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ACOUSTIC SIGNAL ANALYSIS AND CLASSIFICATION BASED ON NEURAL NETWORK ALGORITHMS

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Abstract : This paper presents the results of an innovative approach in the underwater domain of research related to the identification, classification and recognition of maritime targets using acoustic data processed. The "Acoustic Signature" is specific to each target type; it is usually produced by the vibration of the propulsion system of surface vessels caused by their radiation into the water. Therefore, the processing of the frequencies generated by these vibrations is essential for the analysis and the classification of different target type.
The purpose of this study is to build an alternative method to identify and classify targets with passive sonars using the TPWS (Two - Pass Split - Windows) filter.
In this process, the signal generated by the target is processed in time frequency domain. Then a TPSW algorithm is applied in the frequency domain to reduce the background noise and enhance the frequency lines of the target noise. Finally, an artificial intelligence model is applied to classify targets, taking as inputs the narrowband and the broadband analysis. This classification is based on deep learning process, relied on the training, validation, and test phases in order to enhance the accuracy and reduce the loss. Our results showed that the suggested method is accurate (appx 83.5% SNR = 0db), depending essentially on the signal/noise ratio.
Key words: Passive sonar, Target analysis, Submerged target, Classification, Filter, Narrowband Analysis, Artificial intelligence, Target noise.

1. INTRODUCTION

The underwater domain remains a vital domain for various aspects of research. Indeed, civilian and military scientists and operational staff are engaged in a race to apprehend this aera of interest. In this perspective, research based on the most important asset in undersea exploration is the SONAR (Sound Navigation And Ranging) that has a growing importance and cruciality. Due to the complexity of the propagation characteristics of acoustic waves, depending on the effects of absorption or attenuation and the change of undersea celerity [1], the detection and classification of underwater targets remain a vital area of research in need of tangible results.

The processing of undersea acoustic waves generated by various targets is a major way to achieve the objective of classification, identification and localization [2]. In the domain of civilian and military maritime navigation and operations, the processing of the valuable data by sonar is done by two different ways: passive and active [3]. In the first way, a received echo from the bounce of a multi-frequency pulse is processed, in order to locate and classify eventual targets. Differently in the second way, there is no emission by sonar. There is only a continuous reception of environmental sound [4].

Undersea detection relies on sonar systems, which are capable to process any surrounding sounds information to produce and emerge possible sonar contacts [5].

Beside this, the undersea environment suffers from many kinds of noise coming from various sources. This noise could be generated by fish or any other environment event (rain, waves….) causing difficulty to process data from collected sound by sonar. In passive detection, the study of the undersea noise is important in order to extract from raw data the valuable information capable to identify targets.

The conventional solution used today to identify ships and naval systems was based on the acoustic signals radiated by each target. [6]. Therefore, the sonar systems use different techniques to process raw data received by the system in order to identify and classify sonar contacts. The implementation of DEMON (Detection Envelope Modulation On Noise) and LOFAR (LOw Frequency Analysis and Recording) analysis are the keys for sonar processing functions [7]. Indeed, taking more time and less accurate, this conventional

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approach has many difficulties to classify undersea targets.

In this perspective, we have opted to implement a new technique for the classification of different underwater targets. In fact, Deep Learning is a new technique based on Artificial Intelligence field, proposed by Hinton in 2006 [8] and which can offer many interesting features. Nowadays, it has made a revolution in the fields of image recognition and sound analysis. In our case, Deep Learning is able to classify contacts from results of LOFAR and DEMON processing using a multi-layer learning algorithm based on Convolutional Neural Network (CNN). Our work aims to use this network to identify the underwater acoustic targets using a valuable dataset of recognized targets.

2. CLASSICAL METHODS

2.1 Genetic Algorithms:

The term genetic algorithm, almost universally abbreviated nowadays to GA, was first used by John Holland [9], whose book Adaptation in Natural and Artificial Systems of 1975 was instrumental in creating what is now a flourishing field of research and application that goes much wider than the original GA. Many people now use the term evolutionary computing or evolutionary algorithms (EAs) in order to cover the developments of the last years. The main drawback of GAs is premature convergence. The chaotic systems are incorporated into GAs to alleviate this problem. The diversity of chaos genetic algorithm removes premature convergence. Crossover and mutation operators can be replaced with chaotic maps.

Tiong et al [10] integrated the chaotic maps into GA for further improvement in accuracy. Moreover, Crossover and mutation operators are the integral part of GAs. Therefore, if the mutation is not considered during evolution, then there will be no new information available for evolution. If crossover is not considered during evolution, then the algorithm can result in local optima. The degree of these operators greatly affects the performance of GAs [11].

2.2 Fuzzy Logic:

Fuzzy logic was first introduced in 1965 by Lotfi A. Zadeh [12] with the concept of fuzzy sets as an extension of the classical set theory formed by crisp sets. Later he defined a whole algebra, fuzzy logic [13], which uses fuzzy sets to compute with words as an extension of the proper operations of classical logic. In most cases a fuzzy logic system is, in fact, a nonlinear mapping of an input data vector into a scalar output where this relation is defined by linguistic expressions which are obviously computed with numbers. Thus, a fuzzy logic system is unique in that it is able to handle numerical data and linguistic knowledge. The richness of this logic is that there are many possibilities which lead to many different mappings. Since the rules are based on predetermined rules, the decision-making process is based on fuzzy logic. If these rules are flawed, the results may not be acceptable at all. Choosing a membership function and basic rules is one of the most challenging parts of creating fuzzy systems. On the other hand, the implementation of fuzzy logic in standard hardware requires multiple and time-consuming experiments and the efficiency of fuzzy logic in recognizing the pattern is less than the neural network in machine learning which it is less covered in Data Science. Moreover, the use of fuzzy logic may become an obstacle to the verification of system reliability and requires tuning of membership functions Fuzzy Logic
control may not scale well to large or complex problems Deals with imprecision, and vagueness, but not uncertainty. [14]

3. NEW APPROACH

3.1 DEMON-LOFAR analysis and neural network algorithms:

LOFAR and DEMON analysis are the most efficient means of signals analysis in signal processing theory [7]. From signal in time domain, the sonar must mainly compute three different features:

- Broadband signal or continuous spectrum;
- LOFAR signal or discrete spectrum;
- DEMON signal allows to assess whether there are intermodulation products such as broadband cavitation noise, which is modulated with low frequency lines from the propeller rotation.

LOFAR (Low Frequency Analysis & Recording) analysis can be considered as a broadband spectral analysis covering the expected range of noise of the controlled object. Signal normalization by implementing a task-specific algorithm, which consists in estimating the background noise present at each spectrum and computing a normalized frequency range, based on the determined normalization factor. This estimation allows ensuring the removal of signal bias and peak equalization. The frequencies of interest are generally in the band [0-1000Hz]. After filtering out all other frequencies, we decimate the output signal according to the Nyquist-Shannon law:

In addition, DEMON analysis is a narrowband analysis used for cavitation noise processing with subsequent accumulation of data obtained from the controlled object. In terms of practical implementation, DEMON analysis allows to separating the cavitation noise from the overall signal spectrum and to estimating the number of shafts, their rotation frequency, and blade rate. Since this analysis provides comprehensive information about the target propellers [15], it is also quite useful for target detection purposes.

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The frequencies of interest are usually in a small frequency band limited to [0-400Hz]. To obtain normalized peak energy, we applied a TPSW algorithm [15] with specific parameters adjusted after laboratory experiments to obtain more satisfactory results for LOFAR and DEMON visualization.

3.2 Generating the dataset

In the context of deep learning and in particular supervised learning, we need to have a labelled dataset. Thus, this work is based on three kinds of datasets:

- A set of LOFARgram labelled images
- A set of DemonGram labelled images
- A set of Spectrogram labelled images

Each set has 1200 images of 5 different classes: cruisers, cargo ships, passenger ships, frigates, and fast patrol boats. These images are taken from different hydrophones which are installed in the entrance of a harbour. For a matter of efficiency, we applied some pre-processing techniques on the acoustic raw data to improve the signal to noise ratio. In addition to that, we took precautions to prevent noisy environmental conditions from influencing the signal (by using shielded cable).

The images are labelled by an expert, taking into consideration the data that has been acquitted by the hydrophone and the CCTV installed in the entrance of the harbour. Then, they are sorted per category and per class.

Table 1. Categories and classes

Lofagram	Demongram	text table
Cruiser	Cruiser	Cruiser
Cargo ship	Cargo ship	Cargo ship
Passenger ship	Passenger ship	Passenger ship
Frigate	Frigate	Frigate
Fast patrol boat	Fast patrol boat	Fast patrol boat

3.3 Deep learning approach

We used a standard convolutional network called VGG16 to train our model. The network contains 5 convolutional layers and uses the ReLu activation function. This model takes as input lofargram, demongram and the spectrogram.

The Convolutional Neural Network (CNN) is a multi-layered acyclic network that has two parts quite distinct. As input, an image is provided in the form of an array of pixels comprising 3 layers. The image is represented by three dimensions of depth 3, to represent the fundamental colours [Red, Green, Blue].

The first part of a CNN is the convolutional part itself. It works as a feature extractor from the image.

An image is passed through a succession of filters, or kernels, creating new outputs called map of features. In the end, the map feature is flattened and concatenated in a feature vector. We flatten the output of the convolutional layers to create a single long feature vector. And it is connected to the final classification model, which is called a fully-connected layer, called RNC code. This CNN code on the output of the convolutional part is then connected to the input of a second part, composed of fully connected layers (multi-layered perceptron).

The CNN training then consists of optimizing the coefficients of the network, from random initialization, to minimize the classification error at the output. In practice, network coefficients are modified in order to correct the classification errors encountered, using a gradient descent method. These gradients are back-propagated in the network from the output layer, from which comes the name back-propagation of the gradient given to training algorithms for neural networks. Indeed, to be able to appeal to the back-propagation, one must have a collection of images for which we already know the category to select. In other words, it is necessary to have a multitude of recordings of the acoustic noise radiated from the targets of different categories to generate their LOFAR-GRAM, DEMON-GRAM and Propeller sound of each recording. That being said, we did collect several samples belonging to several targets of different categories.

To start learning the RNC, first of all, we select the data from Training. These are composed of three images of each sample with the corresponding category. It is also necessary to define the maximum number of iterations to be carried out, and finally the maximum learning rate of the network.

For the sake of this project, we aimed to do three experiments using the 3 sets defined previously. Our main objective is to do a comparison of the three methods based on some evaluation metrics such as ‘Classification accuracy’ and ‘Confusion matrix’.

- Classification Accuracy is what we usually mean, when we use the term accuracy. It is the ratio of number of correct predictions to the total number of input samples.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions\ made}$$

- Confusion Matrix as the name suggests gives us a matrix as output and describes the complete performance of the model.

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n=165	Predicted: NO	Predicted: YES
Actual: NO	50	10
Actual: YES	5	100

Figure 1 Confusion Matrix

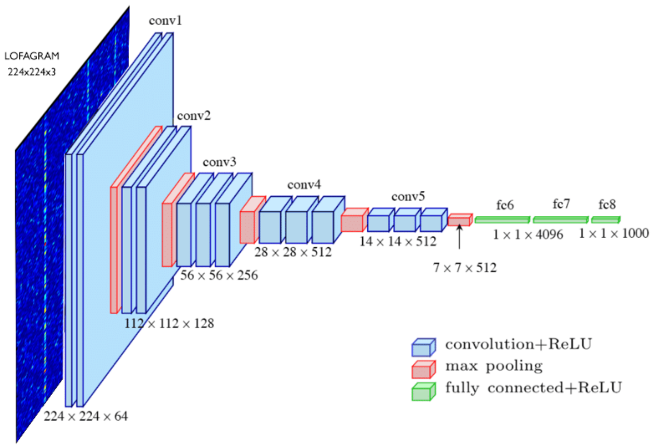

Figure 2 The architectural model used for classification using the Lofagram dataset

4. EXPERIMENTS AND RESULTS

In this section, we will implement the different learning stages from CNN based on the data and methods mentioned above. All classification experiments performed use the same deep learning architecture. The results obtained were validated by data different from those injected during the learning phase.

4.1.Lofagram- Classification using Confusion Matrix.

In the first stage, we tried to explore the classification performances based on lofargram images with a resolution of (224x224). The results of the lofargram study case are promoting. The results are shown in the above figure. As we can see, the proposed architecture predicts well the five classes. Some minor errors are shown in the classification of cruisers, that's because their lofargram is quite similar to cargo ships and to frigates.

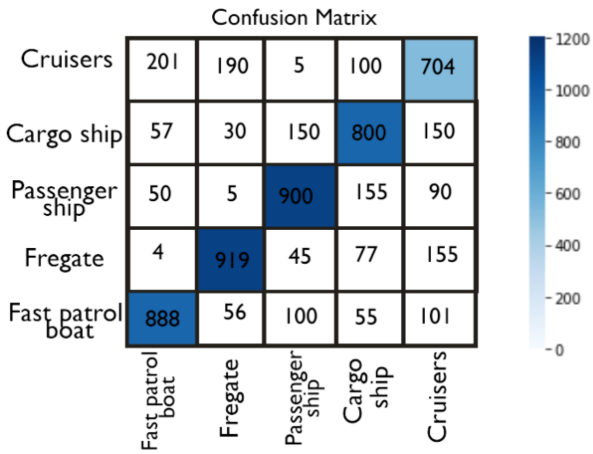

Figure 3 Confusion Matrix of the classification using lofargram dataset.

4.2 *Demogram-classification*

In the second stage, we took advantage of the demongram dataset to classify the same classes discussed previously. Demongram is likely to consider the speed of the propeller in revolutions/minutes, as well as the number of blades of the target. As a result, the classification has showed some good results, especially when it comes to differentiate between ships which have different blade sizes. In our case, the results are presented in the following table:

Table 2. Categories and classes

Class	Validation Accuracy
Fast patrol boats	83.5%
Frigates	79.2%
Passenger ships	81.6%
Cargo ships	65.8%
Cruisers	80.5%

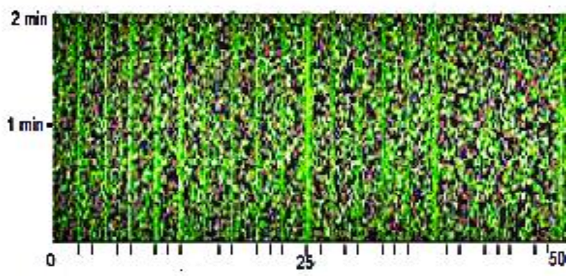

Figure 4 The LOFARGRAM corresponding to a frequency range of 0 to 4200 Hz

4.3 *Spectrogram base experiment*

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In the third stage, our main objective was to find out whether our Artificial Neural Network can predict well the classes of ships based on their spectrogram image. We performed some preprocessing on the dataset to reduce the ambient noise and to convert our raw data to images. The images will construct the main dataset which will be injected to the proposed network. As we can see in Figure 4, the results were not so satisfying. Indeed, we have found that the spectrograms depend on the range between the hydrophone and the ship. In addition to that, our proposed model classifies badly the big ships. It confuses between cargo and passenger ships and can't differentiate between passenger ships and cruisers. However, it classifies well fast patrol boats. The results of this experiment are shown in the graph below.

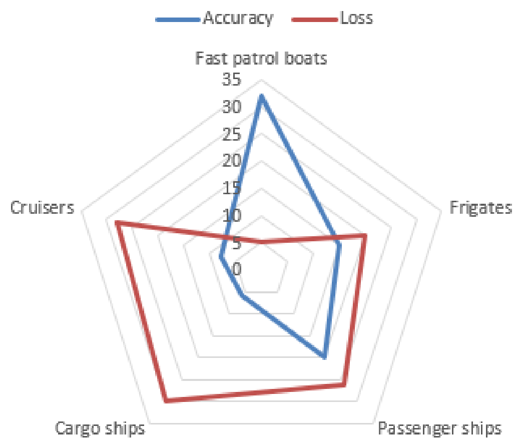

Figure 5 Validation metrics

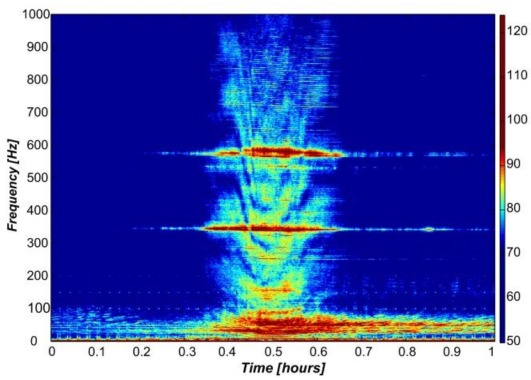

Figure 6 Spectrogram of a container

5. CONCLUSIONS

The main goal of this research was to design a neural network capable of identifying the acoustic signature of a given passive sonar target. To achieve this, we followed these basic steps. First, we processed the signal emitted by many recorded propeller noises and classified them into two categories: ***fishing vessel*** and ***merchant vessel***. Then, we created a program that can generate LOFARGRAM, DEMONGRAM and the Propeller sound of each category. Another program is created to train a CNN model to recognize the target's signature. Once the training was completed, we tested the neural network scheme by providing new target samples that helped us to evaluate the performance of the CNN model.

Our results show that a neural network could be implemented to recognize an acoustic signature by combinig three different steps using separately, Lofagram, Demogram and spectrogram.

We observed that the training of a neural network can process very lengthily, but by optimizing the dataset, adjusting the learning parameters, and using the appropriate threshold function, we could speed up the whole training process. Additionally, we found that by choosing a suitable neural network architecture and combining different training examples, we can significantly improve the overall performance of the CNN model.

Finally, we noticed that neural networks are not 100% foolproof. It is possible that a target maybe identified as another target under certain conditions. This limitation can be improved by retraining the model with a better and large dataset. Moreover, the preprocessing of input data using the appropriate signal processing techniques to improve the signal-to-noise ratio can help specify the performance of the neural network. Consequently, neural networks can be vials in some situations where human pattern identification qualities are required. This technology is a viable option for improving sonar systems. Other categories of vessels will be implemented in the program to classify different kinds of ships. In addition, different signal processing algorithms based on statistical methods such as non-negative matrix factorization [17] and convolutive blind separation [18] may be applied to improve passive sonar target classification. These aspects will be addressed in a future work.

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