t - \tau_{11}) d\tau \tag{4.22}$$

$$C_2(\tau) = \int_{-\infty}^{+\infty} S_{12}(t) S_{13}(t - \tau_{12}) d\tau \tag{4.23}$$

To find out the CCFs for N number of fish and mammals, we have to take the total acoustic signals received by the three acoustic sensors.

Now the composite signals received by H_1, H_2, and H_3 are:

$$S_{rt1} = \sum_{j=1}^{N} \alpha_{j1} S_j(t - \tau_{j1}) \tag{4.24}$$

$$S_{rt2} = \sum_{j=1}^{N} \alpha_{j2} S_j(t - \tau_{j2}) \tag{4.25}$$

$$S_{rt3} = \sum_{j=1}^{N} \alpha_{j3} S_j(t - \tau_{j3}) \tag{4.26}$$

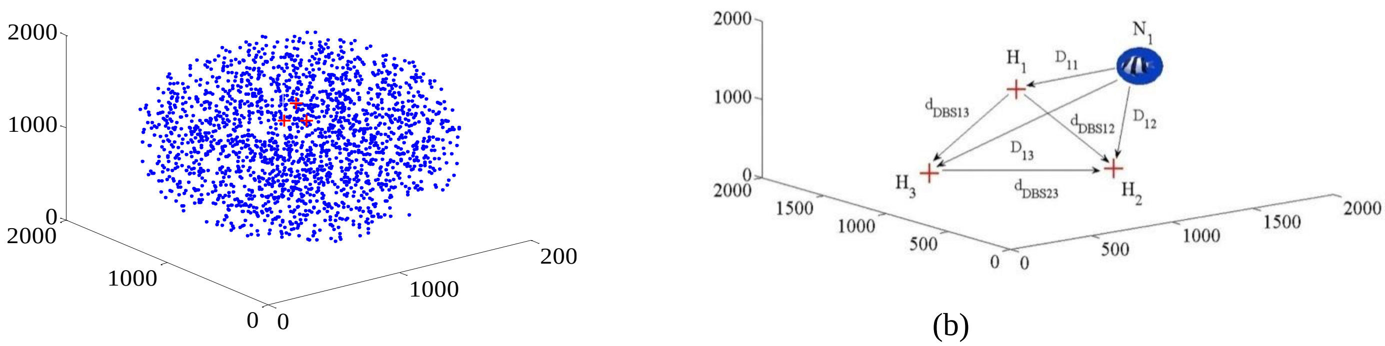
Therefore, the total CCFs are:

$$C_{12}(\tau) = \int_{-\infty}^{+\infty} S_{rt1}(t) S_{rt2}(t - \tau)\, d\tau \tag{4.27}$$

$$C_{23}(\tau) = \int_{-\infty}^{+\infty} S_{rt2}(t) S_{rt3}(t - \tau)\, d\tau \tag{4.28}$$

4.3.2.2 CCF Formulation for Three Acoustic Sensors: AST Case

For AST case, the cross-correlation among the acoustic sensors is taken place for three times (between H_1, H_2; H_2, H_3; and H_3, H_1). So, the total number of CCF is three. That means, an additional CCF will be added with the two CCFs of ASL case. A fish distribution for AST case is illustrated in Fig. 5(a). Three acoustic sensors (AST case), i.e., H_1, H_2, and H_3, and a fish/mammal, N_1 are shown in Fig. 5(b).



(b)

(a)

Fig. 4.4 (a) A distribution of fish and mammals with three acoustic sensors (AST case) and (b) A fish in 3D space with three acoustic sensors (AST case).

Now, the additional CCF is:

$$C_3(\tau) = \int_{-\infty}^{+\infty} S_{13}(t) S_{11}(t - \tau_{13}) d\tau \tag{4.29}$$

Consequently, the additional CCF for composite signal at TS case is

$$C_{31}(\tau) = \int_{-\infty}^{+\infty} S_{rt3}(t) S_{rt1}(t - \tau)\, d\tau \tag{4.30}$$

These take the form of a series of delta functions. Here,

$$\tau = \frac{d_{DBS}}{S_p} \tag{4.31}$$

4.4 Fish Population Estimation using CCF

In this section, we have divided the estimation technique into several parts. At first, a description on theoretical estimation technique will be given. Then, a discussion will be provided on the selection of optimum estimation parameter. And finally, the theory will be verified by simulation. We will use the CCF from previous section to estimate the fish population.

4.4.1 Fish Population Estimation from Theory

In brief, in cross-correlation based fish population estimation technique, a 3D estimation area is considered, where vocalizing fish and mammals produce acoustic signals as a consequence of their acoustic activities. Transmitted acoustic signals from N fish and mammals are received by acoustic sensors at different delay differences and summed at each sensor location forming composite signals. These two composite signals are then cross-correlated to formulate CCF. It is complex to directly use the CCF to estimate fish population. Hence, the discussed cross-correlation technique can be reframed to a probability problem using the renowned occupancy problem, which follows the binomial probability distribution and then a parameter is chosen for our desired estimation. Considering each delta function as a ball and this occupies a bin according to the delay difference of corresponding signals, which are recorded in the acoustic sensors. It is easy to model the cross-correlation problem as a probability problem based on the renowned occupancy problem, i.e., a problem of placing N balls in b bins. It is known from [8] that the occupancy problem follows the binomial probability distribution in which the parameters are number of balls, i.e. N, and the inverse of the b Occupancy problems deal with the pairings of objects and have several applications in different fields containing probabilistic and statistical properties.

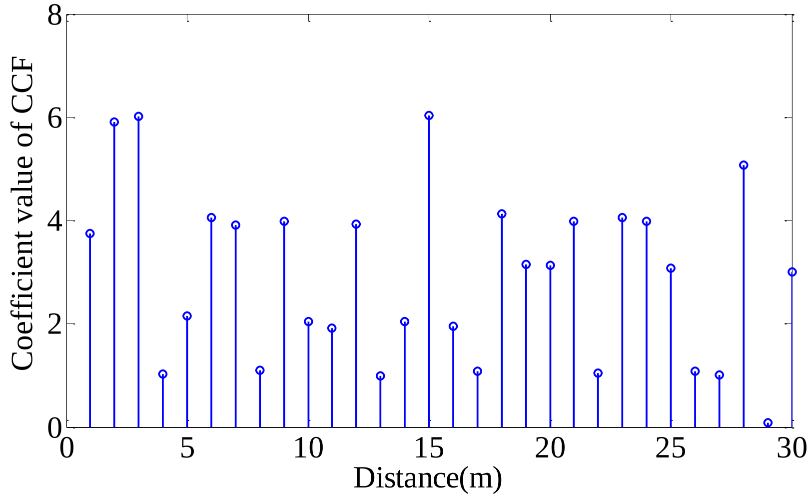


Fig. 4.5 Bins, *b* in the cross-correlation process where each delta function is considered as a ball and this occupies a bin according to the delay difference of corresponding signals, which are recorded in the acoustic sensors.

The basic occupancy problem is about placing *m* balls into *b* bins [9]. If one throws some balls randomly towards several bins, the bins would be randomly filled with the balls, which results in some bins being occupied by more than one ball, some by one while some may have none. In this research, the cross-correlation process for population size estimation is reframed as this occupancy problem. To obtain a CCF, *N* fish and mammals create *N* number of delta functions, which occupy the place in the correlation length. Here, the length is divided by *b* number of bins as shown in Fig. 4.5. Some bins are not occupied by any delta function; some are occupied by only one and others are more than one. Besides, the formation of the cross-correlation function to perform population size estimation satisfies the characteristics of binomial distribution as the number of trials, i.e. *N* is fixed, trials are independent in that sense the fish are sending independent signal. There exist only two possible outcomes, success or failure, for every trial, which indicates that delta for particular fish/mammals is occupying a bin or not, each trial has the same probability of success, which is one on the *b*. The *b* is achieved from the sampling rate S_R, distance between sensors d_{DBS}, and speed of chirp propagation S_P, which all are predefined [5].

$$b = \frac{2 \times d_{DBS} \times S_R}{S_P} - 1 \quad (4.32)$$

However, the main goal of occupancy using occupancy problem is converting the estimation technique into a statistical way, where the parameters are N and $1/b$ [5].

Different estimation parameters can be used to estimate fish population. Our next goal is to choose the optimum one.

4.4.2 Selection of Optimum Estimation Parameter

To select the optimum estimation parameter, we consider two fish acoustics, i.e., chirp and grunt, for comparison purposes. At first, we will implement different types of estimation parameters and then choose the optimum one from there. In this subsection, simulations are executed taking that two acoustic sensors are employed along with a line, where acoustic sensors lay in the center of a sphere. All the simulations are accomplished by the MATLAB simulation. The following parameters are used in the simulation.

Table 4.1 Parameters used in the MATLAB simulation

Parameters	Values
Dimension of the sphere	2000 m
Distance between the equidistant sensors d_{DBS}	0.5 m
Speed of propagation S_P	1500 m/s
Sampling rate S_R	60 kSa/s
Absorption coefficient a	1
dispersion factor k	0
Number of bins b	39
Average number of iterations (chirp)	500
Average number of iterations (grunt)	500

4.4.2.1 Implementation of different estimation parameters

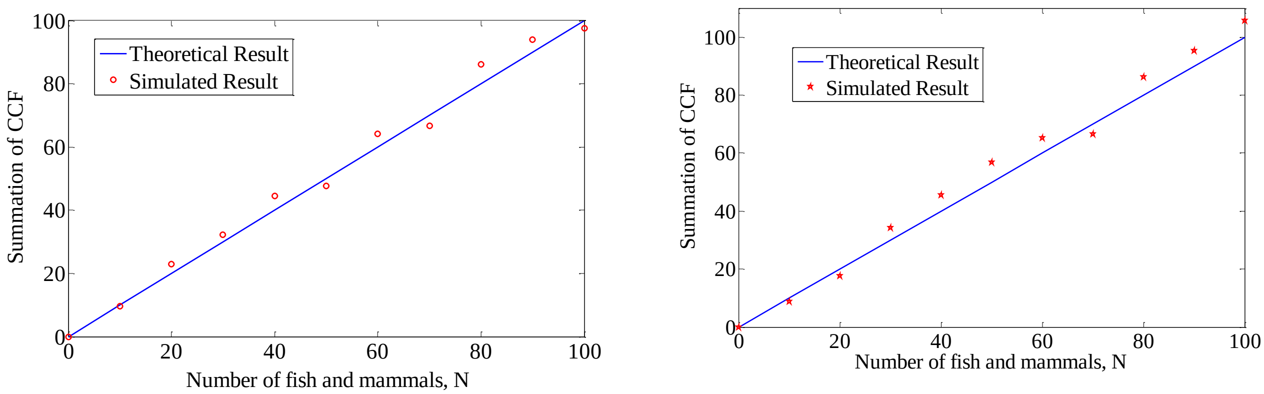
In this subsection, an implementation of different estimation parameters at cross-correlation based fish population estimation is conducted. In every figure, the blue lines represent the theoretical results and the red circles (chirps) or red stars (grunts) correspond to simulated results.

4.4.2.1.1 Sum of CCF *s*

It is the simplest estimation parameter, which is extremely sensitive to noise and signal strength. Sum of CCF s is equal to the N, as it is sum of all deltas in the bins of the CCF resulted for every fish and mammals in the estimation area and can be expressed as:

$$s = Sum\big(C(t)\big) = N, \tag{4.33}$$

where C(t) is the CCF.



(a) (b)

Fig. 4.6 Number of fish and mammals vs. sum of CCF, (a) chirp signal and (b) grunt signal.

In Fig. 4.6, the relationship is achieved by taking the standard deviation of CCF as estimation parameter.

4.4.2.1.2 Mean of CCF μ

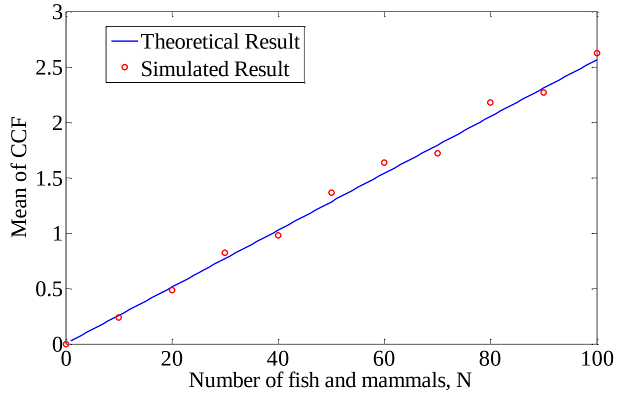
Mean of CCF decreases with the decrease of signal strength and vice versa. By reframing the cross-correlation problem into a probability problem, the mean of CCF μ can be expressed as [10]:

$$\mu = \frac{N}{b} \tag{4.34}$$

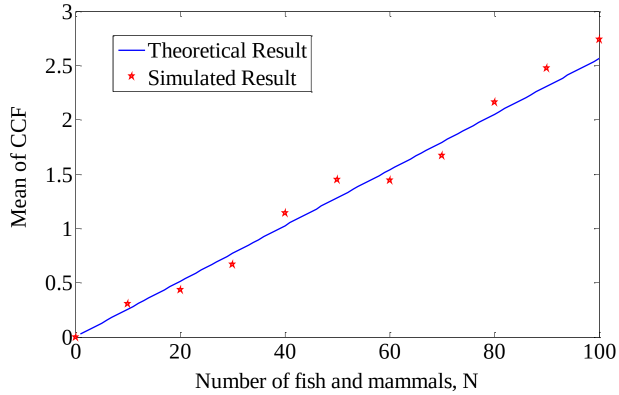
Hence, we can write

$$N = \mu \times b \tag{4. 35}$$

Using the equation (4.35), N can be estimated since b is known and μ can be calculated from the CCF.



(a)



(b)

Fig. 4.7 Number of fish and mammals vs. mean of CCF, (a) chirp signal and (b) grunt signal.

By taking the mean of CCF, μ as estimation parameter, we find the simulated results in Fig. 4.7.

4.4.2.1.3 Standard deviation of CCF, σ

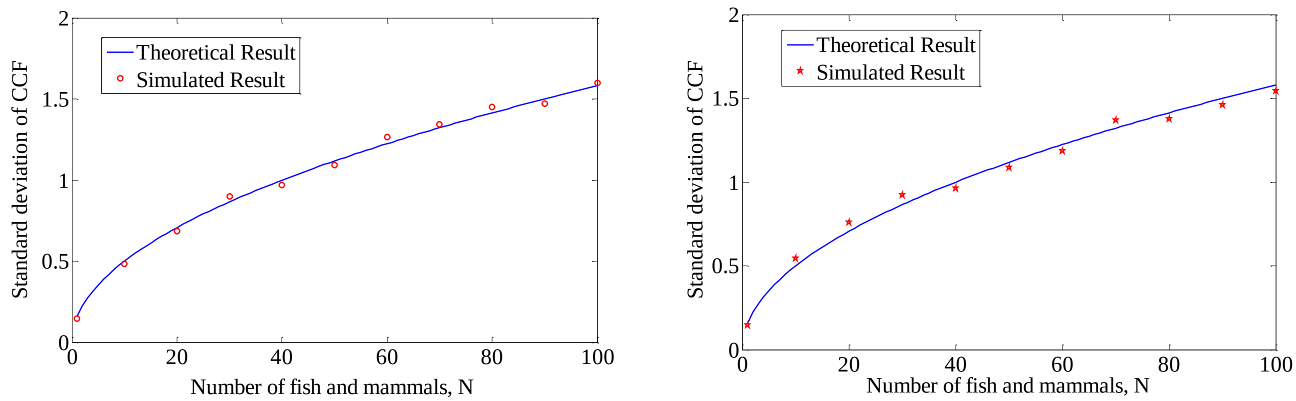
After reframing the standard deviation of the CCF σ into probability problem, we find [6]:

$$\sigma = \sqrt{N \times \frac{1}{b} \times (1 - \frac{1}{b})} \tag{4.36}$$

From (4.36), we can write

$$N = \frac{b^2 \times \sigma^2}{b-1} \tag{4.37}$$

We can estimate the N using the values of σ and b from this expression. Like μ, σ is also sensitive to the signal strength. However, in Fig. 4.8, the relationship is achieved by taking the standard deviation of CCF as estimation parameter.



(a) (b)

Fig. 4.8 Number of fish and mammals vs. standard deviation of CCF, (a) chirp signal and (b) grunt signal.

4.4.2.1.4 Ratio of Mean to the Standard Deviation of CCF, R_{msd}

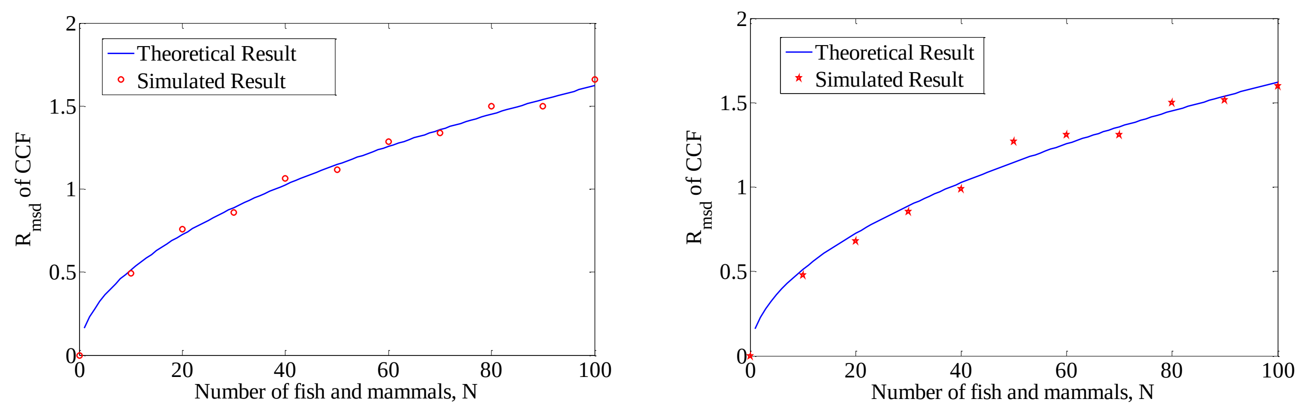
Similarly, R_{msd} can be expressed using equations 4.34 and 4.36 as [7]:

$$R_{msd} = \frac{\mu}{\sigma} = \frac{\frac{N}{b}}{\sqrt{N \times \frac{1}{b} \times (1 - \frac{1}{b})}} = \sqrt{\frac{N}{b-1}} \tag{4.38}$$

From (4.38) we can write,

$$N = (b-1) \times R_{msd}^2 \tag{4.39}$$

This estimation parameter is also independent of signal strength because it is also a ratio of two estimation parameters similar to R of CCF.



(a) (b)

Fig. 4.9 Number fish and mammals vs. R_{msd} of CCF, (a) chirp signal & (b) grunt signal.

Fig. 4.9 shows a relationship between R_{msd} of CCF and population size of fish and mammals for two different signals.

4.4.2.1.5 Ratio of standard deviation to the mean of CCF, *R*

Ratio of the standard deviation to the mean of CCF R can be found using (4.34) and (4.36) as follows [6]:

$$R = \frac{\sigma}{\mu} = \frac{\sqrt{N \times \frac{1}{b} \times (1 - \frac{1}{b})}}{\frac{N}{b}} = \sqrt{\frac{b-1}{N}} \tag{4.40}$$

Equation (4.40) relates R of CCF with the N. Since, it is a ratio of two parameters; it won't be affected by signal strength. This facilitates it over other estimation parameters. However, the simulated results of the population of fish and mammals vs. R of CCF are illustrated in the subsection 4.4.3.1 in the Figs. 4.11(a) and 4.11(b).

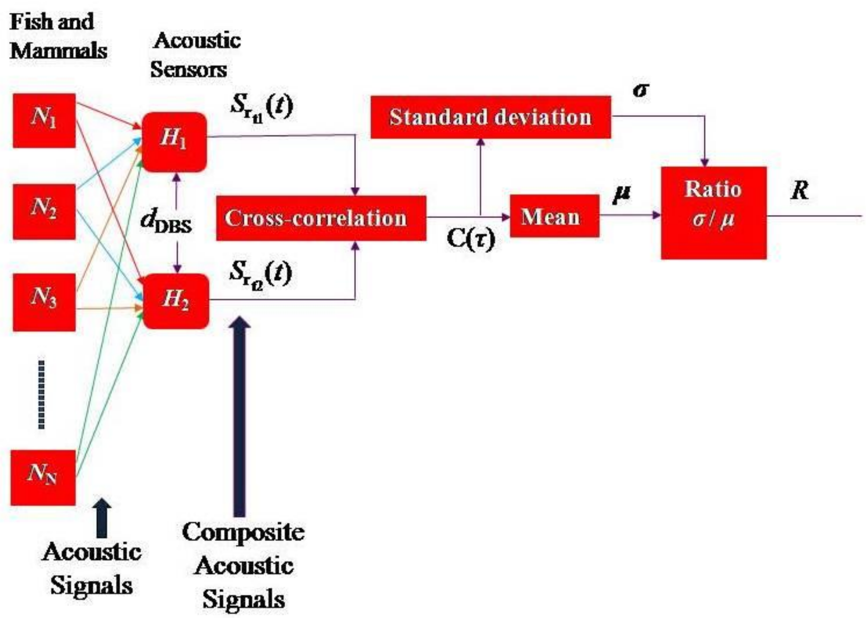
4.4.2.2 Selection of the Optimum

We have used chirps and grunts signals for comparison purposes. We can see from the figures that chirp signals provide better results than grunts signals. To obtain these results, the average iterations used in simulation: 100 for chirps and 500 for grunts (except for the parameter, R_{msd} of CCF). However, when signal strength varies, the strength of the deltas in the bins of the CCF also varies. So, variations of coefficient values of CCF with signal strength affect sum, mean, and standard deviation of the CCF. These three estimation parameters increase or decrease by the same factor with the increase or decrease of signal strength. This is why, the two ratios: R and R_{msd} of CCF are constant for signal strength.

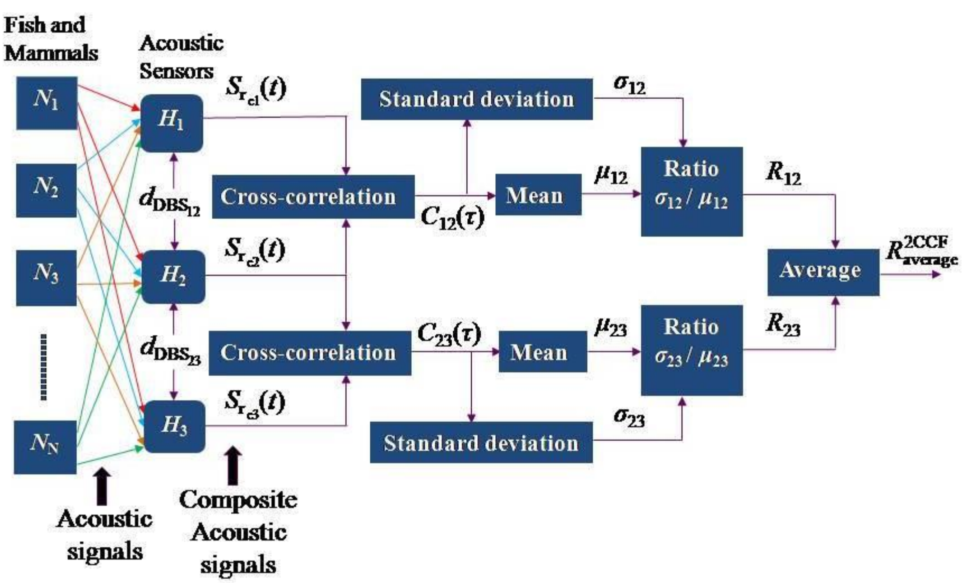
Now, R_{msd} of CCF is found in Figs. 4.11(a) and 4.11(b) by 300 iterations for chirp signal and 1000 iterations for grunt signal. On the other hand, R of the CCF from figure 4.10 is found for 100 iterations for chirp signal and 500 iterations for grunt signal. Hence, though the both parameters (R of CCF and R_{msd} of CCF) are independent of signal strength, R_{msd} requires nearly double times of iteration compared to R of CCF. So, we can conclude that R of CCF is the optimum estimation parameter in cross-correlation based fish population estimation technique. Hence, we have used the R of CCF as our estimation parameter in this thesis.

4.4.2.3 Block Diagram Representation of Obtaining *R* of CCF

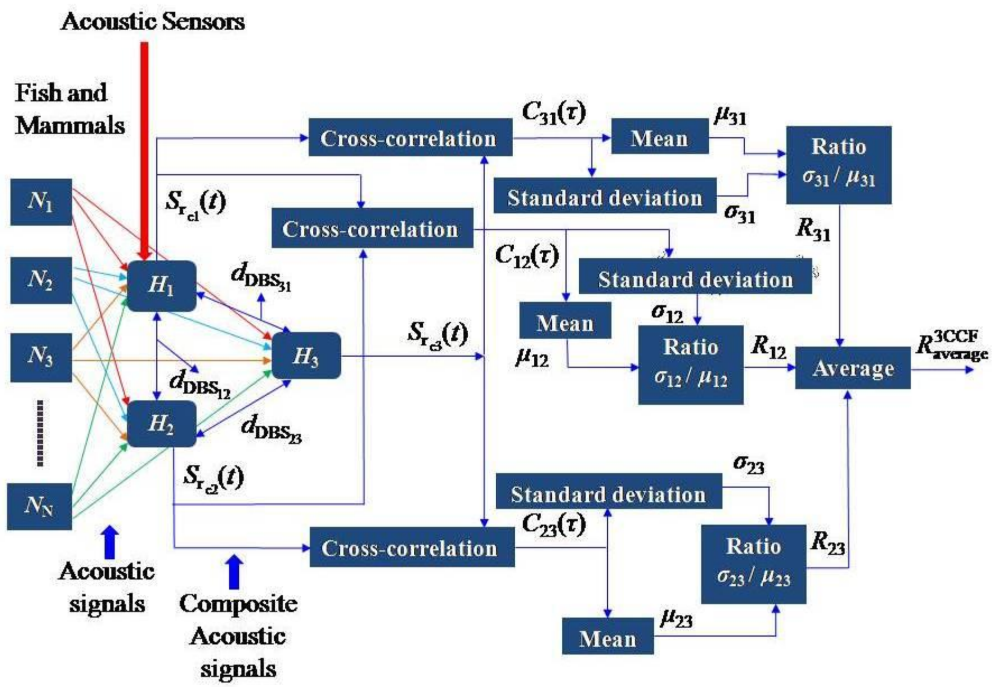
The block diagram representation to obtain *R* of CCF is shown below. Figs. 4.10 (a), 4.10 (b), and 4.10 (c) represents the block diagram to obtain *R* of CCF for two and three acoustic sensors, respectively.



(a)



(b)



(c)

Fig. 4.10 Block diagram representation of the process to obtain R of CCF, (a) two acoustic sensors, (b) three acoustic sensors (ASL case), and (c) three acoustic sensors (AST case).

4.4.3 Fish Population Estimation from Simulation

To establish the theoretical method, simulations are executed to estimate population of fish and mammals. Considering R of CCF as our estimation parameter, we can write the equation (4.40) as:

$$N = \frac{b-1}{R^2} \tag{4.41}$$

From the equation, we can find N since we find R from simulation. Similarly, for three acoustic sensors case, we can find as following:

For ASL case, the final ratio of the standard deviation to the mean will be found from the average of R_{12} and R_{23}. This indicates that two CCFs are used.

$$R^{2CCF}_{Average} = \frac{R_{12}+R_{23}}{2} \tag{4.42}$$

For AST case, the final ratio of standard deviation to the mean is obtained from the average of R_{12}, R_{23} and R_{31}.

$$R_{Average}^{3CCF} = \frac{R_{12}+R_{23}+R_{31}}{3} \tag{4.43}$$

Here, we know b and at the same time we can evaluate $R_{Average}^{2CCF}$and $R_{Average}^{3CCF}$. A point to be noted that b is a function of d_{DBS}, S_R, and S_P as described in equation 4.32. So, finally, we can estimate the N by using the three equations above.

The goals of these simulations are to establish a framework of fish population estimation and to analyze the performance of estimation. However, estimation from simulation is also divided into several parts. The simulated estimation will be performed for two acoustic sensors, three acoustic sensors, and different fish distributions. In this section, simulations are executed taking that the acoustic sensors lay in the center of a sphere. All the simulations are accomplished by the MATLAB. The parameters used in the simulations are same as Table 4.1, except some cases, where we have indicated the new values of parameters. However, to ease the simulation, we have considered a negligible amount of power difference among the acoustic pulses transmitted by each fish/mammal.

4.4.3.1 Fish Population Estimation with Two Acoustic Sensors: Implementation of Different Fish Acoustics

In this subsection, simulations are executed taking that two acoustic sensors are employed along a line, where sensors lay on the center of a sphere. A uniform random distribution of fish and mammals is considered. The estimation is performed with respect to three types of fish signals, i.e., chirp, grunt, and growl. We have used 500 iterations for chirp, grunt, and growl. For simulation, the range of frequency of these acoustic signals is defined in chapter 3.

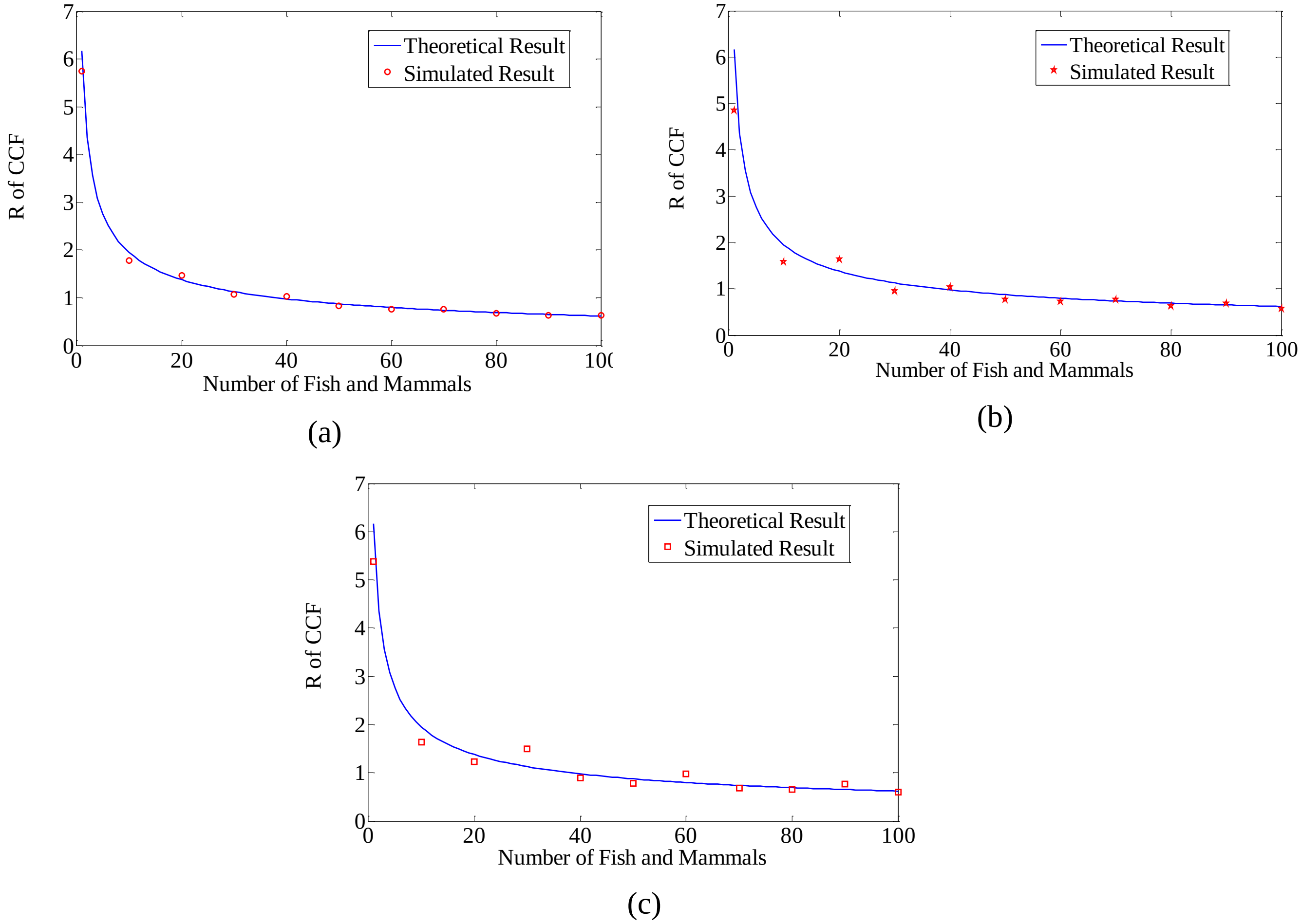
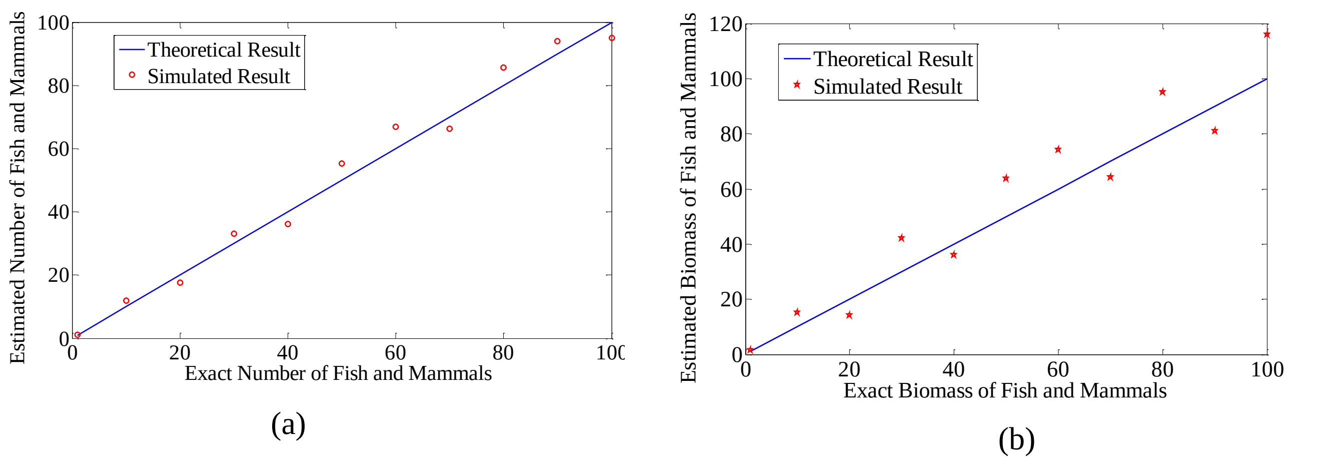
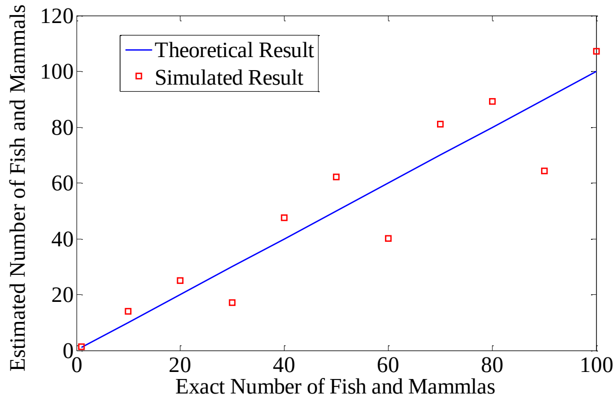


Fig. 4.11 Number of fish and mammals vs. R of CCF, (a) chirp signal, (b) grunt signal, and (c) growl signal.





(c)

Fig. 4.12 Variation of estimated number of fish and mammals from the actual quantity, (a) chirp signal, (b) grunt signal, and (c) growl signal.

Figure 4.11 shows R with respect to the number N for chirp, grunt, and growl signals. Figure 4.12 shows the difference between theoretical and simulated population of fish and mammals for three types of signals. In these figures, the blue lines are corresponding to theoretical results and the red circles, stars, and rectangles are corresponding to simulated results. From Figs. 4.11 and 4.12**,** we can conclude that the chirp signals produce better results in simulation.

4.4.3.1.1 Discussion

A typical analysis on performance of three different fish acoustics is conducted in Table 2.

Table 4.2 Deviation of simulated R from theoretical R for chirps, grunts, and growls signals

Population of Fish and Mammals	R^{Chirp}	R^{Grunt}	R^{Growl}	R from Theory
1	5.741	4.841	5.383	6.164
10	1.778	1.582	1.644	1.949
20	1.469	1.642	1.230	1.378
30	1.072	0.950	1.489	1.125
40	1.026	1.025	0.888	0.975
50	0.828	0.773	0.781	0.872
60	0.754	0.716	0.968	0.796
70	0.758	0.760	0.685	0.737

80	0.666	0.631	0.653	0.689
90	0.635	0.684	0.775	0.649
100	0.632	0.572	0.595	0.616

In Table 4.2, R^{Chirp}, R^{Grunt} and R^{Growl} represent R of CCF from simulation for chirp, grunt, and growl signals. We can see that R^{Chirp} provides least deviation with respect to R of theory among the three acoustic signals. Therefore, we found more accurate results from chirp producing species during estimation among the three.

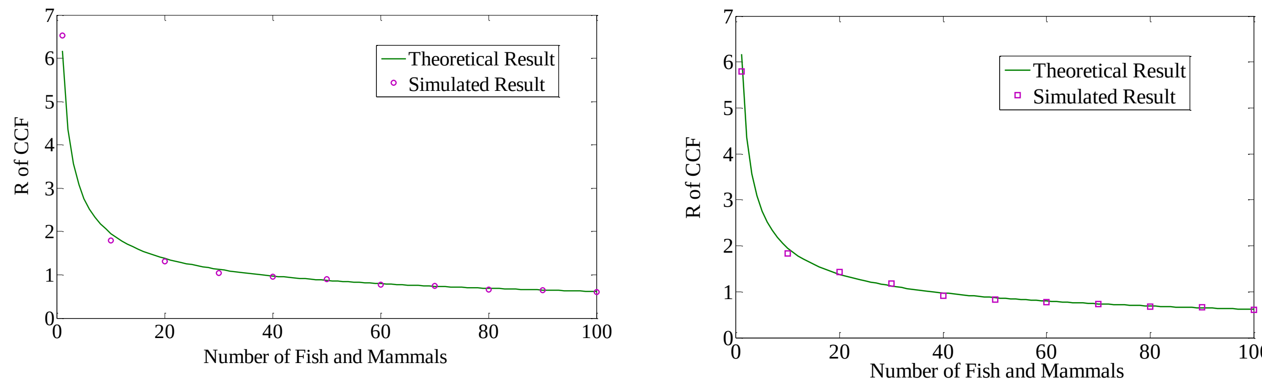
Table 4.3 Experimental and theoretical data of CCF for chirp signal, where b =39 (d_{DBS} =0.5m and S_R =60 kSa/s)

Actual number of fish and mammals, N_a	R of CCF from simulation	Estimated number of fish and mammals, N_e
1	5.741	1.151
10	1.778	12.013
20	1.469	17.59
30	1.072	33.059
40	1.026	36.121
50	0.828	55.332
60	0.754	66.861
70	0.758	66,213
80	0.666	85.599
90	0.635	93.987
100	0.632	96.931

From Table 4.3, we found, when the actual number of chirps generating fish and mammals is 90, we got 93.987. The estimation error is 4.43% (Percentage of error = ((N_a – N_e)/N_a) × 100%. This signifies the suitability of the proposed technique.

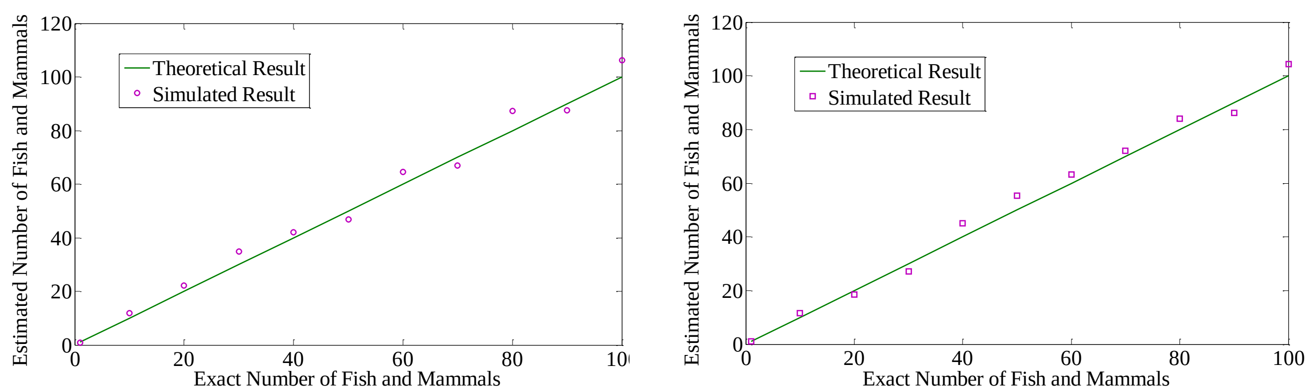
4.4.3.2 Fish Population Estimation with Three Acoustic Sensors

From the previous discussions, we have known that the fish population estimation with three acoustic sensors is classified in to two cases, i.e., ASL and AST. In this subsection, we have considered, the distance between the sensors is 0.5 m. The parameters are same as the previous simulations. We have also considered the chirp signal and a uniform random distribution of fish and mammals to achieve the simulated results. . At first, the simulations have been executed for ASL case and then AST case.



(a) (b)

Fig. 4.13 Number of fish and mammals vs. *R* of CCF (a) ASL case and (b) AST case.



(a) (b)

Fig. 4.14 Variation of estimated number of fish and mammals from the actual quantity (a) ASL case and (b) AST case.

Figure 4.13 represents the *R* with respect to the *N* for ASL and AST cases. Figure 4.14 shows the difference between theoretical and simulated population size of fish and mammals for the two cases. The green lines represent the theoretical results and the purple circles and squares represent the simulated results.

4.4.3.2.1 Discussion

From the figures above, we can see that estimation using AST case provides better accuracy than the estimation using ASL case. But the both ones perform better than two acoustic sensors case, where only one CCF is produced in two acoustic sensors case, two CCF for ASL case and three CCF for AST case is generated. So, we can decide that the greater number of CCF provide the better performance. We also can decide that an increasing number of acoustic sensors can produce better results in cross-correlation based fish population estimation technique.

4.4.3.3 Fish Population Estimation from Different Fish Distributions

In this subsection, we have shown the performance for three different fish distributions, i.e., Exponential, Normal, and Rayleigh. We have considered three acoustic sensors ASL case. The plots are found for three different types of distributions. All the simulations are accomplished in MATLAB. The parameters in the table 4.4 are common for the three different distributions. The simulated results are obtained by averaging 500 iterations.

Table 4.4 Parameters used in the MATLAB simulation for different distributions

Parameters	Values (Exponential distribution)	Values (Normal distribution)	Values (Rayleigh distribution)
Dimension of the sphere	2000m	2000m	2000m
Distance between the equidistant sensors, d_{DBS}	0.5m	0.5m	0.5m
Speed of propagation, S_P	1500 m/s	1500 m/s	1500 m/s
Sampling rate, S_R	60 kSa/s	60 kSa/s	60 kSa/s
Mean parameter, m	5	5	5
standard deviation parameter, s		2	
Scale Parameter, β			2
Absorption coefficient, a	1	1	1
dispersion factor, k	0	0	0
Number of bins, b	39	39	39

We have considered a popular aquarium fish called damselfish and estimate their population size from three different distributions of damselfish. Damselfish are among the best studied soniferous fish, with at least eight of around 29 genera reported to generate sounds [11-12]. Chirp, a sound, commonly produced by males of the bicolor damselfish (family: Pomacentridae). In response, females make aggressive sounds. Two types of aggressive sounds are produced, pops and chirps [11]. Their produced chirp is taken as the simulation acoustics in this subsection. However, we have considered damselfish to introduce the readers with a practical phenomenon regarding this estimation. The simulations are illustrated below:

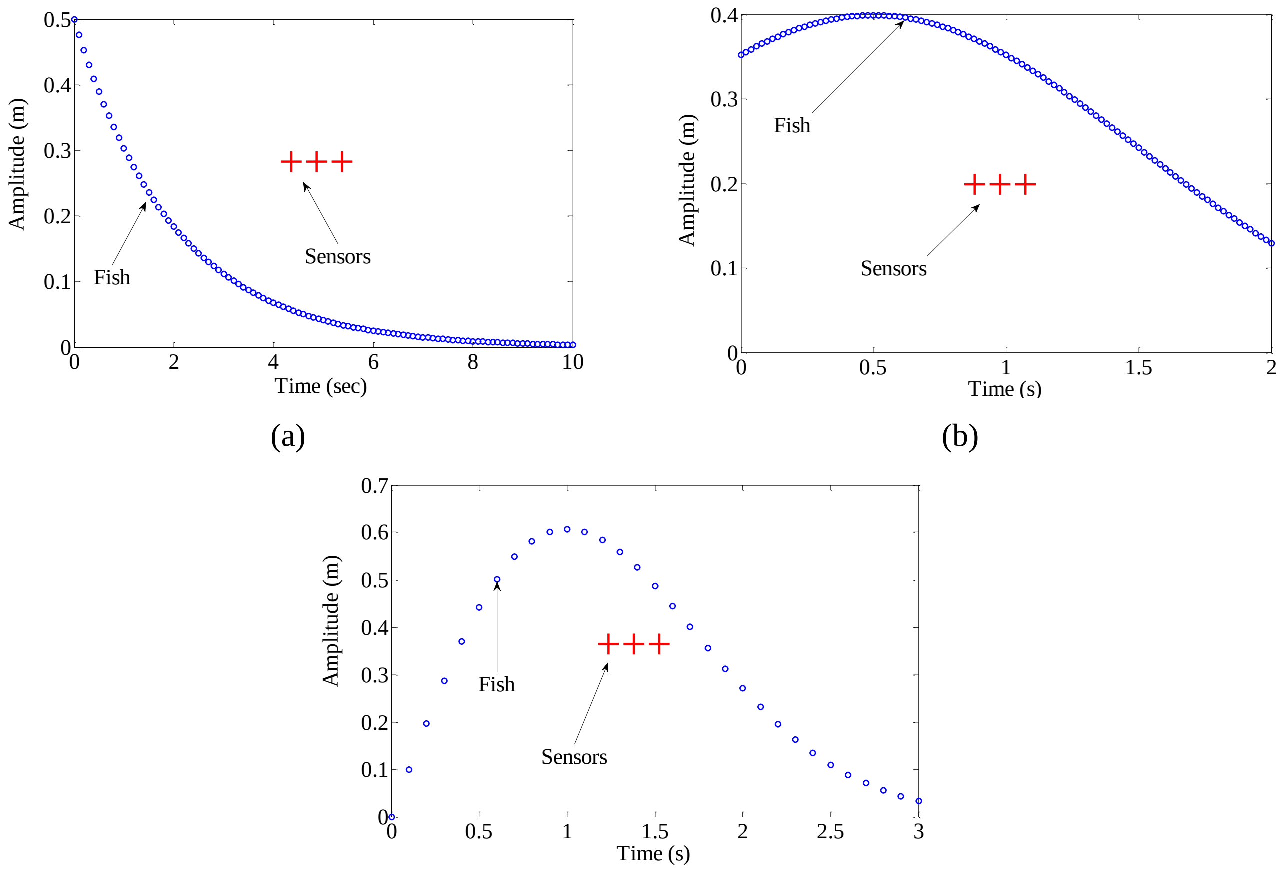
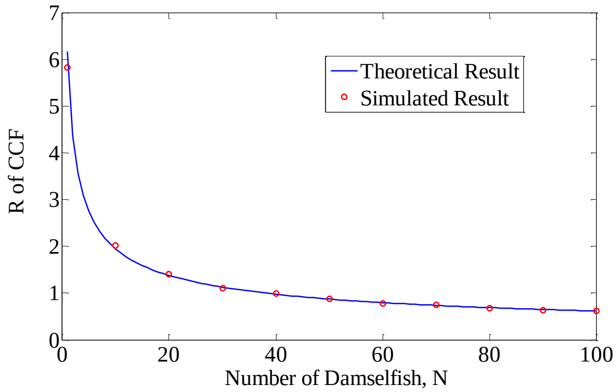
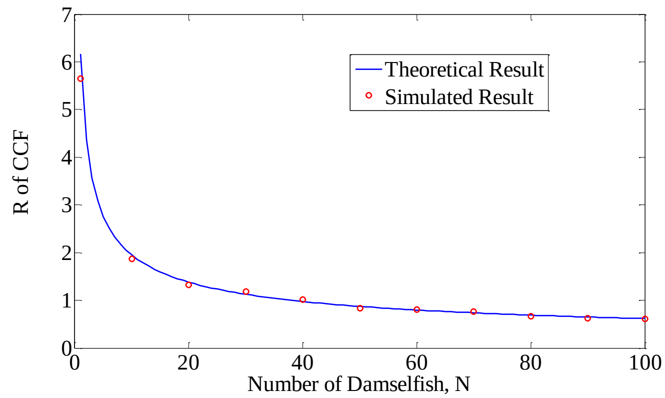


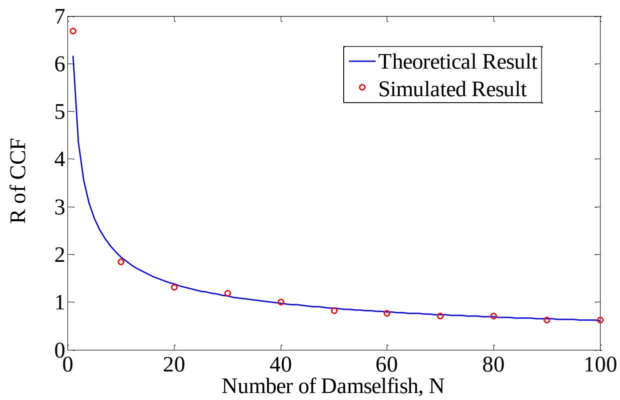
Fig. 4.15 Three different distributions of damselfish at ASL case where (a) Exponential distribution, (b) Normal distribution, and (c) Rayleigh distribution



(a)

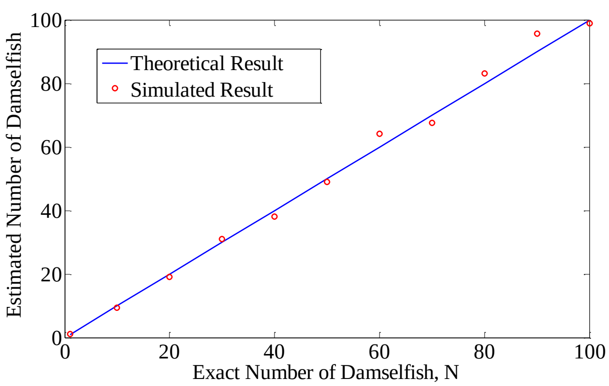


(b)

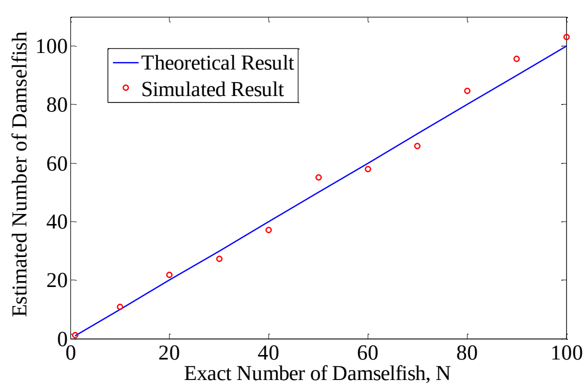


(c)

Fig. 4.16 Number of damselfish, *N* vs. *R* of CCFs, (a) Exponential distribution, (b) Normal distribution, and (c) Rayleigh distribution.



(a)



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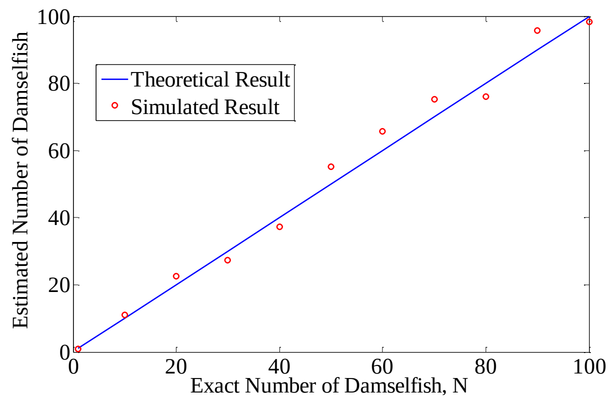


(c)

Fig. 4.17 Actual number of damselfish vs. estimated number of damselfish, (a) Exponential distribution, (b) Normal distribution, and (c) Rayleigh distribution.

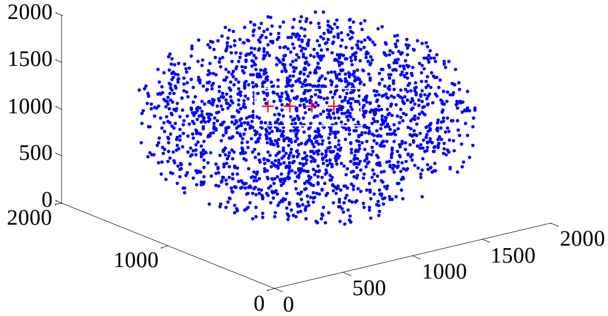
In Figs. 4.16 and 4.17, the lines (blue) represent the theoretical results and the circles (red) represent the simulated results. Figure 4.16 shows the R of CCF with respect to damselfish population N for different distributions. On the other hand**,** Fig. 4.17 shows a variation of our estimated population size of damselfish from actual quantity.

4.4.3.3.1 Discussion

After an analysis on Figs. 4.16 and 4.17, we can come to a decision that Exponential distribution of damselfish provides better results. For 100 damselfish, we got 98.06 damselfish from simulation in exponential distribution. The percentage of error is less than 2%. This shows a good indication of accuracy of our proposed estimation technique.

4.4.3.4 Fish Population Estimation with more than Three Acoustic Sensors

In this subsection, we have implemented four acoustic sensors to estimate the population of fish and mammals. For four acoustic sensors case, different types of topologies, i.e., acoustic sensors in line, acoustic sensors in a rectangular shape, acoustic sensors in a triangular shape, are possible. Similarly, Acoustic sensors in a triangular shape can be a square shape, a rhombus shape or a trapezoidal shape. However, Fig. 4.18 shows four acoustic sensors in a line and rectangular shape with a distribution of fish and mammals. From different topologies, we have considered acoustic sensors in a line shape for estimation.



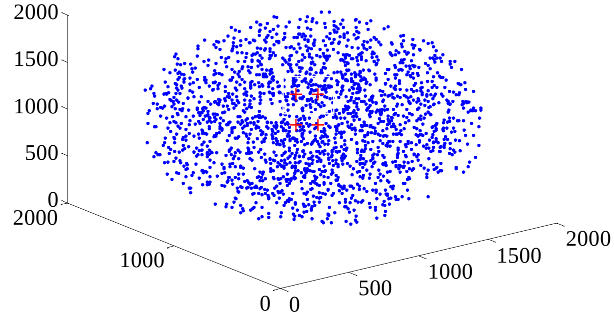


Fig. 4.18 Distribution of fish and mammals with four acoustics sensors (a) acoustic sensors in a line case and (b) acoustics sensors in a rectangular shape case.

However, during the formulation of CCF for four acoustic sensors in a line case, i.e., H_1, H_2, H_3, and H_4 and a fish/mammal, N_1 are located at (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), (x_4, y_4, z_4), and (a, b, c), respectively.

Distance between acoustic sensors H_1 and H_2

$$d_{DBS_{12}} = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{4.44}$$

Distance between acoustic sensors H_2 and H_3

$$d_{DBS_{23}} = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2 + (z_2 - z_3)^2} \tag{4.45}$$

Distance between acoustic sensors H_2 and H_3

$$d_{DBS_{34}} = \sqrt{(x_3 - x_4)^2 + (y_3 - y_4)^2 + (z_3 - z_4)^2} \tag{4.46}$$

We have considered, $d_{DBS_{12}} = d_{DBS_{23}} = d_{DBS_{34}} = d_{DBS}$, which implies that two CCFs are possible.

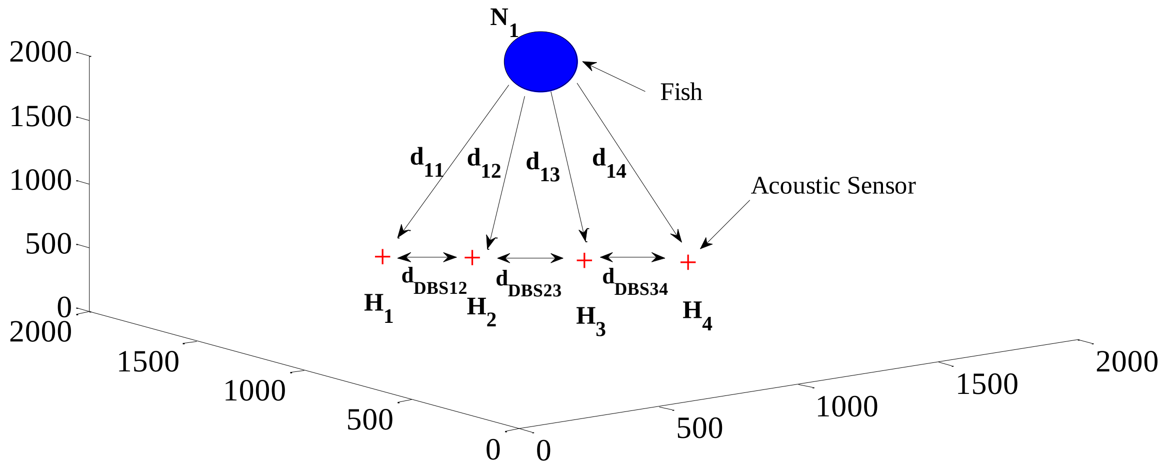


Fig. 4.19 A fish in 3D space with four acoustic sensors.

Analogous to two or three sensors cases, the composite signals received by H_1, H_2, H_3, and H_4 are:

$$S_{rt1} = \sum_{j=1}^{N} \alpha_{j1} S_j(t - \tau_{j1}) \tag{4.47}$$

$$S_{rt2} = \sum_{j=1}^{N} \alpha_{j2} S_j(t - \tau_{j2}) \tag{4.48}$$

$$S_{rt3} = \sum_{j=1}^{N} \alpha_{j3} S_j(t - \tau_{j3}) \tag{4.49}$$

$$S_{rt4} = \sum_{j=1}^{N} \alpha_{j4} S_j(t - \tau_{j4}) \tag{4.50}$$

Therefore, the total CCFs are:

$$C_{12}(\tau) = \int_{-\infty}^{+\infty} S_{rt1}(t) S_{rt2}(t - \tau)\, d\tau \tag{4.51}$$

$$C_{23}(\tau) = \int_{-\infty}^{+\infty} S_{rt2}(t) S_{rt3}(t - \tau)\, d\tau \tag{4.52}$$

$$C_{34}(\tau) = \int_{-\infty}^{+\infty} S_{rt3}(t) S_{rt4}(t - \tau)\, d\tau \tag{4.53}$$

Now, for four acoustic sensors in a line case, the final ratio of standard deviation to the mean is obtained from the average of R_{12}, R_{23}, R_{34}.

$$R_{Average}^{3CCF} = \frac{R_{12}+R_{23}+R_{34}}{3} \tag{4.54}$$

4.4.3.5 Fish Population Estimation with Random Placements of Acoustic Sensors (Two Sensors)

Distribution of fish and mammals of equal delay difference follows a hyperbola [13].

Number of fish and mammals in a bin is equal to the number of fish and mammals inside a hyperbola [5]. Due to the uniform distribution of fish and mammals over the total area, number of fish and mammals inside a hyperbola is proportional to the area of the hyperbola. For each fish or mammal, a delta is obtained in CCF. So, calculating the area of the hyperbola, number of deltas in the associate bin is obtained. The area is calculated with the trapezoidal rule.

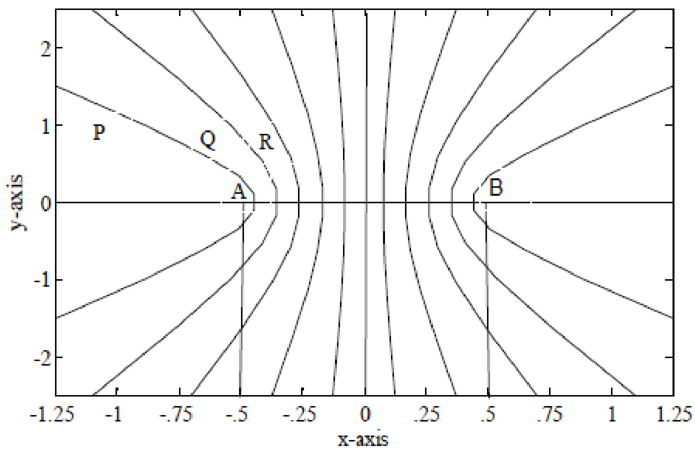


Fig. 4.20 Hyperbola representation of theoretical CCF generation [14].

It can be seen from Fig. 4.20 that the area of the hyperbola (P) is equal to the difference between that of the hyperbolas Q and R.

So, the area of P = Area of R- Area of Q = 0.85m^2

$$\text{Area of P} = (\text{Area of P})/(\text{Total area})$$
$$= 13.6\% \text{ of the total area}$$

So, there are 13.6% fish and mammals of total fish and mammals placed inside the hyperbola *P*. Thus, there are 13.6% deltas of total deltas are placed at bin associated with hyperbola, *P* that is at bin 1. Similarly, number of deltas of all other bin is calculated. Thus, we can achieve the theoretical CCF.

In spherical shaped networks with central placement of acoustic sensors, the area of each hyperbola is same. So the distribution of deltas within the whole CCF is uniform and is shown in Fig. 4.21.

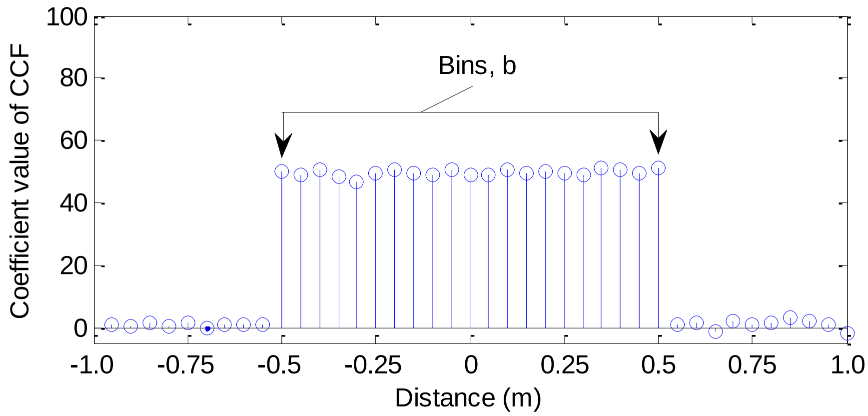


Fig. 4.21 Bins of CCF for 100 fish and mammals

But the distribution of deltas becomes non-uniform for random placement of acoustic sensors. Distribution of fish and mammals with random placements of acoustic sensors is shown in Fig. 4.22.

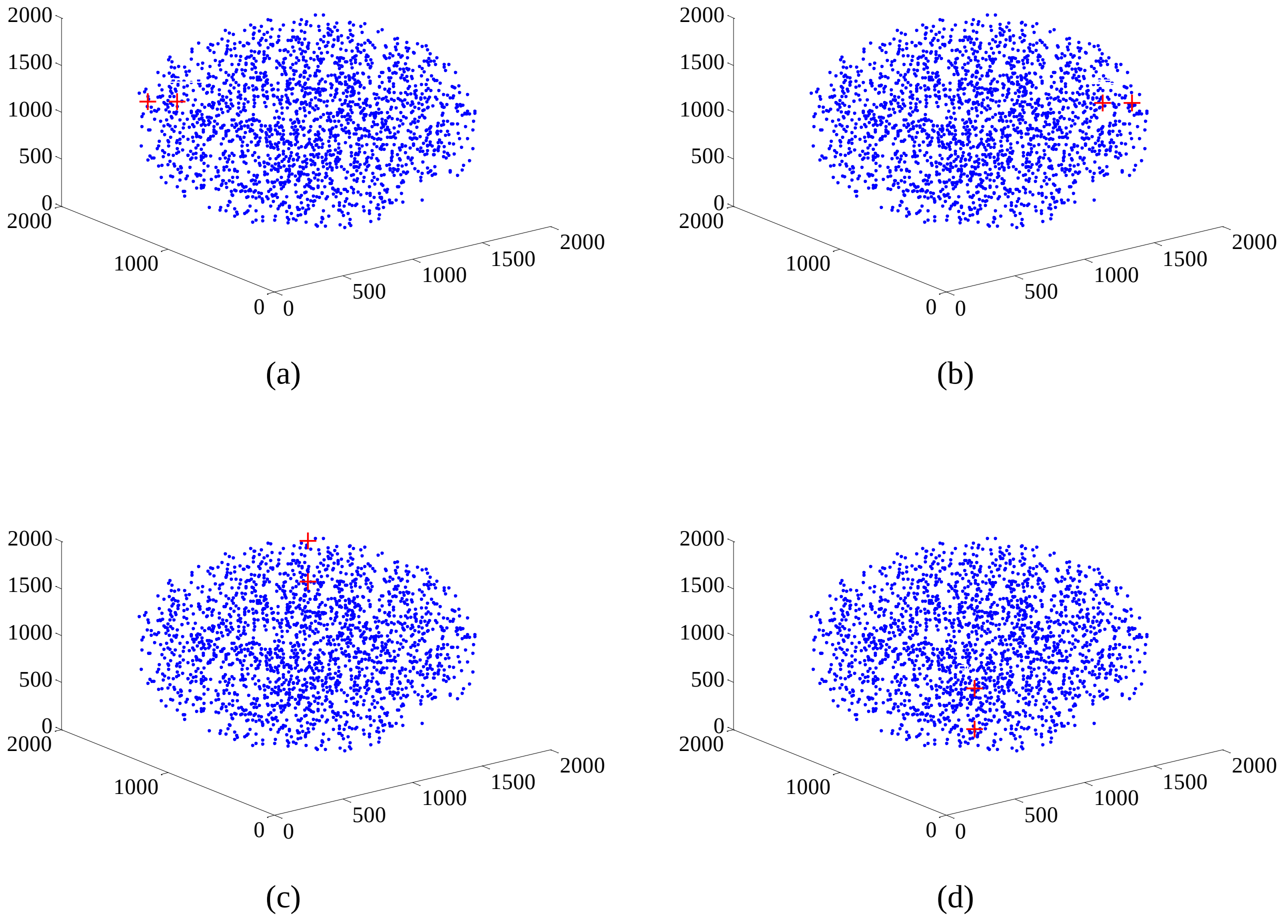


Fig. 4.22 Distribution of fish and mammals with random placement of acoustic sensors, where (a), (b), (c), and (d) represent four different random placements of sensors.

In Fig. 4.22(b), most of the fish and mammals are at right side of the sensors. So, the acoustic signals from most of the fish and mammals first arrive at acoustic sensor 2. Because of this reason, most of deltas placed at the 1st half of bins. So, estimation process of central placement case is not effective for random placement case. We need to make some modifications in estimation process. However, from theoretical CCF, probability of success of a bin, p_i is calculated though, $P_i = N_i/N$, where N_i is the total deltas in i^{th} bin, N is the total number of deltas in CCF. Similarly, probability of success of all other bins is calculated.

Estimation parameter R_T is given by [5]:

$$R_T = \frac{1}{\sqrt{N}} \times \frac{\sqrt{\sum_{i=1}^{b}({p_i}^2 - {p_i}^3)}}{\sum_{i=1}^{b} {p_i}^2} \tag{4.55}$$

After some manipulation we can write,

$$N = \frac{{W_T}^2}{{R_T}^2}, \tag{4.56}$$

where, $W_T = \frac{\sqrt{\sum_{i=1}^{b}({p_i}^2 - {p_i}^3)}}{\sum_{i=1}^{b} {p_i}^2}$

From equation (4.56), we can calculate fish and mammals as we can calculate R_T and W_T from theoretical CCF.

4.4.3.6 Comparison with other Passive Acoustic Techniques

To validate our proposed technique, in this subsection, we compare our technique with two other conventional passive acoustic techniques. A brief discussion on those techniques and a relative comparison with those are conducted below:

4.4.3.6.1 Flood-fill Algorithm-based Passive Acoustic Technique [15]:

Generally, Flood-fill algorithms are utilized in the “bucket” tool of paint programs to fill connected parts of a bitmap with color. They establish the area connected to a given node in a multi-dimensional array. The implementation a recursive flood-fill algorithm is the key topic in this technique. Two elements are defined as connected if a path exists between them along which the value of all elements exceeds some threshold for a given node and threshold. The flood-fill is performed recursively on all elements connected to the node of interest. The researchers employed two applications for passive acoustic monitoring of fish: (1) signal detection via two-dimensional (frequency and time) flood-fill applied to spectrograms; (2) source tracking via four-dimensional (x, y, z, and time) flood-fill applied to source position likelihood volumes (obtained using a localization algorithm that gives the likelihood of a source occupying a point in time and space).

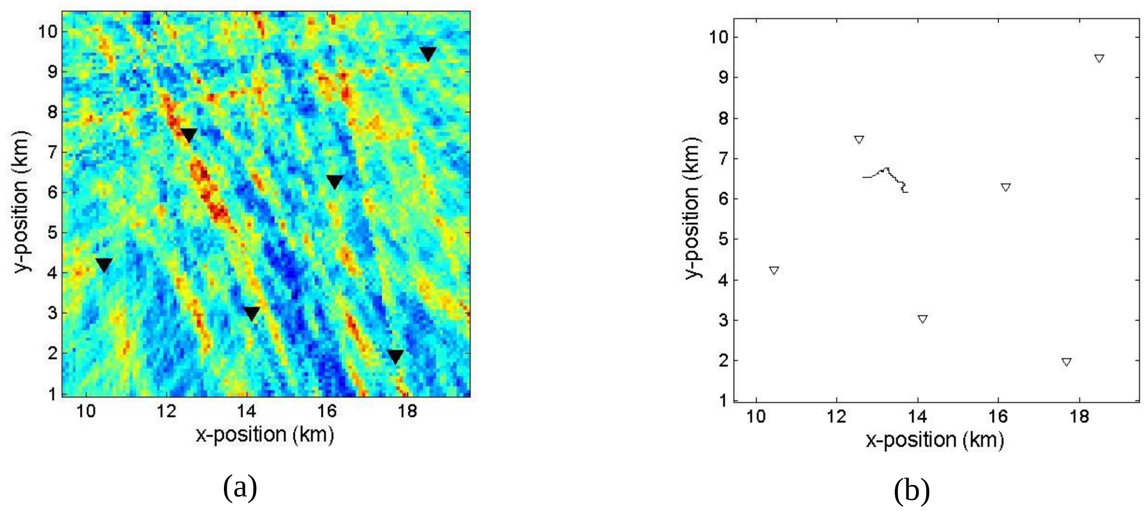


Fig. 4.23. Hydrophone positions indicated with triangles where (a) Slice through a likelihood volume at a single time and depth. Red (blue) indicate high (low) probability of a source at that location, and (b) Most prominent sperm whale track obtained by applying a 4D (x, y, z, time) flood-fill to likelihood volumes for a collection of 3 s time steps spanning 20 minutes [15].

Comparison: One of the limitations of the method is that overlapping tracks are connected. For instance, the calls of multiple animals vocalizing simultaneously are not separated. Separation of overlapping stacks is a challenging problem that requires post-processing the stacks using another method (such as a particle filter). Another problem with the flood-fill method is associated with allowable stack space. That is why, for very long stacks, the number of required recursions can surpass allowable recursion limits. To handle these problems, its needs further procession of data using algorithms. By this way, algorithm complexity and protocol difficulty arise. The main difference with our proposed technique is it (Flood-fill) needs further processing of data after the run of main algorithm. However, our proposed technique can overcome these limitations since we have used a statistical signal processing technique, which is very simple in manner and well accurate. Statistical conversion of complex cross-correlation technique makes it straightforward and low complex.

4.4.3.6.2 Combination of Direct Acoustic Counting and Visual Census Data Collection Algorithm based Technique [16]

Researchers used Visual track census and acoustic counting to estimate the humpback whale (Megaptera novaeangliae) population in the West Indies. Results produced by the two methods are differed to some extent. The average or best estimate was 1018 whales with a range from 785 to 1157. Silver and Navidad banks, containing approximately 85% of the total population, are presently the major nursery grounds in the West Indies. They found that the humpback whale population in the western North Atlantic was increased since the early part of the century.

Comparison: This algorithm is mainly composed of two types of techniques, where visual census suffers from human interaction. The instruments of data collection are costly and mechanical. In this proposed technique, we found the lowest error rate is below 2% in the simulation. But, here the estimation error is 15%. Moreover, the data collection techniques and complexities are also harder compared to our proposed technique.

4.4.3.6.3 Summary

The summary of the above discussion is illustrated below:

Table 4.5 Comparison with other passive acoustic technique

Parameters	Flood-fill algorithm-based Technique [15]	Combination of direct acoustic counting and visual census [16]	Cross-correlation based Passive acoustic technique (Proposed)
Protocol complexity	High	Medium	Low[17-22]
Mechanical instruments	Less needed	Highly needed	Less needed
Accuracy	Well	Low	Well

Human interaction	Less	Human interactive	Very low
Cost	Average	Costly due to mechanical instruments	Average
More times running of different algorithms to achieve results	Yes	Yes	No
Pure passive acoustic technique	Yes	Hybrid	Yes
Practically used	Yes	Yes	No
% of error	Not calculated	15%	< 2%

4.5 Chapter Summary

This is the most important chapter in this thesis. However, if we summarize the above discussions, we can find that chirp signal can give relatively better results in the simulation among the three types of acoustics. We can also find that, the increasing number of CCF produces better results in estimation. This is why, a three acoustic sensors AST case produce relatively better results. Therefore, if we increase the number of acoustic sensors, we will get better results. But such increasing is costly. Besides, Exponential distribution of fish can produce better results in simulation among the three distributions. Such findings can help the researchers greatly during the practical implementation of cross-correlation based fish population estimation technique.

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CHAPTER V

SIGNIFICANT IMPACTS ON FISH POPULATION ESTIMATION

This chapter describes different practical impacts, which will affect the estimation during practical situations. Here, we discuss three impacts, i.e., underwater bandwidth, SNR, and Doppler Effect. Knowledge about these impacts is important for practical estimation.

5.1 Introduction of Significant Impacts on Fish Population Estimation

During practical implementation of the proposed technique, different factors have significant impacts on estimation. Impact of bandwidth, multipath, noise, Doppler Effect, signal strength etc., must be taken into account. In this chapter, we discuss three of them. We have considered two types of fish acoustics, i.e., chirp and grunt, to show a relative comparison for showing the impact of underwater bandwidth and SNR on fish population estimation. However, a relative low impact is posed by Doppler Effect which will be shown. The parameters used in this chapter are same as table 4.1 of chapter 4.

5.2 Impact of Underwater Bandwidth

In practical cases, underwater acoustic channels are band limited due to the frequency dependency of absorption loss. The SNR also fluctuates. Hence, it's often a challenging task to implement the cross-correlation based fish population estimation technique.

Frequency dependent absorption loss is responsible for underwater bandwidth limitation [1], and it is nearly 1-15 kHz. With the increase of bandwidth, this absorption loss also increases, which decreases the transmission range. Channel bandwidth restricts the signal bandwidth, which affects the estimation performance. The reason is that limited bandwidth, we will get sinc function [2] instead of delta function of infinite band signal. So, it will give undesired peaks in the bins. Hence, the CCF will be corrupted as well as the estimation. To illustrate the impact of bandwidth, 5 kHz (low pass is better in underwater to avoid unwanted high frequency attenuation) chirp and grunt signals are used in the simulation instead of infinite bandwidth signals. The ratio of standard deviation to mean of CCF for this finite bandwidth case is obtained and denoted by $R_{finiteBW}$ and for infinite bandwidth case, $R_{infiniteBW}$. Now the ratio of these two R is obtained and plotted against N shown in Fig. 5.1 for chirp signal. It can be seen in the figure that $R_{finiteBW}$ is almost the constant multiple of $R_{infiniteBW}$ and the mean of those constants is 0.59512 for this case.

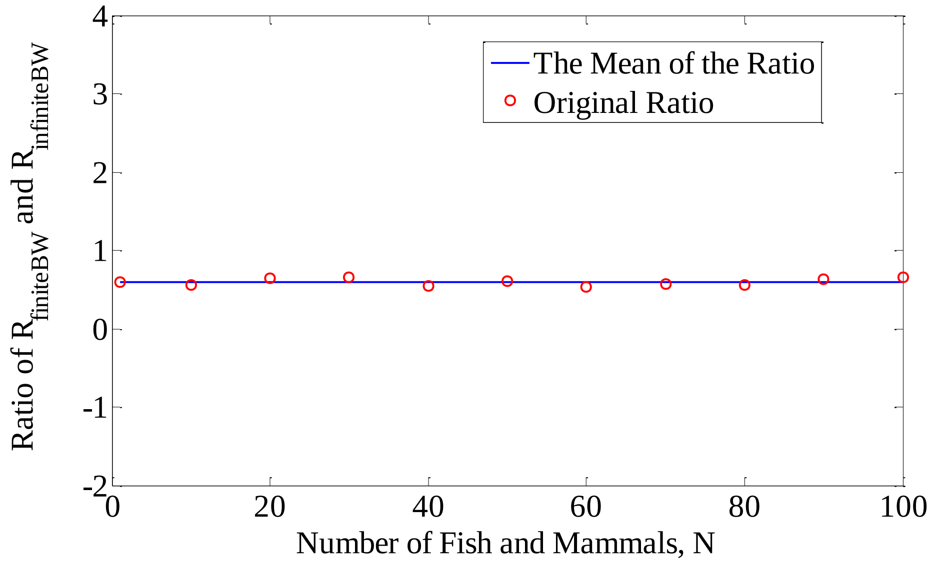


Fig. 5.1 Ratio of $R_{finiteBW}$ and $R_{infiniteBW}$ with respect to population size, N for chirp signal

Now, for chirp signal of fish and mammals, multiplying theoretical infinite bandwidth $R_{infiniteBW}$ by this mean gives the theoretical approximation of finite bandwidth $R_{finiteBW}$ as bellow:

$$R_{finiteBW} = 0.59512 \times \sqrt{\frac{b-1}{N}} \tag{5.1}$$

$$N_{chirp} = \left(\frac{0.59512}{R_{finiteBW}}\right)^2 \times (b-1) \tag{5.2}$$

The result is illustrated in Fig. 5.2.

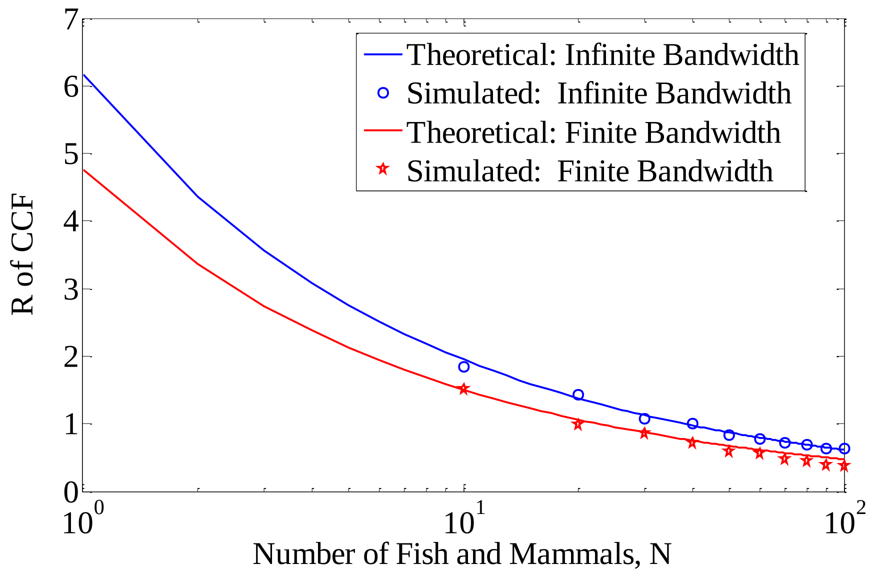


Fig. 5.2 *R* of CCF versus *N* plot (x log and y normal scale) for finite (5 kHz) and infinite bandwidth case with *b* =39 (d_{DBS} =0.5m and S_R =60 kSa/s) for chirp signal.

Similarly, for grunt signal of fish and mammals,

$$R_{finiteBW} = 0.55245 \times \sqrt{\frac{b-1}{N}} \tag{5.3}$$

$$N_{grunt} = \left(\frac{0.55245}{R_{finiteBW}}\right)^2 \times (b-1) \tag{5.4}$$

Thus, the result is illustrated in Fig. 5.3.

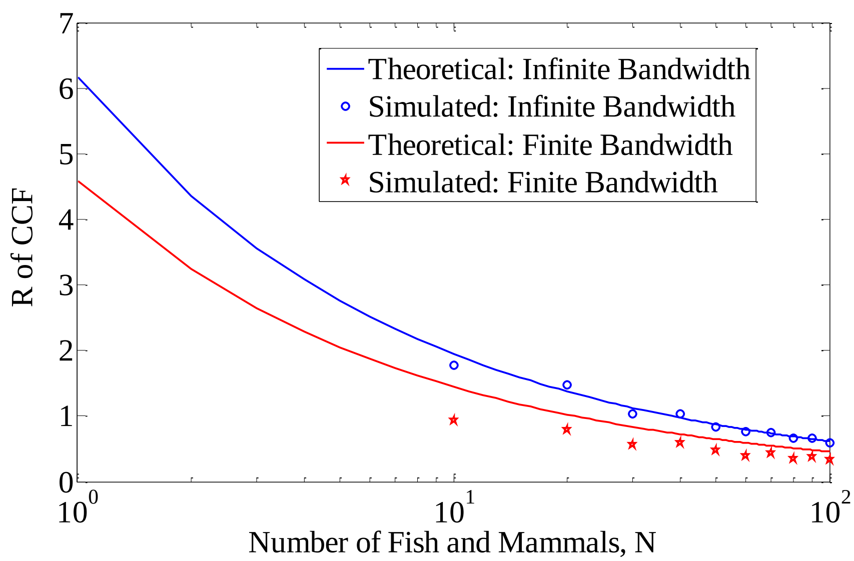


Fig. 5.3 *R* of CCF versus *N* plot (x log and y normal scale) for finite (5 kHz) and infinite bandwidth case with *b* =39 (d_{DBS} = 0.5m and S_R = 60 kSa/s) for grunt signal.

Because of limited underwater bandwidth, cross-correlation of fish signals results in sinc functions [2] in lieu of delta functions, which corrupts the CCF and so $R_{infiniteBW}$. So, scaling is a must to obtain exact population size from the proposed method. Similarly, degrading in estimated fish population occurred due to lower SNR in the estimation area. However, the scaling factor is independent of *b*, which is also a finding in this research.

5.3 Impact of SNR

Although the effect of noise in the proposed population estimation technique will be similar for all sorts of noise (assuming AWGN), the noise strengths be different. Here, the impact of SNR is discussed for internal noise of a receiver. In our proposed estimation technique, SNR is used as the ratio of voltage levels of signal and noise. Let us consider, an acoustic signal received by two noisy acoustic sensors as:

$$f_1(t) = S_1(t) + S_{n1}(t), \tag{5.5}$$

$$f_2(t) = S_2(t) + S_{n2}(t), \tag{5.6}$$

where $S_1(t)$ is the delayed version of the signal transmitted from a fish/mammal to acoustic sensor 1, $S_2(t)$ is the delayed version of the signal transmitted from the same fish/mammal to acoustic sensor 2, $Sn_1(t)$ is the internal noise received in acoustic sensor 1, and $Sn_2(t)$ the internal noise received in acoustic sensor 2. Then the CCF, $C(\tau)$ is [3]:

$$C(\tau) = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} f_1(t) f_2(t-\tau)dt$$

$$= \lim_{T\to\infty} \begin{bmatrix} \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_1(t)S_2(t-\tau)dt + \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_1(t)S_{n2}(t-\tau)dt \\ + \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_{n1}(t)S_2(t-\tau)dt + \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_{n1}(t)S_{n2}(t-\tau)dt \end{bmatrix}$$

$$= C_{S_1S_2}(\tau) + C_{S_1S_{n2}}(\tau) + C_{S_{n1}S_2}(\tau) + C_{S_{n1}S_{n2}}(\tau)C(\tau) = \lim_{T\to\infty} \frac{1}{2T}\int_{-T}^{T} f_1(t) f_2(t-\tau)dt$$

$$= \lim_{T\to\infty} \begin{bmatrix} \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_1(t)S_2(t-\tau)dt + \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_1(t)S_{n2}(t-\tau)dt \\ + \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_{n1}(t)S_2(t-\tau)dt + \dfrac{1}{2T}\displaystyle\int_{-T}^{T} S_{n1}(t)S_{n2}(t-\tau)dt \end{bmatrix}$$

$$= C_{S_1S_2}(\tau) + C_{S_1S_{n2}}(\tau) + C_{S_{n1}S_2}(\tau) + C_{S_{n1}S_{n2}}(\tau), \tag{5.7}$$

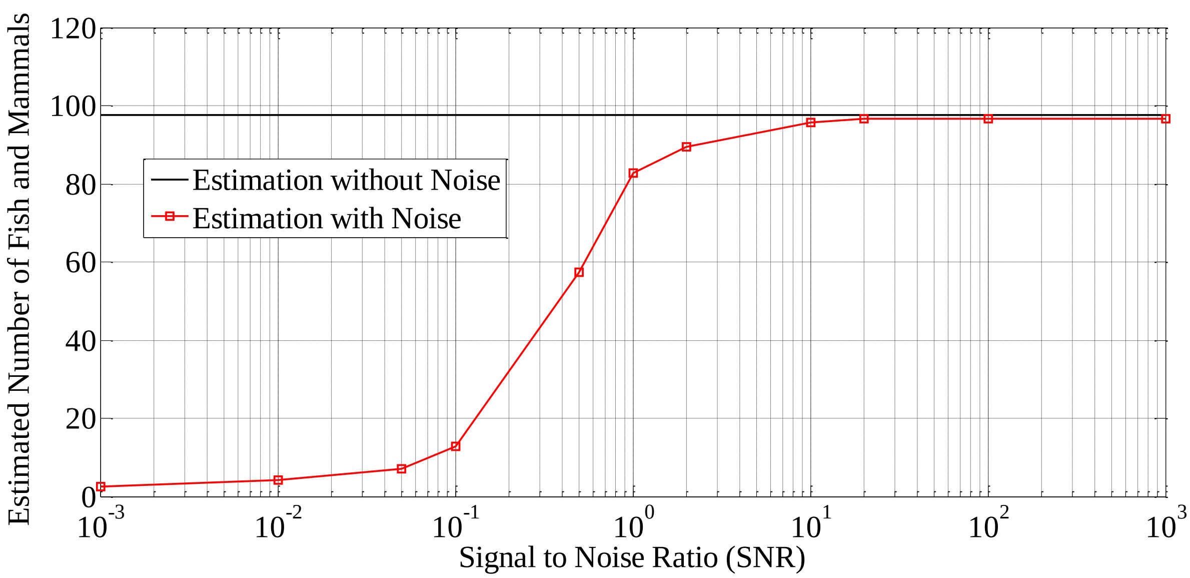
where, $C_{S_1S_2}(\tau)$ is the CCF of $S_1(t)$ with $S_2(t)$, $C_{S_1S_{n2}}(\tau)$ is the CCF of $S_1(t)$ with $Sn_2(t)$, $C_{S_{n1}S_2}(\tau)$ is the CCF of $Sn_1(t)$ with $S_2(t)$, $C_{S_{n1}S_{n2}}(\tau)$ is the CCF of $Sn_1(t)$ with $Sn_2(t)$, and, τ is the time delay in the cross-correlation process.

As S_1 (t) and Sn_2 (t), Sn_1 (t) and S_2 (t), Sn_1 (t) and Sn_2 (t) are independent random processes, their CCFs tend to be zero with the integration time extension and zero when the integration time is infinity. Thus, (5.7) becomes

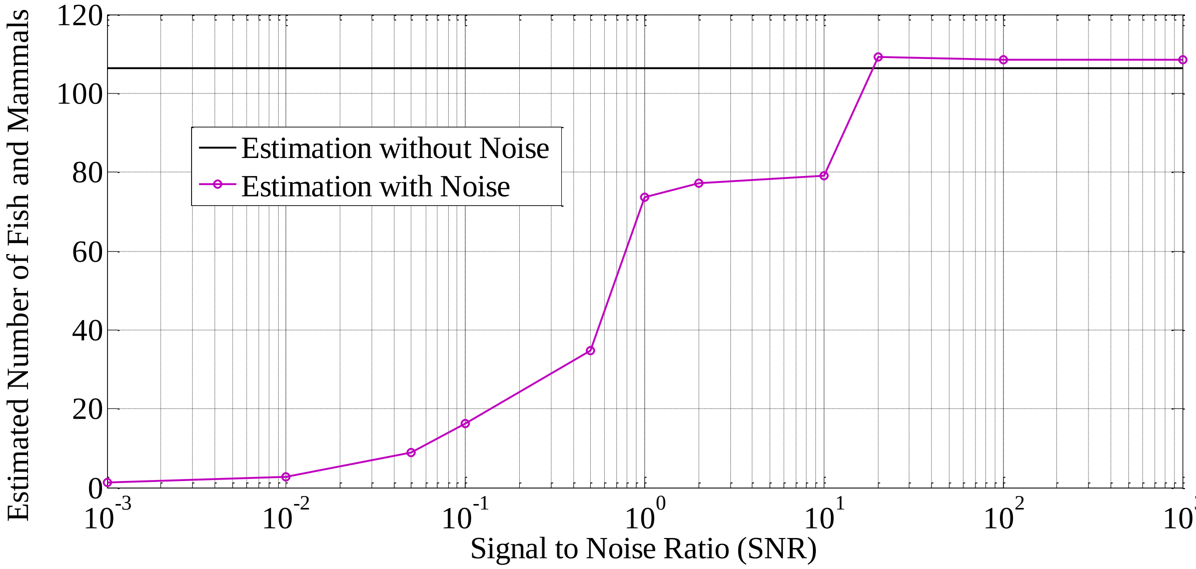
$$C(\tau) \approx C_{S_1S_2}(\tau) \tag{5.8}$$

But, as in practice, it is impossible to take an infinite time interval; it is interesting how the cross-correlation works with finite time integration.

However, to show the impact of SNR on the fish population estimation technique, the simulations are investigated by adding white Gaussian noise to the signals in the receivers. Sometimes it is converted to dB as for example, SNR=1 indicates 0 dB, SNR=10 indicate 20 dB. In this research, the internal noise of the acoustic sensors was added to the estimation process. Simulations are conducted for the variation of estimated population size of fish and mammals with respect to the variation of SNR. The simulation parameters were same as we have used in the basic estimation technique.



(a)



(b)

Fig. 5.4 SNR vs. estimated number of fish and mammals, (a) chirp signal and (b) grunt signal.

In Fig. 5.4, the *x* axis is taken in logarithmic scale, whereas the *y* axis is taken as normal scale. Figures 5.4(a) and 5.4(b) are plotted for chirp and grunt signals of fish and mammals, respectively, to show the impact of SNR on cross-correlation based fish population estimation technique. In Figs. 5.4(a) and 5.4(b), the black solid line represents the estimated population of fish and mammals for 100 fish and mammals without noise; whereas the red and purple lines with circles represent the estimated population of fish and mammals for similar 100 fish and mammals with different SNR. It can be seen from the Fig. 5.4 that, with the increase of SNR the estimation accuracy also increases. When the SNR is 20, the estimation begins to show the similar results as without noise case. The result remains nearly same with further increasing of SNR after the value of SNR = 20. Hence, we can say that SNR =20 or 26.02059 dB SNR is the optimum SNR in cross-correlation based passive acoustic technique of fish population estimation.

5.4 Impact of Doppler Effect

Due to Doppler Effect, there will be a slight variation in the propagation wavelength and, thus, in propagation delay, which can affect the placing of balls in the bins of the cross-correlation process and might lead to fractional-sample delays being created. However, fractional samples have no significant effect on estimation.

5.5 Chapter Summary

Though Doppler effect has a small impact, impact of underwater bandwidth and SNR are two key terms in cross-correlation based fish population estimation technique. Limited underwater acoustic channel bandwidth creates an impediment to utilize infinite band fish signals. Hence, scaling with proper scaling factor is a mandatory task to estimate an accurate population size using cross-correlation based fish population estimation technique. Similarly, proper fish population estimation requires a better SNR. With the decrease of SNR, the estimation performance also decreases. So, an appropriate SNR must be maintained. However, to estimate the fish population in practical cases using cross-correlation based fish population estimation technique; these findings will benefit the researchers.

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CHAPTER VI

CONCLUSION AND FUTURE DIRECTION

Because of various drawbacks of conventional techniques, in this thesis, a cross-correlation based fish population estimation technique is proposed, which can solve the major problems of conventional ones. But, implantation of this technique in practice is challenging. Different factors affect the estimation performance. The objective of this thesis is to build a framework to implement cross-correlation based fish population estimation technique. We have not only proposed the framework but also analyzed its performance with respect to different fish acoustics, different number of sensors, and different distributions of fish and mammals. We have carried an investigation to select the optimum estimation parameter. We have also analyzed different practical impacts, i.e., underwater bandwidth, SNR, and Doppler Effect, which will assist the researchers during its implementation at practical situations.

6.1 Summary and Discussion

With the thesis, a comprehensive framework is built, which can estimate population size of fish and mammals by eradicating the limitations of conventional methods. In this thesis, an elaborate description on different types of conventional fish population estimation technique is illustrated. Their benefits and limitations with respect to our proposed technique is the focus of chapter 2. A sophisticated description on fish acoustics is the cardinal goal of chapter 3. However, we have generated different fish acoustics using MATLAB, which are the main items for simulations in chapter 4. The main findings of this thesis are:

(a) Cross-correlation based fish population estimation technique can overcome the major limitations of conventional techniques.
(b) In the proposed technique, with the increasing of CCFs the estimation performance is growing better.
(c) So, an increasing number of acoustic sensors provide better results in this technique.

(d) Among different fish acoustics, chirp signal can produce more accurate results.
(e) Among the three fish distributions, i.e., Exponential, Normal, and Rayleigh, Exponential distribution of fish and mammals can produce better results.
(f) Limited underwater bandwidth affects the estimation. A scaling can solve it.
(g) With the decrease of SNR, the performance of estimation also decreases. So, increase of SNR is a must. We have found that the optimum SNR is 20.
(h) Doppler Effect has not any significant impact on this statistical method.

6.1.1 Limitations

The research has some limitations, like:

(a) Negligence of multipath interference
(b) Assuming the delays to be integer
(c) Consideration of a negligible amount of power difference among the fish acoustics
(d) Consideration of acoustic sensors to be laid at the middle of the estimation area

6.2 Future Directions

Some assumptions are considered in this thesis, such as the center placement of acoustic sensors, equal distance between acoustic sensors, insufficient CCFs for better performance etc. We also have considered three types of acoustics of fish and mammals, where the acoustics types can be more. Some future directions are given bellow for the future researchers.

6.2.1 Random Placement of Acoustic Sensors

In this thesis, we have considered the acoustic sensors are placed in the middle of the assumed estimation area. But, in practice, the acoustics sensors position can be random for two reasons.

(a) The fish and mammals randomly change their positions and hence distributions.
(b) The acoustic sensors position can be random to track the fish population

However, such randomly placement of acoustic sensors might affect CCF and hence the estimation performance.

6.2.2 Unequal Distance Between Acoustic Sensors

In our research, we have considered equal distance between the sensors for both two and three acoustic sensors cases. An unequal distance between the acoustic sensors can be occurred in practice due to necessities. These types of distance affect the CCF and thus estimation performance. Investigation on it can be a goal of the future researchers.

6.2.3 Estimation with *N* Number of Acoustic Sensors

In this thesis, we have worked with two and three acoustic sensors cases. We have found that the increasing number of acoustic sensors produce a better result. If we take N number of sensors then this will give N-1 number of CCFs. The more number of CCFs, the more accuracy will be provided for the estimation process. So, the estimation performance becomes more accurate. However, implementation of increasing number of acoustic sensors is costly.

6.2.4 Estimation with More Acoustics of Fish and Mammals

In this thesis, we have considered three types of acoustic signals of fish and mammals for two sensor cases and one type for three sensors case, pop, hoot, whistle etc. are different sound types, which can be implemented in future. Those implementations must consider the frequency of those signals when using the proposed technique.

6.2.5 Impact of Multipath

The impact of multipath is a significant case for the proposed estimation technique. To reach the acoustics from fish to acoustic sensors, it must face multipath phenomenon in practical cases. This affects the estimation performance. This can be another goal of research.

LIST OF PUBLICATIONS

International Journals:

Published:

[1] **Hossain, S. A.**, Hossen, M., & Anower, S. (2018). Estimation of damselfish biomass using an acoustic signal processing technique. *Journal of Ocean Technology*, *13*(2).

[2] **Hossain, S. A**., Hossen, M. (2018). Abundance Estimation from Different Distributions of Damselfish Using Cross-correlation Technique with Three Acoustic Sensors in Line. *Journal of Acoustical Society of New Zealand*, *31*(3).

[3] **S. A. Hossain**, M. Hossen, Mallik, A. and Hasan, S. M. (2019) "A Technical Review on Fish Population Estimation Techniques: Non Acoustic and Acoustic Approaches", *Akustika*, *31*, March.

Submitted:

[1] **Hossain, S. A.**, Hossen, M. (2018). Statistically Processing of Different Fish Acoustics with Two Acoustic Sensors to Estimate Fish Population of Vocalizing Fish and Mammals. Under Peer Review in the *Marine Technology Society Journal*

[2] **Hossain, S. A.**, Hossen, M. (2018). Selection of Optimum Estimation Parameter in Cross-correlation Based Fish Population Estimation Technique. Under Peer Review in the *Canadian Acoustics*.

[3] **Hossain, S. A.**, Hossen, M. (2018). Impact of Underwater Bandwidth and SNR on Cross-correlation Based Fish Population Estimation Technique. Under Peer Review in the *Archives of Acoustics.*

International Conference:

Hossain, S. A., Hossen, M. (2018). Biomass Estimation of a Popular Aquarium Fish Using an Acoustic Signal Processing Technique with Three Acoustic Sensors. *Proc. of Int. Conf. on Advancement in Electrical and Electronic Engineering*, Bangladesh.