A

Report

On

Effective Detection Model for Passive Sonar Simulator

By

Sanskar Soni

Acknowledgments

I would also like to express my gratitude to all those people whose efforts have made possible our professional experience at Maritime Research Centre, Pune a success even in this remote work from home mode.

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Abstract

To predict the detection range of passive sonar in different detection probability, the sonar equation is used as the logical basis. The underwater acoustic channel transmission characteristic curves are given in combination with a specific marine environment. Then, the influence of the passive sonar detection range under the typical detection probability is obtained. The study provides quantitative information for the tactical decision-making of ship commanders and provides theoretical support for the effective use of sonar equipment. The tropical littoral waters of the Indian Ocean Region (IOR) and the South China Sea (SCS) present incredibly unique challenges for any sonar operator. In the proposed Passive Sonar Simulator (PSS), we will attempt to address the challenges and opportunities of undersea deployments from an operational perspective.

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Introduction

Sonar detection range is one of the most important indexes to investigate the performance of sonar equipment. The prediction of sonar action range plays a vital role in mastering sonar detection performance and improving the probability of target detection. The primary function of passive sonar is to detect a target in the context of ambient noise in the background and transmission loss related to underwater sound propagation. The sonar performance model quantifies sonar performance in effective detection by careful and detailed analysis of terms associated with the passive sonar equation. Representation of transmission loss curve, low-frequency environment noise mapping curve solution,3D mapping of radiated noise, and receiver operating characteristic (ROC) using complex mathematical calculations Models are essential for effective use of sonar and help us visualize and solve real-world problems. With support receiver operating characteristics (ROC) for different values of SNR (signal to noise ratio), detection threshold (DT), and studying existing models and techniques for path loss, the effective range can be calculated. The detected range can therefore be used to search or monitor any area of interest in the ocean and provide theoretical support for the effective use of sonar equipment. Range in terms of passive sonar states that according to detection probability and false alarm probability, how efficiently passive sonar can work and how much area can it cover given the detection probability and false alarm probability. The Probability of Detection (Pd) is the probability of making a correct 'signal present' decision. It is the probability of saying that a "1" event is true, given that a "1" event occurred. The probability of False Alarm (Pfa) is the probability of making an incorrect 'signal present' decision. It is the probability of saying that event "1" is true given that event "0" occurred. We are solving a problem that can play a significant role in developing passive sonar simulation, which can help the government and corporate sector and can help develop all the maritime domains. The detection range against a submarine is a crucial parameter in the planning and executing a strategy and tactics of anti-submarine warfare (ASW) operations, and precise information about the performance characteristics of submarines, such as the amount of noise they produce, is not available in unclassified sources. This can be a key benefit because it certainly increases the effective search area, and it can work efficiently at better locations. The deployment certainly depends upon the range of passive sonar so that we can easily cover our reason of interest and give valuable insights.

Sonar

Sonar (sound navigation and ranging) is a technique that uses sound propagation (usually underwater, as in submarine navigation) to navigate, measure distances (ranging), communicate with or detect objects on or under the surface of the water, such as other vessels. Two types of technology share the name "sonar": passive sonar is essentially listening for the sound made by vessels; active sonar is emitting pulses of sounds and listening for echoes. Sonar may be used as a means of acoustic location and of measurement of the echo characteristics of "targets" in the water.

Active Sonar

Active sonar uses a sound transmitter (or projector) and a receiver. When the two are in the same place it is monostatic operation. When the transmitter and receiver are separated it is bistatic operation. When more transmitters (or more receivers) are used, again spatially separated, it is multistatic operation. Most sonar is used monostatically with the same array often being used for transmission and reception. Active sonobuoy fields may be operated multistatically.Active sonar creates a pulse of sound, often called a "ping", and then listens for reflections (echo) of the pulse. This pulse of sound is created electronically using a sonar projector consisting of a signal generator, power amplifier and electro-acoustic transducer/array. A transducer is a device that can transmit and receive acoustic signals ("pings"). A beamformer is usually employed to concentrate the acoustic power into a beam, which may be swept to cover the required search angles. The electro-acoustic transducers are of the Tonpilz type, and their design may be optimized to achieve maximum efficiency over the widest bandwidth, to optimize performance of the overall system. Occasionally, the acoustic pulse may be created by other means, e.g., chemically using explosives, air guns or plasma sound sources.

Active Sonar Equation:

$$SL - 2TL + TS - (NL - AG) = DT$$

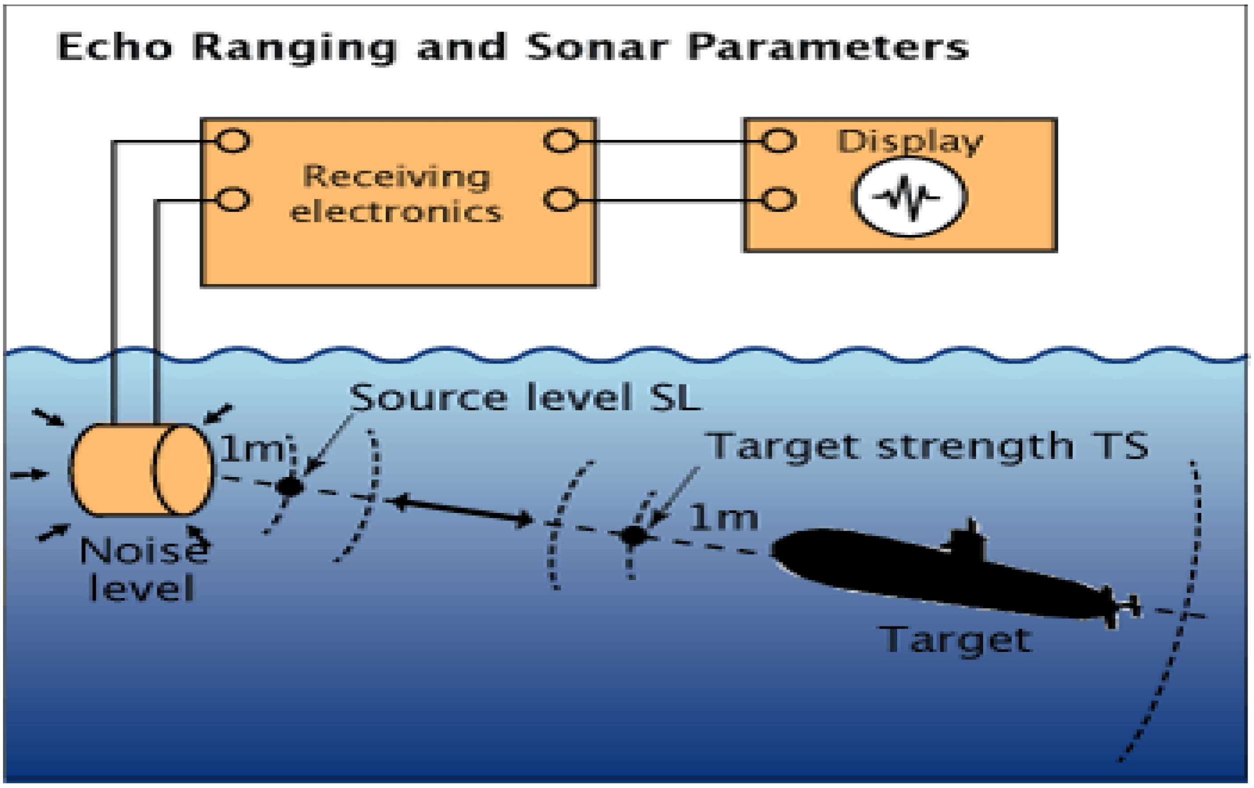
SL: Source Level

TL= Transmission Loss

NL = Noise Level

AG = Array Gain

TS= Target Strength DT = Detection Threshold



Passive Sonar

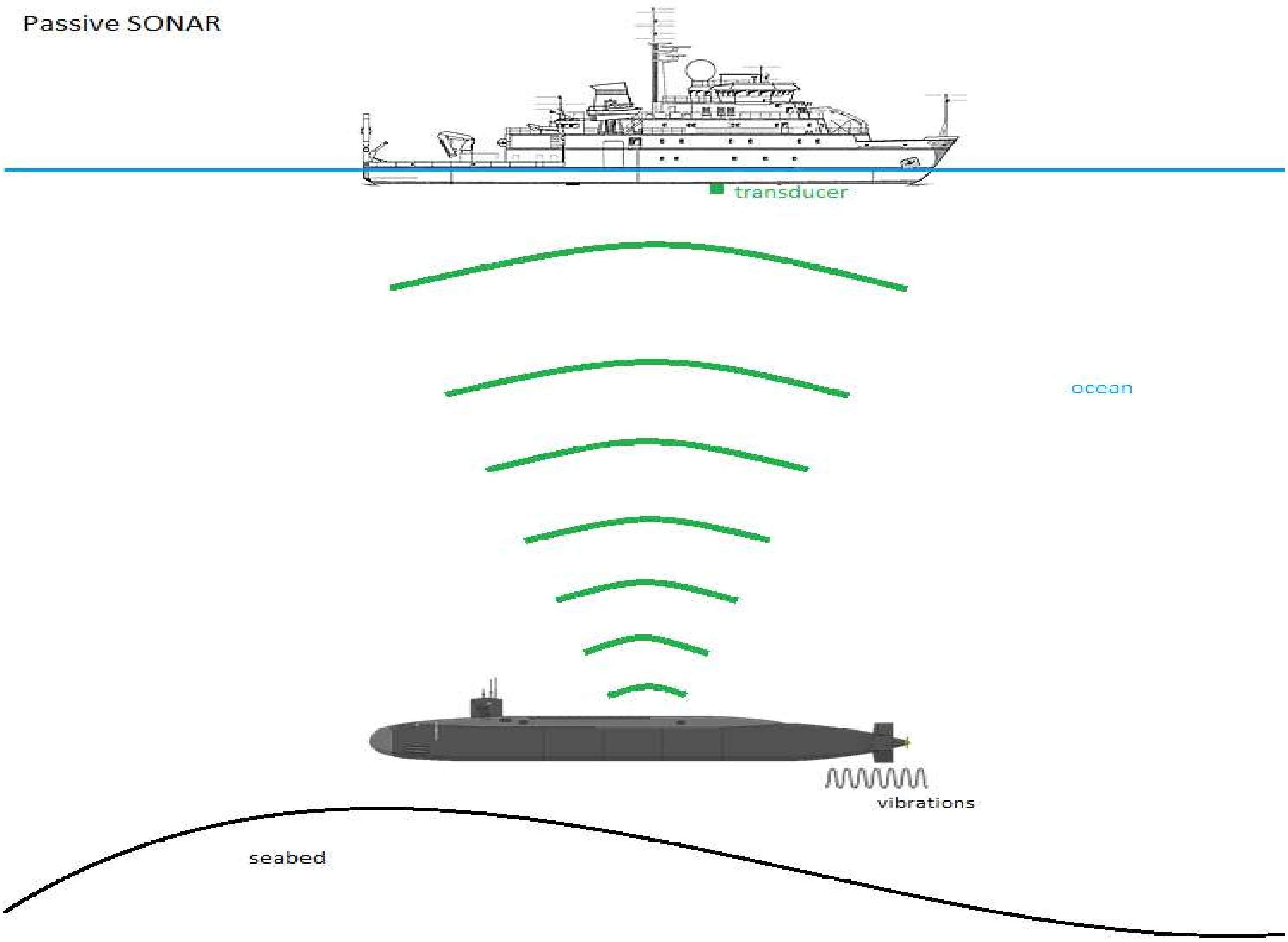
Passive sonar is a method for detecting acoustic signals in an underwater environment, usually the ocean. The difference between passive and active sonar is that a passive sonar system emits no signals; instead, its purpose is to detect the acoustic signals emanating from external sources. From an historical perspective, the main impetus for the research and development of passive sonar has been its military applications the acoustic detection of submarines. The pace of military research has abated in recent years, as the introduction of increasingly quiet submarines into service has shifted the focus to active sonar. However, new applications of passive sonar continue to appear; for example, a heightened awareness of environmental issues has spurred the development of passive techniques for detecting whales.

Unlike active sonar, only one-way propagation is involved. Because of the different signal processing used, the minimal detectable signal-to-noise ratio will be different. The equation for determining the performance of a passive sonar is

$$SL - TL = NL - AG + DT$$

where SL is the source level, PL is the propagation loss, NL is the noise level, AG is the array gain and DT is the detection threshold. The figure of merit of a passive sonar is

FOM = SL + AG − (NL + DT).



Sonar Equation

The “sonar equation” is a systematic way of estimating the expected signal-to-noise ratios for sonar (Sound Navigation and Ranging) systems. The signal-to-noise ratio determines whether a sonar will be able to detect a signal in the presence of background noise in the ocean. It considers the source level, sound spreading, sound absorption, reflection losses, ambient noise, and receiver characteristics. The sonar equation is used to estimate the expected signal-to-noise ratios for all types of sonar systems.

SNR

SNR or signal-to-noise ratio is the ratio between the desired information or the power of a signal and the undesired signal or the power of the background noise. SNR is a measurement parameter in use in the fields of science and engineering that compares the level of the desired signal to the level of background noise. In other words, SNR is the ratio of signal power to noise power, and its unit of expression is typically decibels (dB). Also, a ratio greater than 0 dB or higher than 1:1, signifies more signal than noise.

Signal-to-noise ratio is defined as the ratio of the power of a signal (meaningful input) to the power of background noise (meaningless or unwanted input):

$$\mathrm{SNR} = \frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}},$$

where P is average power. Both signal and noise power must be measured at the same or equivalent points in a system, and within the same system bandwidth.

Source Level

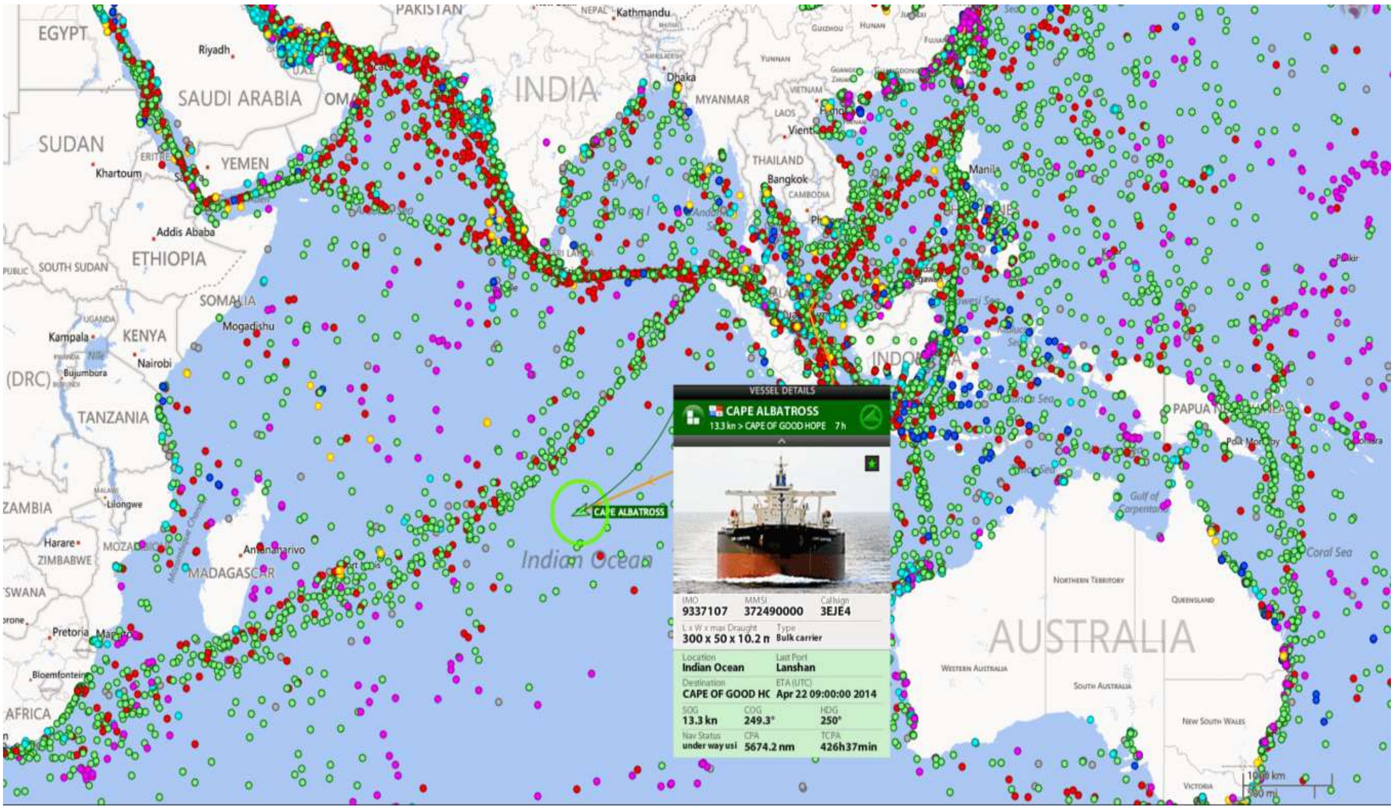
It is the amount of sound radiated by a sound source. It is defined as the intensity of the radiated sound at 1 meter from the source, where intensity is the amount of sound power transmitted through a unit area in a specified direction. Source level is given as a relative intensity in units named decibels (dB). In underwater sound, decibels are referenced to a pressure of 1 micro-Pascal (µPa). Therefore, source level is reported in units of dB re 1 µPa @ 1 m.

AIS

Among the numerous security regulations that came into effect after September 11, 2001, was the requirement for most commercial marine vessels to be fitted with Automatic Identification Systems (AIS). AIS provides a means for ships to electronically send data including vessel identification, position, speed, and course with Vessel Traffic Services (VTS) stations as well as with other ships. AIS uses Global Positioning Systems (GPS) in conjunction with shipboard sensors and digital VHF radio communication equipment to automatically exchange navigation information electronically. Vessel identifiers such as the vessel name and VHF call sign are programmed in during initial equipment installation and are included in the transmittal along with location information originating from the ship's global navigation satellite system receiver and gyrocompass. AIS is used by marine vessels in coordination with VTS to monitor vessel location and movement primarily for traffic management, collision avoidance, and other safety applications.

AIS transmitters send data every 2 to 10 seconds depending on a vessel's speed while underway, and every 3 minutes while vessels are at anchor. This data include:

C The vessel's Maritime Mobile Service Identity (MMSI) – a unique, nine-digit identification number; C Navigation status – "at anchor", "under way using engine(s)", or "not under command" C Rate of turn – right or left, 0 to 720 degrees per minute; C Speed over ground – 0 to 102 knots with 0.1 knot resolution; C Position accuracy; C Longitude and Latitude – to 1/10,000 minute (about 7 days); C Course over ground – relative to true north to 0.1 degree; C True Heading – 0 to 359 degrees from gyro compass; and C Time stamp – Coordinated Universal Time (UTC) time accurate to nearest second when this data was generated. In addition, the following data are broadcast every 6 minutes whether underway or at anchor: C International Maritime Organization's (IMO) ship identification number – a seven digit number that remains unchanged upon transfer of the ship's registration to another country; C International radio call sign, up to seven characters, assigned to the vessel by its country of registry; C Vessel Name – 20 characters to represent the name of the vessel; C Type of ship/cargo; C Dimensions of ship – to nearest meter; C Type of positioning system – such as GPS, Differential Global Positioning Systems (DGPS) or Long Range Navigation (LORAN) -C; C Location of positioning system's antenna onboard the vessel; C Draught of ship – 0.1 meter to 25.5 meters; C Destination – max 20 characters; and C Estimated time of arrival (ETA) at destination – UTC date hour: minute



Wittekind Model

The Wittekind model depends on:

- The displacement;
- The cavitation inception speed;
- A block coefficient as an indicator of wake field variations; (The block coefficient is the ratio of the displacement to length × breadth × draft of the ship).
- The mass of diesel engine(s); and
- A Boolean flag indicating resilient mounting of the diesel engine.

These parameters are combined to the three main factors of underwater propagated noise: low-frequency cavitation noise, denoted by F1, high-frequency cavitation noise denoted by F2, and diesel engine noise denoted by F3. Each of these factors should be considered as an averaged sound pressure level in one-third octave bands. The overall source level (SL) yields by the following equation:

$$SL = 10\log(10\frac{F_1}{10} + 10\frac{F_2}{10} + 10\frac{F_3}{10}).$$

a standard selection of center frequencies with one at 10 Hz is considered, then the rest of f can be yielded by the 1/3-octave ratio. The equation for F1 is obtained by a curve fitting to data from Arveson and Vendittis , and leads to:

$$F_1 = \sum_{n=0}^{5} c_n f^n + A(V, V_c, c_B) + B(D_T),$$

where Vc is the cavitation-inception speed, cB is the ship hull block coefficient, and the coefficient values ci are given in Table I. $A(V, V_c, c_B)$, $B(D_T)$ in model the scaling with speed and displacement respectively and are defined by:

$$A = 80\log_{10}(\frac{4c_B V}{V_c}), \qquad B = \frac{20}{3}\log_{10}\frac{D_T}{D_{T,ref}},$$

where DT, ref = 10000 t, is a reference displacement. Also, F1 is suitable for low frequencies below 400 Hz. For the high-frequency cavitation noise, F2, again a curve fitting is used based on databases [3], which yields:

$$F_2 = -5\ln f - \frac{1000}{f} + 10 + B(D_T) + C(V, V_c, c_B).$$

Table- I: Coefficients in the expression for F_1.

Coefficient	c_0	c_1	c_2	c_3	c_4	c_5
Value	125	0.35	-8×10^{-3}	6×10^{-5}	-2×10^{-7}	2.2×10^{-10}

$$C(V, V_c, c_B) = 60\log_{10}(\frac{1000c_B V}{V_c}).$$

Finally, for the engine noise F3, the following equation is defined

$$F_3 = 10^{-7} f^2 - 0.01 f + 140 + D(m, n) + E,$$

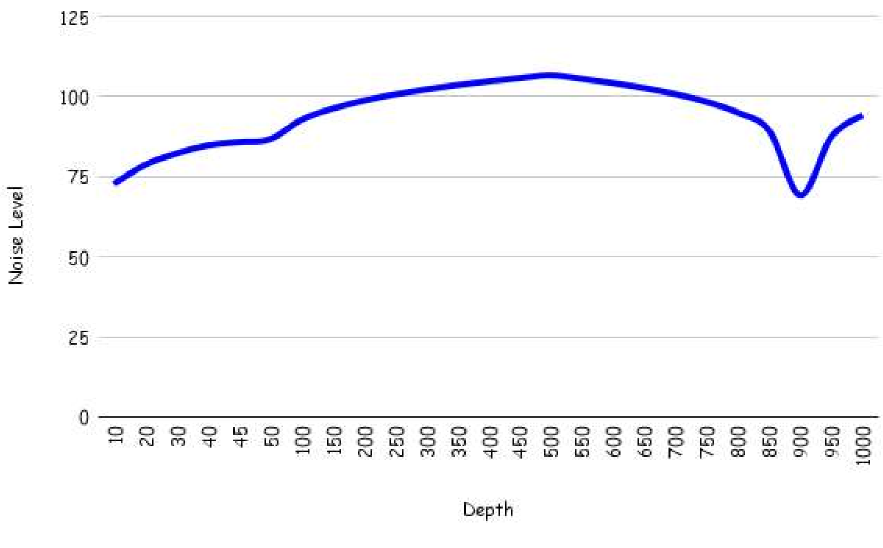
where D is a factor modeling the engine mass and the number of engines. Also, E = 0 indicates that the engine is resiliently mounted, and E= 15 indicates that the engine is rigidly mounted. Finally,

$$D(m, n) = 15\times\log(m) + 20\times\log(n),$$

where, m is the engine mass in tons, and n is equal to the number of engines operating at the same time.

Noise Level

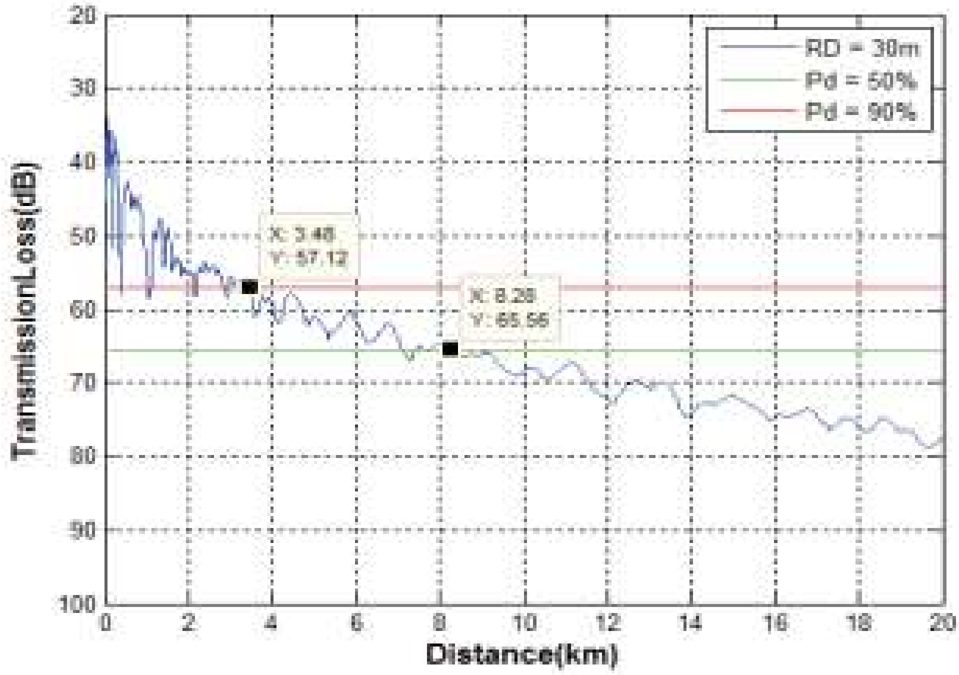
URN (Underwater Radiated Noise) represents a ship as an underwater noise source, expressing the radiated energy along frequency at a reference distance. An URN Pattern is a generic model, expressing ship URN along frequency, ship speed and size. The main objective here is to define improved models, for distinct categories of ships and use this in the development of SNR map and the sonar equation for the calculation of Detection range. Also, the purpose is to obtain an estimate of the source level (SL) of a ship, consistent with its use for the computation of noise maps in a maritime area of interest, allowing the assessment of the impact on marine life The global URN of a ship can be decomposed into three noise components (machinery, propeller, and cavitation), each component having a characteristic URN pattern with respects to frequency and speed. By fitting these characteristic patterns with experimental data, it is possible to derive URN models for different vessels present in the ocean The Noise Level (NL) is caused either by the Ambient noise present in the ocean due to distant shipping, biological noise made by underwater mammals etc. and the self-noise due to sonar platform itself in the context of propeller noise, the flow and machinery noise. Noise Level (NL) is broadband in nature. The Wittekind model requires some information data from AIS data as its input is used to find Noise Level. The low frequency ambient noise mapping from screen 1 will be used to map the noise level by performing linear interpolation for each receiver point.



Transmission Loss

Forecasting the transmission loss is the key to predicting the detection range of passive sonar. When the acoustic signal travels in the underwater acoustic channel, it is often distorted by the multipath effect and attenuated due to various loss mechanisms. Transmission loss is a standard measure of signal strength as a function of distance. In the field of hydroacoustic, acoustic propagation in the ocean is mathematically described by wave equations, and the parameters and boundary conditions of the wave equation are described by different marine environments. While the source can often be regarded as a point source, and the sound field of the point source satisfies the wave equation. Transmission Loss is primarily due to spreading and attenuation of sound signals while propagation and can be found out by channel modelling of underwater. Although the wave equation is simple in form, it has an analytical solution only under certain boundary conditions. To obtain a general solution, it is necessary to make certain assumptions about the wave equation, that is, to allow mathematical changes and simplifications of the wave equation under certain conditions. According to the different mathematical transformation forms used, it can be divided into four types: ray method, normal wave method, wave number integral method and parabolic equation method hod in this project the Transmission Loss curve solution is essential in finding the detection range of the working sonar. The core purpose is to obtain the relationship between the Transmission Loss and distance in accordance with the specified sound velocity profile and the seafloor acoustic parameters.

For this to happen, the real time sound velocity profile of the test sea area should be obtained by real-time measurement or model prediction; the second step would involve the acquisition or calculation of sea area environmental information, including the sea state, seafloor sediment, seabed topography, etc. This can be done through real-time measurement, database or inversion. The ocean model parameter information required by the underwater acoustic propagation model; secondly the largest target situation information is obtained or analyzed by using the measurement and positioning device, including the target depth, the receiving array depth and the like. Finally, according to the obtained environment and situation information, combined with the information of frequency band used, the transmission loss curve is calculated. In the solution of sonar detection range, the more concerned about the variation of transmission loss with distance under specific receiving depth conditions, namely the transmission loss curve, is shown in Figure, which represents the transmission loss curve for a particular situation as an example purpose.



SSP

Underwater acoustic propagation models rely on accurate environmental inputs to provide reliable predictions of transmission loss and reverberation level. One of the most critical environmental parameters in a propagation model is the vertical sound speed profile (SSP). Measurements of SSPs are ideally performed using a sound velocimeter or a conductivity-temperature-depth (CTD) profiler.

In the former case the SSP is measured directly while in latter case, the salinity, temperature, and depth can be used to accurately calculate the SSP. However, in practice SSPs are frequently measured using an expendable bathythermograph (XBT), which measures only temperature and requires the user to make assumptions about salinity to calculate the SSP. It is common to use several XBT profiles in conjunction with a single nearby profile acquired using an expendable sound velocimeter (XSV). When using XBTs and XSVs it is necessary to make some assumptions about the water column properties that may not be appropriate in all situations. The remainder of this document will explore some of the more common assumptions used and discuss how to determine when assumptions are appropriate

The speed of sound in seawater is a complicated function of temperature T, depth z, and salinity S. Depending on the specific situation, approximations to the full equation are adequate for acoustic propagation modelling. For example, in water depths of 1000 m (about 3280.84 ft (about 1 km)) or less, the following equation [1] can be used to calculate sound speed[1] : $c(T,S,z) = 1449.2+4.6T -0.055T2 +0.0029T3 +(1.34-0.01T)(S-35) +0.016z$ (1) where T is the temperature in ◦C, S is the dimensionless salinity (frequently quoted as Practical Salinity Units, or PSU), and z is the depth in m. From Equation 1 it is evident that the sound speed depends most strongly on T, with a weaker dependence on S and z.

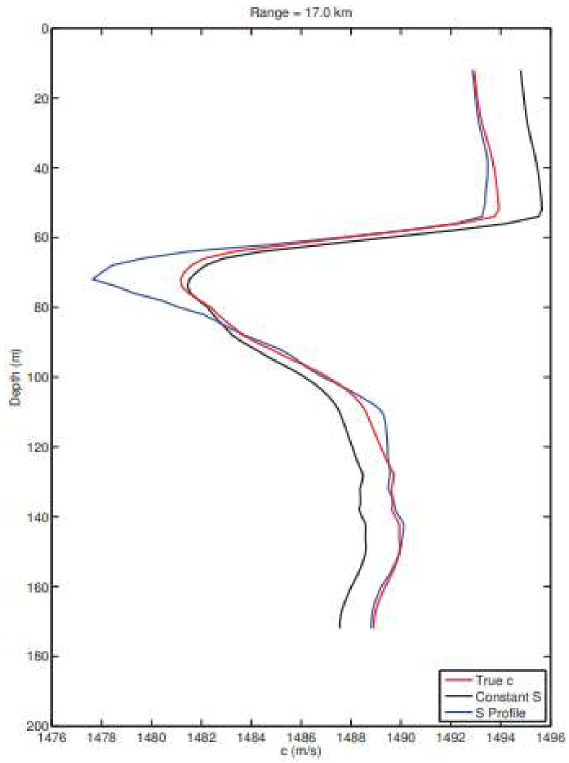
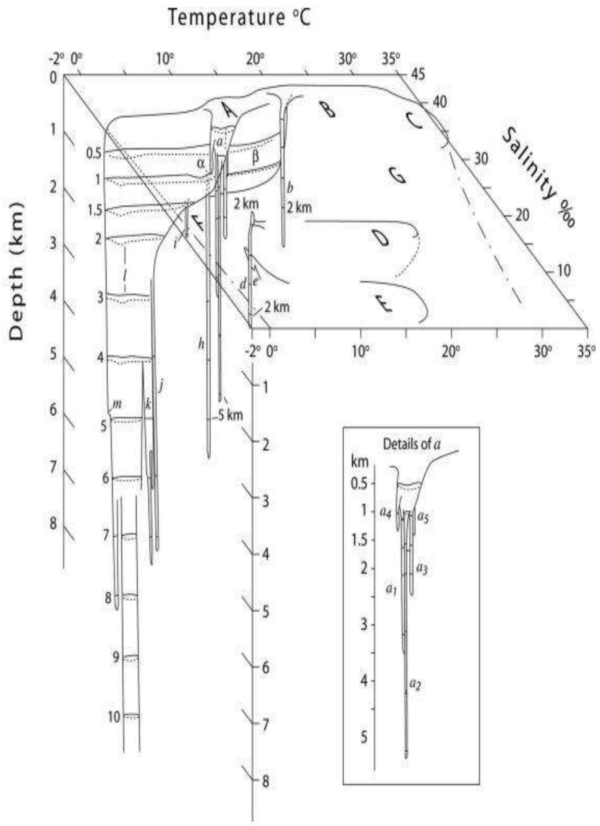
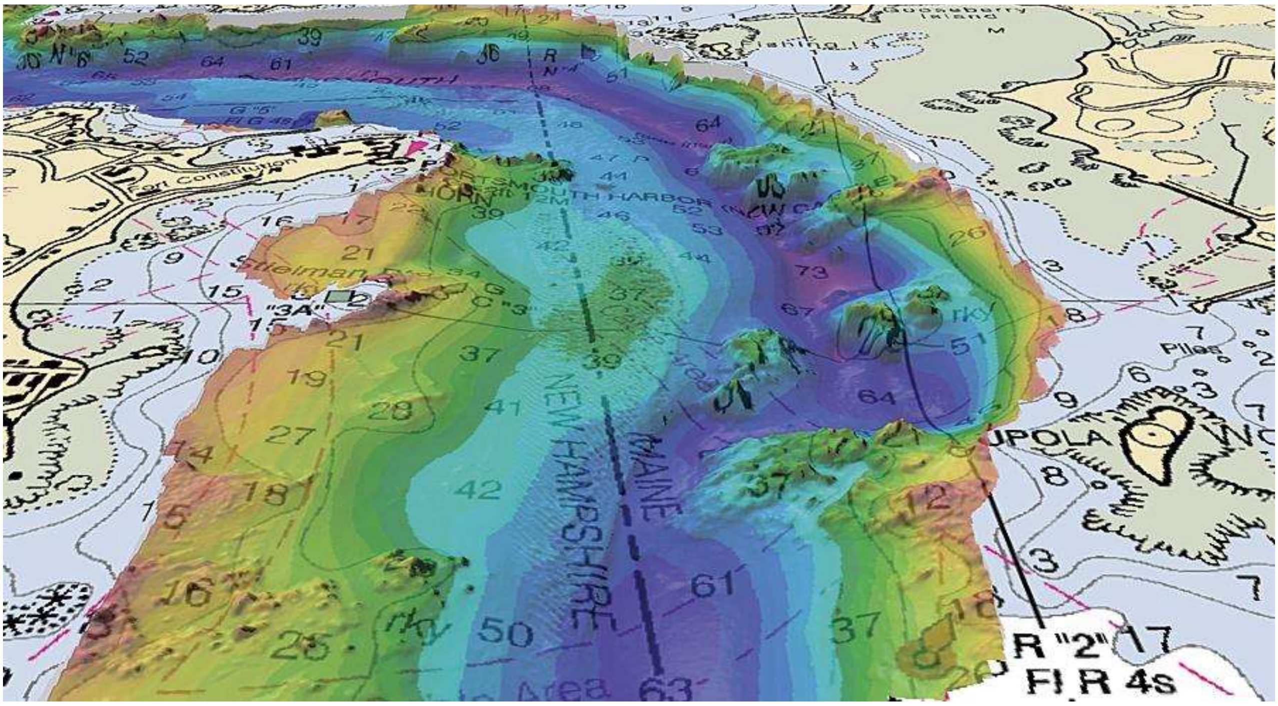


Figure 6: *SSPs for each scenario at a range of 17.0 km.*



Bathymetry Data

Bathymetry is the study of the "beds" or "floors" of water bodies, including the ocean, rivers, streams, and lakes. Bathymetry is the information that describes the topography of the seabed. It is an essential component in understanding the dynamics of the marine environment, both in terms of sediment transport but also in the prediction of tides, currents and waves. Safe ocean navigation relies on accurate bathymetry data, which are also essential for planning marine installations and infrastructure such as wind turbines, coastal defenses, oil platforms and pipelines. Bathymetry plays also a key role in the distribution of marine species. Overall bathymetry forms the foundation of any comprehensive marine dataset; without it, the picture is incomplete.



Array Gain

In array antenna systems, array gain is the measure of the improvement in signal-to-noise ratio (SNR) achieved by the array. It is calculated as the SNR of the array output signal divided by the SNR of the array input signal. Intuitively, the array gain is realized by the fact that the signal is coherently added from N array elements, while the noise is incoherently added from those same elements. If the noise is presumed to be uncorrelated the array gain is ≤ N, the number of array elements, and the array gain reduces to the inverse of the square of the 2-

norm of the array weight vector, under the assumption that the weight vector is normalized such that its sum is unity, so that

$$A = \frac{1}{\vec{w}^H \vec{w}}$$

For a uniformly weighted array (un-tapered such that all elements contribute equally), the array gain is equal to N.

Array gain is not the same thing as "gain," "power gain," "directive gain," or "directivity," but if the noise environment around the array is isotropic and the array input signal is from an isotropic radiator, then array gain is equal to gain defined in the usual way from the array beam pattern.

Effective Detection

Sonar detection range is one of the most important indexes to investigate the performance of sonar equipment. The prediction of sonar action range plays a vital role in mastering sonar detection performance and improving the probability of target detection. The primary function of passive sonar is to detect a target in the context of ambient noise in the background and transmission loss related to underwater sound propagation. The sonar performance model quantifies sonar performance in effective detection by careful and detailed analysis of terms associated with the passive sonar equation. Representation of transmission loss curve, low-frequency environment noise mapping curve solution,3D mapping of radiated noise, and receiver operating characteristic (ROC) using complex mathematical calculations Models are essential for effective use of sonar and help us visualize and solve real-world problems. With support receiver operating characteristics (ROC) for different values of SNR (signal to noise ratio), detection threshold (DT), and studying existing models and techniques for path loss, the effective range can be calculated. The detected range can therefore be used to search or monitor any area of interest in the ocean and provide theoretical support for the effective use of sonar equipment.

First we worked on getting source level for which I used the Wittekind model and feed the AIS data in it which gives me the source level for each vessel present in the region so from that we get the data of source level and then we took average of the source level which is the exact source level we are using for an given area or the region we are in or the AIS data we are feeding in the model .

```
def wittekind_model(f, V, Vc, Cb, Dt, m, n, E):
    Dt_ref = 10000
    Coeff = [125,0.35,-8*(10**-3),6*(10**-5),-2*(10**-7),2.2*(10**-10)]

    A = 80 * (math.log10(4*Cb*V/Vc))
    B = (20/3) * (math.log10(Dt/Dt_ref))
    C = 60 * (math.log10(1000*Cb*V/Vc))
    D = 15 * (math.log10(m)) + 10 * (math.log10(n))

    # SL1 represents the Low-Frequency Cavitation Noise
    SL1 = A + B
    for i in range(6):
        SL1 += Coeff[i] * (f**i)
    # SL2 represents the High-Frequency Cavitation Noise
    SL2 = -(5 * math.log2(f)) - (1000/f) + 10 + B + C
    # SL3 represents the Diesel Engine Noise
    SL3 = (10**-7) * (f**2) - 0.01*f + 140 + D + E

    if f >= 400:
        SL = 10* math.log10( 10**(SL2/10) + 10**(SL3/10))
    elif f<400 and SL1<=3082:
        SL = 10 * math.log10(10**(SL1/10) + 10**(SL2/10) + 10**(SL3/10))
    else:
        SL1 = 3082
        SL = 10 * math.log10(10**(SL1/10) + 10**(SL2/10) + 10**(SL3/10))


    return SL
```

Then we moved on to Noise level which is the most crucial factor we are dealing with because this is the extra noise, we are getting at a certain level which is the ambient noise which we get using subtracting source level with transmission loss occurred so we can get the data of noise level at a certain location using 2D ambient noise mapping. As we got the data, we used the NumPy interp function to predict the noise level at a certain depth.

For transmission loss there is a lot to cover on, first major thing is of the SSP which is the deciding factor in calculation of transmission loss accurately because this is what which has a possessive weight on it.

So, to calculate the ssp we used the salinity and temperature data we get from the official sources and used the described formula in earlier section to calculate the SSP data.

$$c(T,S,z) = 1449.2 + 4.6T - 0.055T^2 + 0.0029T^3 + (1.34 - 0.01T)(S - 35) + 0.016z$$

SALT			LONGITUDE			
TIME	DEPTH	LATITUDE	1	2	3	4
1	1	1	-1E+34	-1E+34	35.292	35.335
1	1	2	-1E+34	-1E+34	-1E+34	35.365
1	1	3	-1E+34	-1E+34	-1E+34	35.39
1	1	4	-1E+34	-1E+34	-1E+34	35.391
1	1	5	-1E+34	-1E+34	-1E+34	-1E+34
1	1	6	-1E+34	-1E+34	-1E+34	-1E+34
1	1	7	-1E+34	-1E+34	-1E+34	-1E+34
1	1	8	-1E+34	-1E+34	-1E+34	-1E+34
1	1	9	-1E+34	-1E+34	-1E+34	-1E+34
1	1	10	-1E+34	-1E+34	-1E+34	-1E+34
1	1	11	-1E+34	-1E+34	-1E+34	-1E+34
1	1	12	-1E+34	-1E+34	-1E+34	-1E+34
1	1	13	-1E+34	-1E+34	-1E+34	-1E+34
1	1	14	-1E+34	-1E+34	-1E+34	-1E+34
1	1	15	-1E+34	-1E+34	-1E+34	-1E+34
1	1	16	-1E+34	-1E+34	-1E+34	-1E+34
1	1	17	-1E+34	-1E+34	-1E+34	-1E+34

TEMP			LONGITUDE		
TIME	DEPTH	LATITUDE	1	2	3
1	1	1	-1E+34	-1E+34	25.751
1	1	2	-1E+34	-1E+34	-1E+34
1	1	3	-1E+34	-1E+34	-1E+34
1	1	4	-1E+34	-1E+34	-1E+34
1	1	5	-1E+34	-1E+34	-1E+34
1	1	6	-1E+34	-1E+34	-1E+34
1	1	7	-1E+34	-1E+34	-1E+34
1	1	8	-1E+34	-1E+34	-1E+34
1	1	9	-1E+34	-1E+34	-1E+34
1	1	10	-1E+34	-1E+34	-1E+34
1	1	11	-1E+34	-1E+34	-1E+34
1	1	12	-1E+34	-1E+34	-1E+34
1	1	13	-1E+34	-1E+34	-1E+34
1	1	14	-1E+34	-1E+34	-1E+34
1	1	15	-1E+34	-1E+34	-1E+34

As we are done with SSP we collected the bathymetry data and set up a grid for our required region of interest.

LATITUDE	LONGITUC	Noise	Dmax
-0.125	60.125		-4529
-0.125	60.375		-4569
-0.125	60.625		-4697
-0.125	60.875		-4739
-0.125	61.125		-4754
-0.125	61.375		-4354
-0.125	61.625		-4646
-0.125	61.875		-4220
-0.125	62.125		-4183
-0.125	62.375		-3710
-0.125	62.625		-4246
-0.125	62.875		-4167
-0.125	63.125		-4496
-0.125	63.375		-4737
-0.125	63.625		-4753
-0.125	63.875		-4923
-0.125	64.125		-4673
-0.125	64.375		-4277
-0.125	64.625		-4112

For detection threshold we took input from the user of snr and then using the Matlab function rocsnr(User must need to have Matlab on their system to use the software developed) we get the detection probability required to have the maximum effective range.

As we get closer to the calculation of variables we needed, we are jumping on to the calculation of effective detection range which is our main target.

So, to calculate the FOM we used the equation provided earlier and calculations.

$$FOM_{P_d} = SL + (AG - BW) - NL - DT_{P_d}$$

After we get the FOM we need to calculate the range from it so as we have the transmission loss and range data accordingly to the given location, we used gaussian process regression on the live data and using this model we predict the range for the given location .

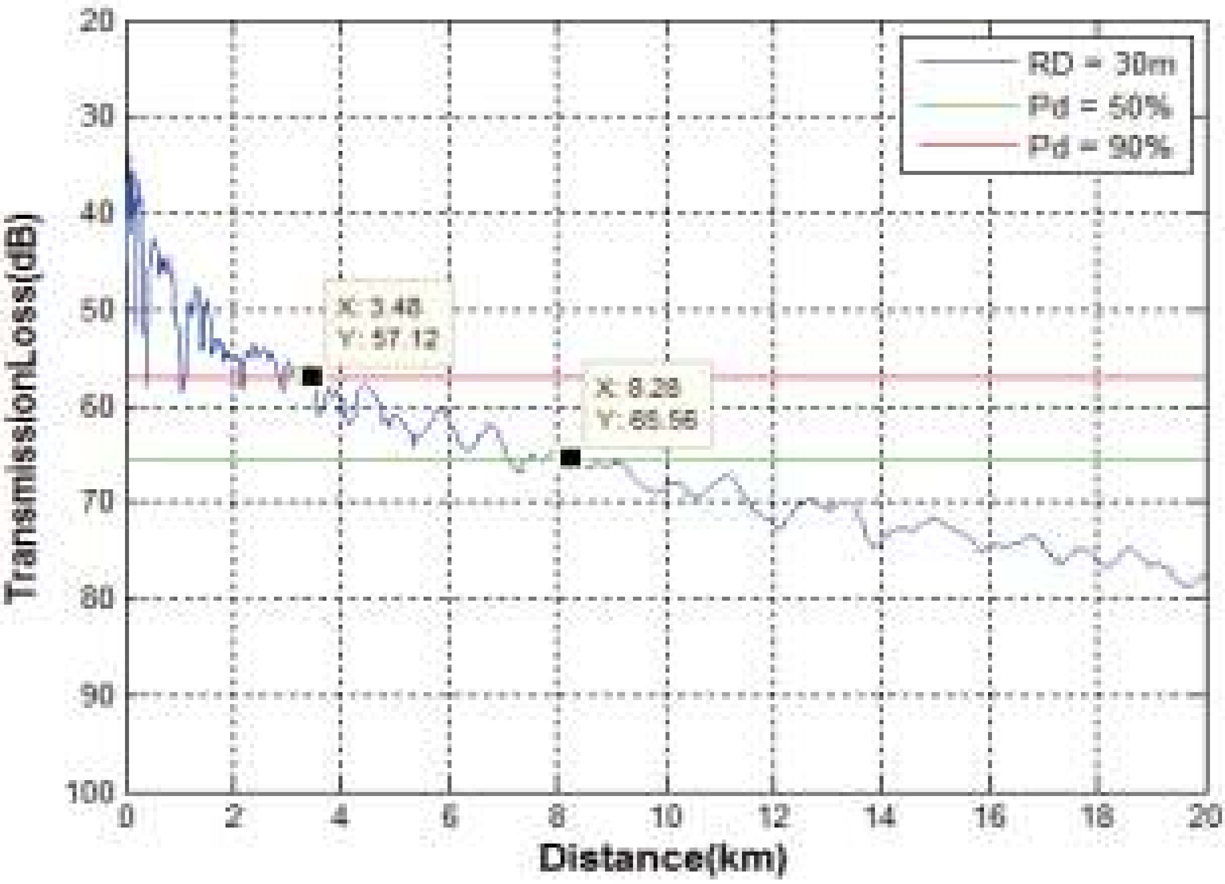


Figure 8. Relationship of Pd and sonar detective distance

Conclusion

With the constraint of passive sonar array gain and signal processing method, the relationship between the probability of detection and the passive sonar detection range is established using the ROC curves, the propagation characteristic curve, and the passive sonar equation. Numerical calculation analysis results show that the passive Sonar detection range will change significantly under different detection probability conditions. In addition, the method processing flow can also be applied to other environmental parameter changes, which can provide quantitative information for the ship commander's tactical decision and also provide a reasonable reference for the use of sonar equipment.

Path Ahead

Advancements in signal processing and oceanographic modelling

Work towards increasing sophisticated sonar performance prediction models predicting the fluctuations in the signal and background waveforms along with oceanographic features that cause them. Increasingly sophisticated sonar hardware and processing software, leading to a need for increasingly detailed modelling of linear or non-linear pressure and particle velocity fields; increasingly sophisticated knowledge and understanding of the oceanographic features responsible for fluctuations in both signal and background (surface waves, internal waves, multiscale seabed roughness, etc.); increasingly powerful computing facilities, leading to an increasing ability to model this detail, including closer integration of sonar models with oceanographic databases and ocean forecasting models

Autonomous Platforms

Autonomy in the working of autonomous vehicles and sonar platforms can be applied in the field of oceanic survey, marine archaeology, military reconnaissance to execute a designated task. A possible scenario involves a group of small autonomous platforms working together or separately to execute a designated task. Specific applications for such platforms might include —

Ocean survey: In this scenario the vehicles gather data independently, exchanging findings with any neighboring platforms within acoustic communication distance, and surfacing occasionally to upload data, recharge batteries, and perhaps receive new instructions. Applications requiring less development or software might consist of a seabed survey, monitoring of 26 gas exchange processes with the atmosphere for climate analysis and its prediction and modelling, and documentation and counting of protected species.

Military reconnaissance or marine archaeology: The vehicles rendezvous at a predetermined location and proper planning of any mission or specific task to be carried out to coordinate some covert measurements can be done successfully and with ease.

Effective deployment and vulnerability assessment

The vulnerability assessment is done by calculating the reverse SNR using the sonar equation. A reverse SNR map can be developed by considering and analyzing certain statistical models thus giving a closer look to the vulnerability aspect of any anti-submarine warfare. Various Quitting techniques can be used by studying the pattern of noise radiated by the submarines and deriving mechanisms and models to reduce the same. Effective deployment of sonar will take place where vulnerability of sonar is low, and the detection range is high. The effective deployment of any sonar takes into consideration 2 major factors 1st is the effective detection of target in the ocean thus achieving its primary goal. Along with this a comprehensive study of its own vulnerability by having primitive knowledge on the reverse SNR map can help in the effective deployment of sonar equipment in the ocean. Effective detection and SNR map act as crucial input and play a significant role in deciding this.

USE OF ARTIFICIAL NEURAL NETWORKS(ANN) FOR ESTIMATING SOUND SPEED PROFILE

Sound speed profile which is an input to the PE-RAM model is typically computed by traditional mathematical models. In the paper Jain, S., & Ali, M. M. (2006). Estimation of sound speed profiles using artificial neural networks. IEEE Geoscience and Remote Sensing Letters, 3(4), 467-470 discusses the following- Lack of direct observations of vertical profiles of velocimeters and/or temperature and salinity, from which sound speed can be calculated, limits specifications and investigation of temporal and spatial variabilities of the three-dimensional structure of the sound speed in the oceans. The parameters used in this study are net surface heat flux (NSHF), net radiation, sea surface wind stress (SSWS), dynamic height (DH), and vertical profiles of temperature and salinity. The vertical resolution of salinity is less compared with the temperature observations. We considered only 27 (6) depths, up to 250 m (about 820.21 ft), where temperature (salinity) measurements are available throughout. Due to these quality checks, we could not analyze SSPs during the entire months of February, August, and September 1995. Out of the total number of 8858 hourly observations, 5281 profiles have been used. We linearly interpolated salinity measurements to the temperature depths. Two types of DHs were calculated, namely, 1) using the temperature and interpolated salinity values (27 depths: DHI hereafter) and 2) using only the actual available salinity and corresponding temperature values (six depths: DHA hereafter). Page 31 of 38 In the paper cited above, The ANN-estimated SSPs had a root-mean-square error of 1.16 m/s and a coefficient of determination of 0.98. About 76% (93%) of the estimates lie within ±1 m/s (±2 m/s) of the SSPs obtained from in situ temperature and salinity profiles seems promising enough and more research can be ventured out in this direction.

INCLUDING NOISE FROM DARK SHIP DATA FOR ENHANCED ACCURACY

The noise from the dark ships can be included in the noise mapping for enhanced accuracy of the noise mapping. Although not much research is done on detecting the dark ships in the past, given the National Security concerns, it is slowly gaining pace. Detection of dark ships is first of all a herculean task. But once these dark ships are detected, and since these too contribute to the ambient noise, they can be included in the model for better accuracy. Sea surface analysis can be used for ship detection from optical satellite images can be away forward in this domain. In the paper by Yang, Guang, et al. "Ship detection from optical satellite images based on sea surface analysis." IEEE Geoscience and Remote Sensing Letters 11.3 (2013): 641-645, He discusses the following Ship detection from remote sensing images is essential for traffic monitor, maritime management and illegal fishing surveillance. Synthetic aperture radar (SAR) images are often adopted for ship detection as they are less influenced by weather conditions and time, and they can be utilized to estimate velocities of moving targets However, SAR images are usually with high-level speckles, insensitive to wood materials, and difficult for human interpretation. Therefore, high-resolution panchromatic satellite images have recently been employed for ship detection, as they can provide more detailed information for small target detection and ship recognition. Page 28 of 38 Ship candidate selection and false alarm (caused by sea waves, ship wakes, clouds, etc.) elimination are two key issues for ship detection in optical images. Several notable methods have been presented in recent literature. The method in selected ship candidates by morphological filtering and eliminated false candidates by wavelet analysis and Radon transform. Zhu et al. detected ships based on the SVM classifier with shape features and texture features, which could eliminate false alarms to some extent. Proia et al. assumed Gaussian distribution of the sea background density function and employed Bayesian decision theory to identify some small-sized ships. Inspired by human visual search, a multiscale and hierarchical method was proposed to detect ships with little computational time. These methods can achieve impressive results due to the robust ship descriptor and candidate classifier. However, ship appearance is not the only access for ship detection. The sea surface can provide more valuable information than the ship's appearance. The proposed method efficiently blocks out no-ship regions and automatically assigns weights to intensity and texture abnormality to bnormality to optimize detection performance. Compared with existing works, the proposed linear candidate selection function is more computational efficient. The experiments on panchromatic satellite images demonstrate that SDSSA not only outperforms the state-of-the-art methods on Recall, Precision recisionunning time but also is robust to some extreme cases (e.g., dark ships, low contrast, rough waves, ship wakes, and cloud coverage).

USE OF STATISTICAL CLASSIFIERS FOR TARGET DETECTION

Generally, in passive sonar, the targets are detected by sonar equation (with constant threshold) that increases the detection error in shallow water. This is a method for detecting targets in passive sonars using adaptive threshold. In this method, target signal (sound) is processed in time and frequency domain. For classifying, Bayesian classification is used, and posterior distribution is estimated by Maximum Likelihood Estimation algorithm. Finally, the target was detected by combining the detection points in both domains using Least Mean Square (LMS) adaptive filter. Results of this paper have shown that the proposed method has improved true detection rate by about 24% when compared other the best detection methods such as the LOFAR and DEMON analyses.

Appendix

Pyram

RAM is based on the split-step Pade solution, which allows broad range steps and is the most efficient PE algorithm that has been developed. Range dependence is handled accurately by applying an energy conservation correction as the acoustic parameters vary with range. An initial condition (or starting field) is constructed using self-starter, which is an accurate and efficient approach based on the PE method. It calculates solutions using 2D acoustic wave equation taking bathymetry, temperature, sediment, sound speed profile as inputs. The 2D acoustic wave equation is as follows

$$\frac{\delta^2 p}{\delta r^2} + \rho \frac{\delta}{\delta z}\left(\frac{1}{\rho}\frac{\delta p}{\delta z}\right) + k^2 p = 0$$

Parabolic form assumes forward energy dominates, and calculates solutions to the forward component of the wave equation

$$\frac{\delta \rho}{\delta r} = i k_0 (1 + X)^{\frac{1}{2}} p$$

Where,

$$k_0 = \frac{\omega}{v} \text{ and } X = k_0^{-2}(\rho \frac{\delta}{\delta z} \frac{1}{\rho} \frac{\delta}{\delta z} + k^2 - k_0^2)$$

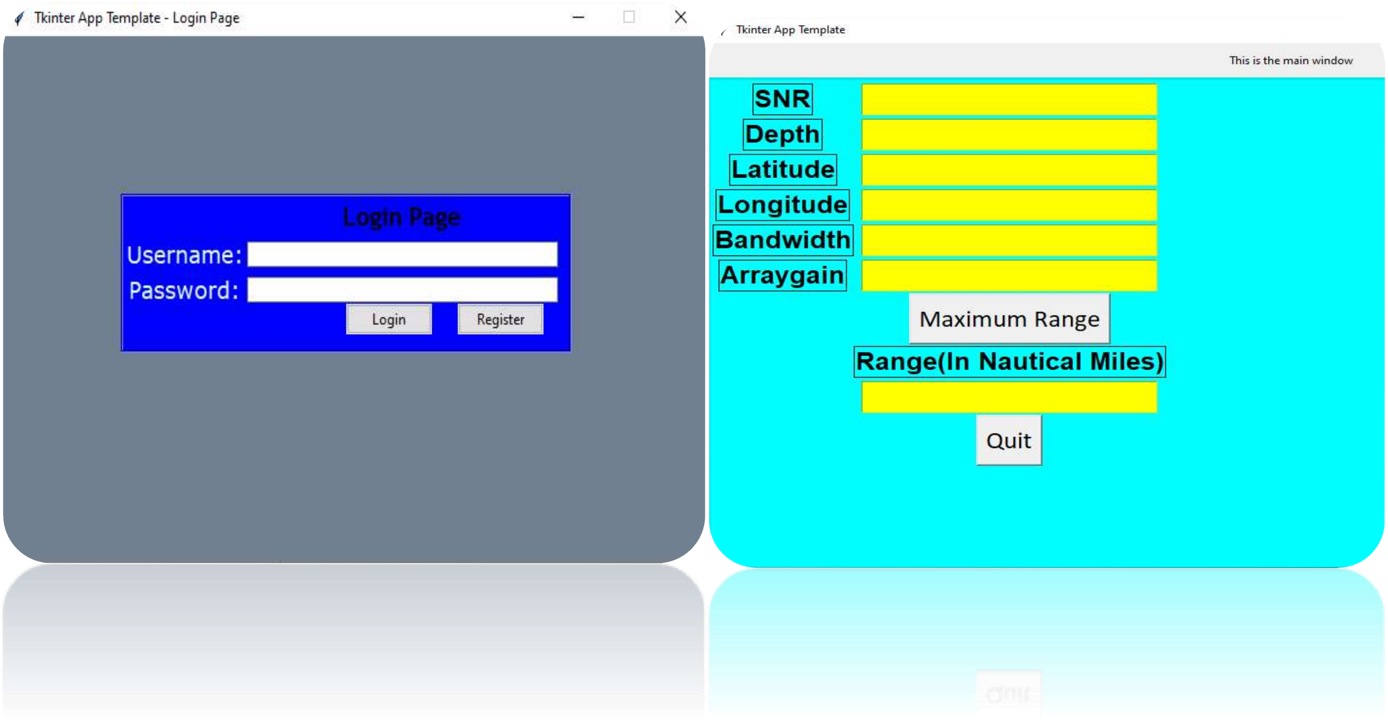
The purpose of PyRAM is to provide a version of RAM which can be used within a Python interpreter environment (e.g., Spyder or the Jupyter notebook) and is easier to understand, extend and integrate into other applications than the Fortran version. It is written in pure Python and achieves speeds comparable to native code by using the Numba library for JIT compilation.

The PyRAM class contains methods which correspond to the original Fortran subroutines and functions (including retaining the same names). The variable names are also mostly the same. However, some of the original code (e.g., subroutine zread) is unnecessary when the same purpose can be achieved using available Python library functions (e.g., from NumPy or SciPy) and has therefore been replaced.

A difference in functionality is that sound speed profile updates with range are decoupled from seabed parameter updates, which provides more flexibility in specifying the environment (e.g., if the data comes from different sources).

PyRAM also provides various conveniences, e.g., automatic calculation of range and depth steps (though these can be overridden using keyword arguments).

Tkinter



Tkinter is the standard GUI library for Python. Python when combined with Tkinter provides a fast and effortless way to create GUI applications. Tkinter provides a powerful object-oriented interface to the Tk GUI toolkit.

Creating a GUI application using Tkinter is an easy task. All you need to do is perform the following steps –

- Import the *Tkinter* module.
- Create the GUI application main window.
- Add one or more of the above-mentioned widgets to the GUI application.
- Enter the main event loop to act against each event triggered by the user.

ROC curve

A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of binary classifier system as its discrimination threshold is varied. The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at

various threshold settings. The true-positive rate is also known as sensitivity or probability of detection in machine learning. The false-positive rate is also known as probability of false alarm and can be calculated as (1 − specificity). It can also be thought of as a plot of the power as a function of the of the decision rule (when the performance is calculated from just a sample of the population, it can be thought of as estimators of these quantities). The ROC curve is thus the sensitivity or recall as a function of fall-out. In general, if the probability distributions for both detection and false alarm are known, the ROC curve can be generated by plotting the area under the probability distribution from to the discrimination threshold i.e., the cumulative distribution function of the detection probability in the y-axis versus the cumulative distribution function of the false-alarm probability on the x-axis. ROC analysis provides tools to select possibly optimal models and to discard suboptimal ones independently from (and prior to specifying) the cost context or the class distribution. ROC analysis is related in a direct and natural way to cost/benefit analysis of diagnostic decision making. The ROC curve was first developed by electrical engineers and radar engineers during World War II for detecting enemy objects in battlefields and was soon introduced to psychology to account for perceptual detection of stimuli. ROC analysis since then has been used in medicine, radiology, biometrics, forecasting of natural hazards, meteorology model performance assessment, and other areas for many decades and is increasingly used in machine learning and research. 30 The ROC is also known as a relative operating characteristic curve, because it is a comparison of two operating characteristics (TPR and FPR) as the criterion changes.

MATLAB Engine API

The MATLAB® Engine API for Python® provides a Python package named Matlab that enables you to call MATLAB functions from Python. You install the package once, and then you can call the engine in your current or future Python sessions. For help with installing or starting the engine, refer to:

Install MATLAB Engine API for Python

Start and Stop MATLAB Engine for Python

The Matlab package contains the following:

The MATLAB Engine API for Python

A set of MATLAB array classes in Python (see MATLAB Arrays as Python Variables)

The engine provides functions to call MATLAB, and the array classes provide functions to create MATLAB arrays as Python objects. You can create an engine and call MATLAB functions with Matlab. Engine. You can create MATLAB arrays in Python by calling constructors of an

array type (for example, Matlab. Double to create an array of doubles). MATLAB arrays can be input arguments to MATLAB functions called with the engine.

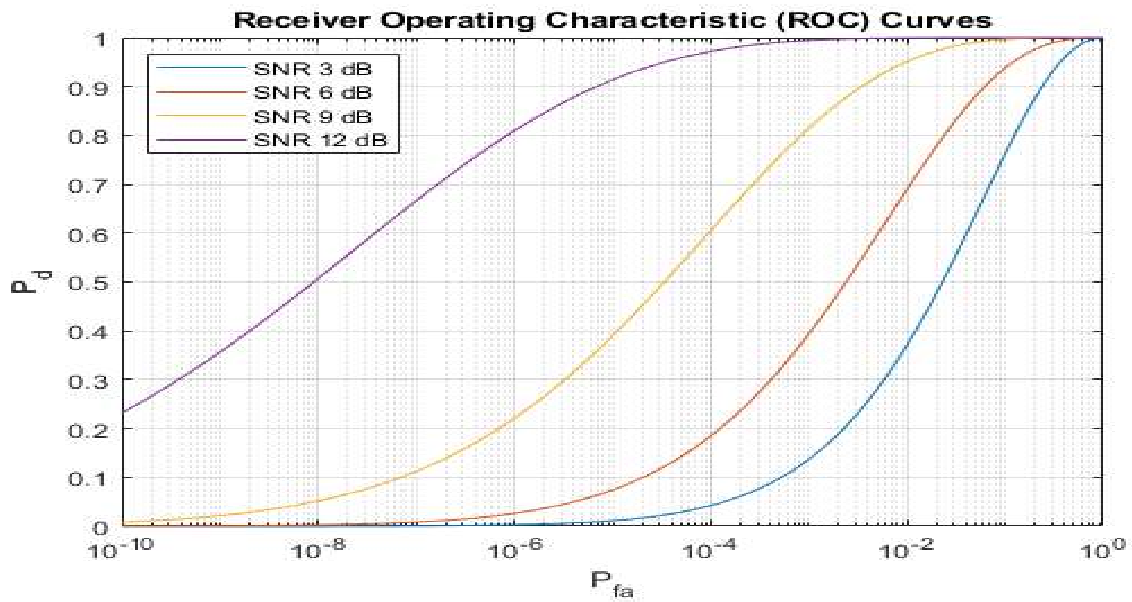
Rocsnr

[Pd,Pfa] = rocsnr(SNRdB) returns the single-pulse detection probabilities, Pd, and false-alarm probabilities, Pfa, for the SNRdB. By default, for each SNR, the detection probabilities are computed for 101 false-alarm probabilities between 1e–10 and 1. The false-alarm probabilities are logarithmically equally spaced. The ROC curve is constructed assuming a coherent receiver with a nonfluctuating target.

[Pd,Pfa] = rocsnr(SNRdB,Name,Value) returns detection probabilities and false-alarm probabilities with additional options specified by one or more Name,Value pair arguments.

rocsnr(...) plots the ROC curves.

```
SNRdB = [3 6 9 12];
[Pd,Pfa] = rocsnr(SNRdB,'SignalType','NonfluctuatingCoherent');
semilogx(Pfa,Pd)
grid on
xlabel('P_{fa}')
ylabel('P_d')
legend ('SNR 3 dB','SNR 6 dB','SNR 9 dB','SNR 12 dB',  'location','northwest')
title ('Receiver Operating Characteristic (ROC) Curves')
```



Detection Probability: Detection probabilities corresponding to the false-alarm probabilities. For each SNR in SNRdB, Pd contains one column of detection probabilities.

False alarm probability: False-alarm probabilities in a column vector. By default, the false-alarm probabilities are 101 logarithmically equally spaced values between 1e–10 and 1.

Gaussian Process Regression

Gaussian process regression (GPR) is a nonparametric, Bayesian approach to regression that is making waves in the area of machine learning. GPR has several benefits, working well on small datasets and having the ability to provide uncertainty measurements on predictions.

Unlike many popular supervised machine learning algorithms that learn exact values for every parameter in a function, the Bayesian approach infers a probability distribution over all possible values. Let us assume a linear function: y=wx+ϵ. How the Bayesian approach works is by specifying a prior distribution, p(w), on the parameter, w, and relocating probabilities based on evidence (i.e., observed data) using Bayes' Rule:

$$p(w|y,X) = \frac{p(y|X,w)p(w)}{p(y|X)}$$

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{marginal likelihood}}$$

The updated distribution *p(w|y, X)*, called the ***posterior distribution***, thus incorporates information from both the prior distribution and the dataset. To get predictions at unseen points of interest, *x**, the ***predictive distribution*** can be calculated by weighting all possible predictions by their calculated posterior distribution [1]:

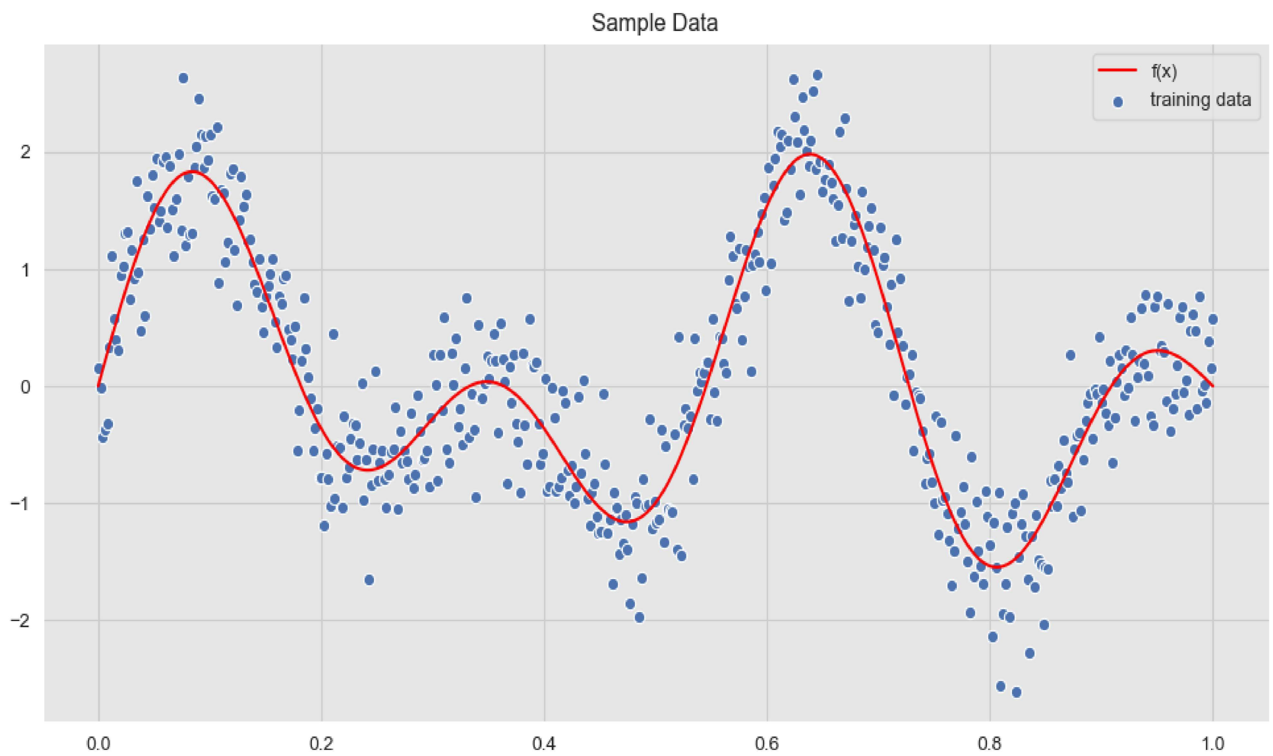
$$p(f^*|x^*,y,X) = \int_w p(f^*|x^*,w)p(w|y,X)dw$$

Gaussian process regression is nonparametric (i.e., not limited by a functional form), so rather than calculating the probability distribution of parameters of a specific function, GPR calculates the probability distribution over all admissible functions that fit the data. However, similar to the above, we specify a prior (on the function space), calculate the posterior using the training data, and compute the predictive posterior distribution on our points of interest.

In GPR, we first assume a ***Gaussian process prior***, which can be specified using a mean function, *m(x),* and covariance function, *k (x, x')*:

$$f(x) \sim GP(m(x), k(x, x'))$$

More specifically, a Gaussian process is like an infinite-dimensional multivariate Gaussian distribution, where any collection of the labels of the dataset are joint Gaussian distributed. Within this GP prior, we can incorporate prior knowledge about the space of functions through the selection of the mean and covariance functions. We can also easily incorporate independently, identically distributed (i.e.) Gaussian noise, $\epsilon \sim N(0, \sigma^2)$, to the labels by summing the label distribution and noise distribution.



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