Research Note

ML Applications in Underwater Channel Modelling

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1. BACKGROUND

Underwater acoustics is the study of the propagation of sound in water and the interaction of the acoustic waves with the water, its contents and its boundaries[1]. Due to the heavy signal loss and fading undergone by EM waves underwater, acoustic waves are the main medium of propagation of signals under the water. This makes it immensely important to understand the propagation characteristics and model them for various applications, including but not limited to ocean mapping, military and sonar applications, etc, more so in the IOR due to its strategic location wrt military and trade aspects. The developments till now have been purely mathematical and involve solving differential equations of the acoustic field pressure numerically, providing us with the transmission loss at different conditions[24]. Different approaches have been taken, each based on different assumptions, leading to various models created, such as the ray tracing model, the normal modes model, and the Parabolic Equation model, which is the most suitable for the Indian ocean region, due to the range dependent nature of the ocean[24], which is solved numerically to arrive at the transmission loss. Such numerical solutions run into many errors and bottlenecks, where Machine Learning and Deep Learning techniques fare better than these.

Machine Learning, or automated learning, is broadly defined as the study of computer algorithms that learn through experience. Such algorithms work on identifying patterns in the underlying data, and making predictions or decisions based on them[2]. Since there is a mathematical solution in place, it can be certainly assumed that some patterns do exist, which can be relatively easy to learn for a machine learning algorithm.

Moreover, the Indian ocean is physiographically different from the rest of the oceans in the world, characterised by salinity hotspots, lower depths, shallow littoral waters, wild temperature fluctuations, among others. These can be tough to account for in mathematical models, where ML and DL models can perform better. We take a look at both approaches, and the research directions ahead.

2. DOMAINS INVOLVED

The Underwater channel model, in the traditional sense of the word, refers to a mathematical model for propagation of sound waves under the water. The different models arise from a single wave equation, which is derived from the more fundamental equations of state, continuity and motion. Acoustic propagation models can vary considerably, all starting from the 3D wave equation, and modified on the basis of governing assumptions and intended applications[3]. The various solutions and their domain of applications differ considerably, and can be classified into 5 categories, corresponding to 5 canonical solutions[4] [5] [6].

- **Mathematical Aspects - The PE model**
  The Parabolic equation is one such solution to the wave equation, that assumes that the propagation depends on the range as well as depth, a range dependent problem. This equation is not exactly solvable, and requires numerical techniques to arrive at an approximate solution, the state of the art being the split step Pade solution[7] [8] and an initial value of the solution to start with, calculated using inversion techniques[9] [10] with the risk of it suffering from problems stated above. Various computer programs have been written, to make use of parallel computing, in order to solve this equation [references], and the various modifications to 3D etc, referred to as the Parabolic Equation Range dependent Acoustic Model (PE-RAM in short)

  These programs require the sound speed values, bathymetry, sea state, and absorption values as inputs. The sound speed values depend on temperature and salinity [reference]. The IOR is characterised by saline hotspots and temperature fluctuations, which may lead to errors. Bathymetry data as well as absorption data[11] is readily available for the IOR.

  The PE-RAM model does have a really high accuracy, provided some manual input terms are input appropriately. These include the range and depth step sizes, and the number of Pade terms to calculate for (See Split step Pade solution[7]). The model then undergoes a complex matrix decomposition task, for each of the range steps provided, finally providing the transmission loss as a function of range. These manual parameters, if selected too low, can drastically improve accuracy, but increase computational costs as well, whereas large step sizes can lead to inaccurate transmission loss.

- **Machine Learning aspects -**
  Machine Learning is a very recent field, owing its advances to increase in computational power, and availability of data. These effectively learn to model the data provided, without being explicitly told to do so, in other words, converting experience into expertise or knowledge[12]. Traditional Machine Learning techniques were limited to linear methods, with emphasis on human intuition to generate better features from the available data for better performance in prediction[reference]. Deep Learning, being an extended version of Machine Learning, takes it a step further, and is able to solve many more complex modelling tasks[13] [14]. Deep Learning models (also referred to as Artificial Neural networks or ANNs) also make use of non-linearities[15], which are able to capture the non-linear dependence on features effectively, implying less reliance on human intuition for feature engineering.

  These approaches are first, given an input, called “train data”, which helps the model develop its features and dependencies. In real time usage, it uses its learnt model and features to predict. Non linearities used mean that the usage is limited to matrix multiplications[16], which is a pretty easy task for computers. One of the main advantages of this approach can be the reduced dependencies on manual inputs (step sizes, Pade terms as mentioned above). The next is that matrix multiplications can be done instantly by a computer, whereas matrix decomposition takes a lot of computation, thus reducing the computational cost in real time usage. However, training times for ANNs can be huge[17], but this step has to be performed only once for usage of the model in real time.

Moving on with the assumption that underlying patterns do exist in the data, since a mathematical model does give accurate results, ML and DL methods can improve efficiency calculation of the transmission loss, and reduce its dependency on manual inputs.

3. CHALLENGES AND OPPORTUNITIES

- **Monitoring the complexity of modelling -** Even though ANNs can learn really complex data, it might end up utilizing many hidden layers to do so. Even though matrix multiplications are easy to compute, too many of them may lead to slower processing, and very deep networks may end up taking more compute than the original PE RAM model, essentially rendering the ANN useless in front of it.
- **Data Availability and Hardware Limitations -** Data for the Indian Ocean is scarce as compared to the other oceans and seas. Since we are aiming at a model specifically for the IOR, not training on high quality data may lead to the ANN learning wrong representations of features[19], detrimental to the calculation of the loss in real time scenarios. Moreover, training ANNs requires efficient and state of the art hardware, the lack of which might limit the search for the best possible ANN[18].
- **Using PE RAM model as a benchmark -** While training, the outputs from the PE RAM model is being used. This implies that the model is limited to the accuracy obtained by this model, and it might prove difficult for the ANN to perform better than this.
- **Reduction of data required -** Since ANNs are fairly accurate at forming feature maps, the output of all the hidden layers can be analysed to see how much each feature contributes[20]. This may help us get rid of features that do not contribute anything to the final output, essentially reducing the complexity of the problem being addressed
- **Automation of Data collection -** Using scripting languages, datasets may be parsed to collect the relevant data. This implies that real time usage entails only the input of Sender and receiver latitude and longitude, which when run through the model, produces the transmission loss of a signal between two points
- **Tailored for the IOR -** ANNs, as stated above, are really good at learning feature dependencies. Since this particular ANN is being trained on data obtained from the ANN, this model will be fairly accurate upon being deployed for the IOR.

4. RESEARCH DIRECTIONS

- **Choosing the best ANN architecture -** There exist almost infinitely many ways one can build their ANN. This implies there are architectures not explored yet, that may lead to better results. Some things that can be optimized are the number of hidden layers, the number of neurons for each of these hidden layers, the activations to be used, maybe shortcut learning [23], and so many more to explore. The key catch must not cross the time taken by the PE-RAM to calculate the transmission loss, else it defeats the purpose of the ANN replacing the PE-RAM.
- **Hardware and Software -** Since this is a system to be run on ships, a further research topics may be to optimise the ANN to run on hardware present on ships. Moreover, even this process of prediction can be sped up using parallel computation, if such technology is present on the ship, then they may be leveraged
- **Neural ODEs -** The approach being employed essentially gets rid of the Parabolic equation, and replaces it with a black box. Recent developments in solving ODEs using ANNs[22] shows some promise in this direction. Instead of scrapping the PE, we may employ this technique to solve the PE more accurately. There are still questions unanswered about the computational efficiency of this technique.
- **Training on empirical data -** As mentioned above, this model is limited to the accuracy obtained by the PE RAM model. There is a possibility of extending beyond this upper bound, by letting the ANN learn directly from experimental data
- **Comprehensibility -** An added disadvantage from using an ANN is the model becomes less comprehensible. Even though the ANNs can learn non linear feature dependencies, it isn't easy to exactly decode what these are. Several works have been published in this field [21] and this still remains an unsolved problem. Hence, the ANN may have to be treated as a black box

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