MARITIME RESEARCH CENTER
FOUNDATION FOR UNDERWATER DOMAIN AWARENESS

Research Note

LOW FREQUENCY SHIPPING AMBIENT NOISE MAPPING FOR PASSIVE SONAR SIMULATOR

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1. INTRODUCTION

The complex tropical littoral waters of the Indian Ocean Region, provide us with challenges to be able to detect our adversaries with us being less vulnerable for detection. This ingenious Passive Sonar Simulator(PSS) that we aim to develop using real time data inputs will be a critical tool for fulfilling our audacious objectives. It requires that we need to enhance our signal to noise ratio, and assessing our vulnerability requires a real time comprehensive understanding of the prevailing noise in the region of our interest. Therefore this real time low frequency ambient noise mapping lays the foundation for our endeavour that lies ahead, which is developing an interactive real time PSS GUI. And this research note deals with the same.

2. PASSIVE SONAR SIMULATOR

Using a passive sonar, basically listens to the ocean mitigates our vulnerability for detection by our adversaries. Given greater depths of the sound channel axis in the tropical waters of the Indian Ocean Region(IOR) , an actual maritime exercise for improving the capability of submarine sonar operator in the complex littoral waters of the IOR leads to a lot constraints and costs. A sonar simulator bypasses these constraints and maximises the capability of sonar operator and training effect by solving these problems and simulating a realistic battlefield environment[1].

State of the art Passive Sonar Simulators

A. PROTEUS PASSIVE SONAR SIMULATOR - Developed by KONGSBERG

B. SonSim SONAR SIMULATOR - Developed by 5K systems

C. GENERIC SONAR SIMULATOR - Developed by DSIT Solutions Ltd

These simulators stimulate the hydrophone output of real sonar systems and are mainly focused on operator and crew *training purposes*. Also, sonar receivers and processors are simulated by performing real signal processing of the *simulated* acoustic signals (identical to the real sonar system) in order to generate realistic video and audio.

What sets our proposed PSS apart?

The proposed PSS is not a training system but a comprehensive *on board* sonar simulator that aids in target detection, which uses offline and real time online data from open source sources such as Automatic Identification System(AIS) and Marine Traffic using the proposed models for effective detection of the foe. The output of the PSS will also enable us to assess our vulnerability to detection so as to position ourselves appropriately. The proposed PSS will be an effective tool, independent of the on-board sonar that will facilitate effective operational deployment of the platform in any operational area anchored to the ground realities in real time.

3. ALGORITHM

- There are three stages involved for the effective deployment of the PSS. The foremost one is a comprehensive understanding of the prevailing low frequency ambient noise (noise ranging from very low frequencies to about 1kHz). This is achieved by *mapping the ambient noise* in the IOR. This ambient noise that we focus on is the shipping noise. This is followed by *enhancing the Signal to Noise Ratio (SNR)* which is crucial in effective detection of the adversaries. The last step involved in the effective deployment of the PSS is the *vulnerability assessment.* This involves assessing our vulnerability by factoring the areas of promising effective detection and also with a little of ambient noise. Because the quieter the place we are in, it gets more easier for our foe to detect us. Therefore integrating both the outputs of promising areas for effective detection and promising areas for deployment with minimal vulnerability, the simulator enables the submarine operator to balance the tradeoffs and deploy the submarine with maximum operational effectiveness.

4. NOISE MAPPING

The ambient noise mapping as aforementioned is the first step in the development of the Passive Sonar Simulator. Along with the signal transmitted and also the Transmission Loss associated with it due to the underwater channel model, we also get a considerable amount of noise level owing to the various factors and activities present in the underwater ocean. The noise of our interest can be classified into two types - Ambient noise and Transient noise. In the ocean, ambient noise is the noise associated with a given environment. This noise depends on factors that are generally beyond our control. Potential sources of this noise are turbulence, shipping, wave action, thermal agitation, seismic events, rainfall, marine animals, and ice sheets cracking.[6] While transient noise as the name suggests is transient which includes noise due to the local passing ships, marine animals (dealt upon in a later section), and passing rain showers (This frequency of rains dominates at 13kHz - 15kHz).

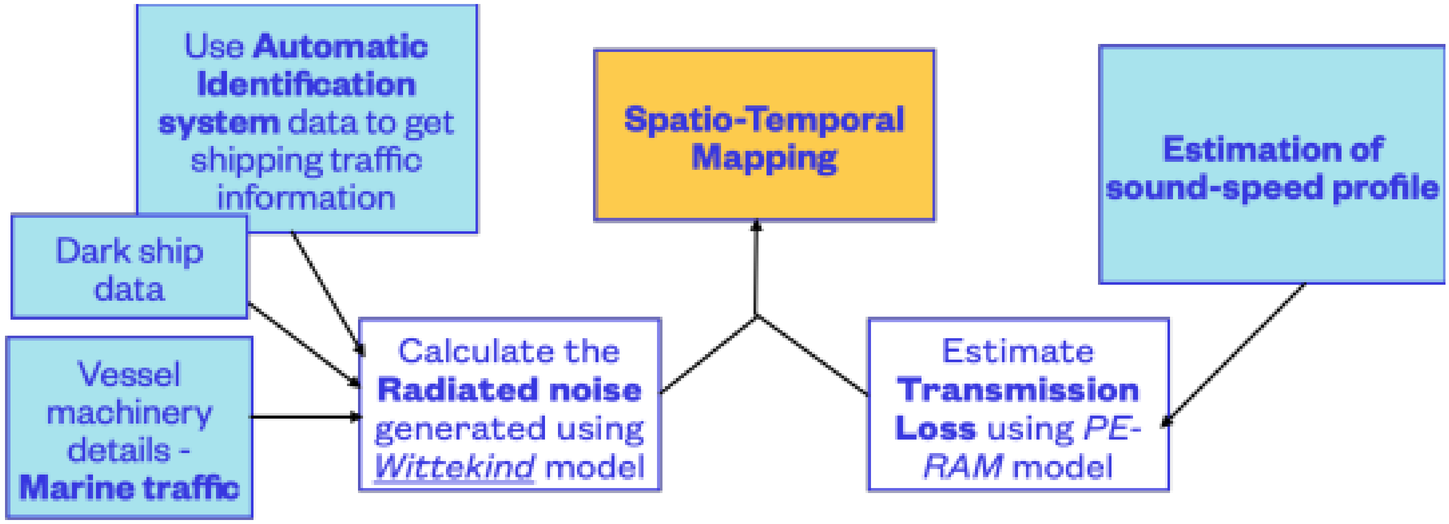

Figure 1

On one hand we input the vessel details into the Wittekend model[7] and get the Source Level (SL) component. On the other hand from the estimated sound-speed profile which will be the input to RAM-PE[8] (Range Dependent Acoustic Model using Parabolic equation) model, we estimate the Transmission Loss(TL). This outputs the Transmission Loss versus range at a specified receiver depth.

The Wittekind model relies upon inputs from AIS data and Marine Traffic such as velocity, ship hull block coefficient, gross tonnage, engine mass and number of engines. RAM-PE model is Range Dependent Acoustic Model - using parabolic equation. It outputs the transmission loss versus range at a specified receiver depth. It calculates solutions using 2D acoustic wave equation taking bathymetry, temperature, sediment, sound speed profile as inputs. Parabolic form assumes forward energy dominates, and calculates solutions to the forward component of the wave equation.

Using these outputs from the Wittekind model and the RAM-PE model, we noise map the ocean. This is achieved by the s*patio-temporal mapping*. For spatio-temporal mapping, we pixelate the ocean map into small grids, and at every node, we account for Source Level component (output of Wittekind) and Transmission Loss component (output of RAM-PE) in a neighbourhood of the node for say in a 100km radius (We can change this radius for different resolutions depending on our needs). After getting the noise at every node, we interpolate the values for all other coordinates and ultimately produce the ambient noise heat map.

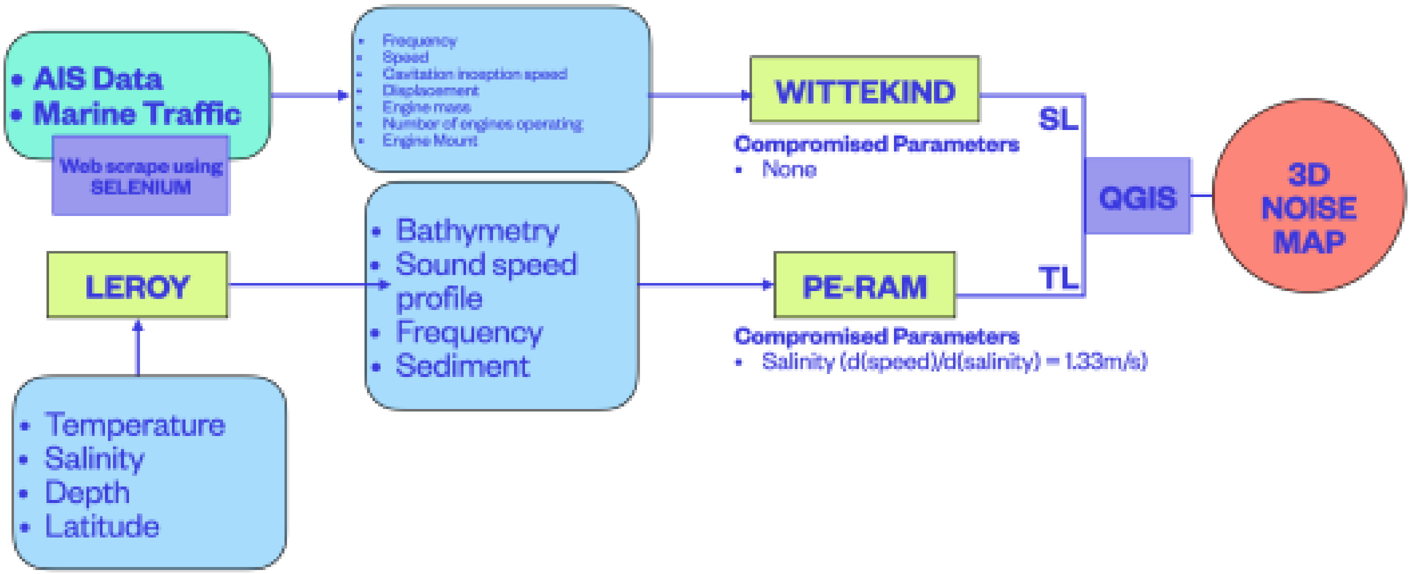

Figure 2

It is to be noted that this computations are performed and the ambient noise map is a real time output using the real time data as aforementioned. When our vessel is docked, the noise mapping takes place using the online data. But it has to rely upon the offline data when it is submerged in stealth mode.

5. CHALLENGES

• REAL TIME ONLINE DATA INTEGRATION

The online dynamic data from the AIS gets updated every 3 minutes. This 3 minute window can be taken advantage by the enemy. Therefore it is necessary that we look up to alternate sources or methods so as to we have much more accurate real time noise map.

• OPTIMISING THE 2D MODEL

Due to the broadband, multi-source nature of the computational model, the model is very computationally demanding. Typically, a single RAM-PE execution for a propagation range of 800m requires 45s of CPU time. Computing such propagation for the typically 1700 discrete frequencies and 100 source depths leads to extremely long computation times, on the order of a week. [2]

• BUILDING AN EFFICIENT 3D MODEL

The ever growing demands and developments reckon to us to make the noise models much more accurate and reliable. Therefore it is essential for us to develop a more promising model. The development of a 3D model including the azimuth dimension, which is currently a work in progress provides us with far better accuracy and reliability and takes the PSS to the next level. Just like for every other upgrade comes with a clause, adding one more variable, the complexity would be of one degree higher than the current 2D model in use, and therefore longer computational times. This is indeed an inevitable tradeoff for accuracy.

6. PATH AHEAD

• USING MACHINE LEARNING/ARTIFICIAL INTELLIGENCE ALGORITHMS

A. As mentioned, the online dynamic data from the AIS gets updated every 3 minutes and this 3 minute window can be taken advantage of the enemy. Use of Machine learning/ Artificial intelligence to predict the path of the vessels and therefore the noise to fill in the noise levels during this interval will ameliorate the simulator.

B. Also, as mentioned that the RAM-PE model is computationally very demanding, use of Artificial Neural Networks to estimate the Transmission Loss component may reduce the computational time and complexity and therefore we will be able to map the noise for multiple resolutions and depths simultaneously.

• 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, can be included into the model for better accuracy. Sea surface analysis can be used to for ship detection from optical satellite images can be away forward in this domain[9].

• 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, target was detected by combining the detection points in both domains using Least Mean Square (LMS) adaptive filter. Results of this paper has showed 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.[3]

• INCLUDING MARINE BIO ACOUSTIC NOISE

The presence of the marine bio acoustic noise can be a serious hinderance for the optimal working of the sonar. For example, the noise from the snapping shrimps (family *Alpheus* and *Synalpheus*) which are present in the warm shallow water produce loud snapping sounds by extremely rapid closure of their snapper claw. The closure produces a high-velocity water jet leading to the formation of a cavitation bubble, which collapses rapidly, causing a loud broadband snapping sound [4]. The shrimp are usually found in such large numbers that there is a permanent crackling background noise in warm shallow waters throughout the world. The snapping shrimp source levels can be as high as 190 dB (peak-to-peak) re 1 micro Pa at 1 m[5]. Therefore marine bio acoustic noise can also be used to map for optimal working of the PSS.

• USE IN COMBAT MANAGEMENT SYSTEMS

The PSS could further be upgraded to a Combat Management System (CMS) with advanced features of undersea warfare. The PSS post validation in multiple operational deployments will provide a significant understanding of the tropical littoral characteristics that will allow development of advanced deep learning algorithms and voluminous databases of varied kinds for mapping the environment and the system behaviour.

• 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. 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[10]. 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.

7. CONCLUSION

Ultimately, it is to be noted that, modelling and simulating an environment is to reduce the number of variables that effect the environment and make it as simple as possible. Very accurately predicting the environment requires more and more variables to be taken care of which in turn is the problem that we are trying to solve. Therefore it is necessary to weigh the parameters and variables and include only them that carry more significant relative weight than including every parameter that we stumble across.

8. REFERENCES

1. Jung, Y.-C., Kim, B.-U., An, S.-K., Seong, W.-J., Lee, K.-H., & Hahn, J.-Y. (2013). 잠수함 수동소나 시뮬레이터 알고리즘. 한국음향학회지, *32*(6), 472–483. https://doi.org/10.7776/ASK.2013.32.6.472

2. Laws, Nathan, "A Parabolic Equation Analysis of the Underwater Noise Radiated by Impact Pile Driving" (2013). Dissertations and Theses. Paper 1083. 10.15760/etd.1083

3. Komari Alaei, Hamed & Farsi, Hassan. (2018). Passive Sonar Target Detection Using Statistical Classifier and Adaptive Threshold. Applied Sciences. 8. 61. 10.3390/app8010061.

4. M. Versluis, B. Schmitz, A. Heydt, and D. Lohse, “How snapping shrimp snap: Through cavitating bubbles,” *Science*, vol. 289, no. 22, pp. 2114–2117, Sep. 2000.

5. W. W. L. Au and K. Banks, “The acoustics of the snapping shrimp synalpheus parneomeris in Kaneohe bay,” *J. Acoust. Soc. Amer.*, vol. 103, no. 1, pp. 41–47, 1998.

6. Etter, Paul C. *“Underwater Acoustic Modelling and Simulation.” (*2003).

7. Wittekind, DK. *“A Simple Model for the Underwater Noise Source Level of Ships”,* Journal of Ship Production and Design, Vol. 30, No. 1, February 2014, pp. 7–14 http://dx.doi.org/10.5957/JSPD.30.1.12005

8. Collins, M. D. (1995). User’s Guide for RAM Versions 1.0 and 1.0 p. *Naval Research Lab, Washington, DC*, *20375*, 14.

9. G. Yang, B. Li, S. Ji, F. Gao and Q. Xu, "Ship Detection From Optical Satellite Images Based on Sea Surface Analysis," in IEEE Geoscience and Remote Sensing Letters, vol. 11, no. 3, pp. 641-645, March 2014, doi: 10.1109/LGRS.2013.2273552.

10. 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.

D. Ross, "Ship sources of ambient noise," in IEEE Journal of Oceanic Engineering, vol. 30, no. 2, pp. 257-261, April 2005, doi: 10.1109/JOE.2005.850879.

Horton, J. Warren (1957). *Fundamentals of Sonar*. U. S. Naval Institute, Annapolis, MD

Hodges, R. P. (2011). Underwater acoustics: Analysis, design and performance of sonar. John Wiley & Sons.

Jalkanen, J. P., Johansson, L., Liefvendahl, M., Bensow, R., Sigray, P., Östberg, M., ... & Pajala, J. (2018). Modelling of ships as a source of underwater noise. *Ocean Science*, *14*(6), 1373-1383.