PASSIVE SONAR DETECTION AND CLASSIFICATION BASED ON DEMON-LOFAR ANALYSIS AND NEURAL NETWORK ALGORITHMS

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ABSTRACT

This paper focuses on an experimental study that used passive sonar sensors as the primary information source for the submerged target in order to identify, classify, and recognize naval targets. Surface vessels and submarine generate a specific sound either by propulsion systems, auxiliary equipment or blades of their propellers, producing information known as the "acoustic signature" that is unique to each type of target. Consequently, the analysis and classification of targets depend on the processing of the frequencies produced by these vibrations (sound). utilizing the TPWS (Two-Pass-Split Windows) filter, this work aims to develop a novel technique for target identification and classification utilizing passive sonars. This technique involves processing the target's signal in the time-frequency domain. subsequently, in order to improve the frequency lines of the target noise and decrease the background noise, a TPSW algorithm is implemented in the frequency domain. By integrating narrowband and broadband analysis as inputs of an artificial intelligence model that can classify a target into one of the categories given in the training phase, the target has finally been classified. Our findings demonstrated that the suggested approach is dependent upon the size of the target noise data collection and the noise-to-effective-signal ratio.

KEYWORDS

Passive sonar, Target analysis, Submerged target, Classification filter, Narrowband Analysis &Artificial Intelligence.

1. INTRODUCTION

One of the biggest challenges in underwater research is continuing to increase SONAR (SOund Navigation and Ranging) capabilities. The understanding of underwater life and the advancement of underwater navigation systems depend on the quick and precise detection and classification of sonar targets due to the characteristics of acoustic wave propagation and the effects of attenuation and absorption for sound intensity in the sea [1].

Acoustic waves are a useful information source used in underwater signal processing applications to locate and identify other vessels as well as access the surrounding environment [2]. Sonar devices can analyze sound waves in two different ways when it comes to civil or military maritime navigation: actively and passively [3]. As opposed to the second scenario, which involves just sound reception rather than sound generation, the first involves the emission of a multi-frequency pulse, the echo of which is then utilized to identify and categorize potential targets [4].

Therefore, the passive sonar using only reception of acoustic waves generated by a target is the only way to classify it, because active sonar gives only distance, bearing and speed of the target.

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Sonar systems play a major role in underwater detection. They gather information about the surrounding environment via sound waves emitted by various types of potential targets with the ultimate goal of identifying them [5].

The undersea environment produces a lot of noise all the time. Research on underwater acoustic noise can be conducted in a variety of domains, and each one favors a particular style of representation based on its requirements and interests. In the context of passive detection, the examination of underwater noise encompasses not only the features of the waves as studied in oceanography, but also their investigation as a source of environmental disturbance or information. The design, implementation, and application of a system for classifying ships and other naval equipment according to the acoustical signals they emit is also the ultimate objective [6].

As a result, the sonar operating system's identification and classification accuracy can be improved and decision-making speed increased with the use of computational techniques. Thus, the application of novel techniques for the identification of various undersea targets is crucial. In the realm of machine learning, deep learning is a novel approach that Hinton introduced in 2006 [7]. It has advanced significantly in the last several years in areas like picture recognition and speech analysis. The capacity of deep learning to extract the deep functionalities concealed in the target signals using multi-level network architecture without the need for artificially created structured features is one of its most remarkable aspects. To this objective, the supervised learning model is employed by Convolution Neural Network (CNN), a well-known deep learning technique. Y. Lecun's multi-layer learning algorithm CNN has demonstrated success in handwriting recognition [8]. With remarkable outcomes, the deep-convolution neural network was applied to Image Net in 2012 [9]. The goal of our effort is to identify the underwater acoustic targets using this network.

Conversely, the application of LOFAR (LOW Frequency Analysis and Recording) and DEMON (Detection Envelope Modulation On Noise) analysis [10] has enhanced our comprehension of the sound retrieved from the SONAR sensor. In this sense, the DEMON analysis sheds light on the cavitation noise [11] to determine the number of ship blades and the rotation of the propeller shaft. Furthermore, it is well known that LOFAR analyzes the received sound spectrally, enabling the presentation of multiple frequency bands at once. So, in the time domain, the LOFARGRAM matches the LOFAR analysis, allowing for the depiction of spectrum fluctuations over time. It is possible to display the lines that correspond to the tones in the signal sound and then link them to the ship's gear.

2. METHODOLOGY

Theory of the Used Technique

In contemporary digital sonar systems, a single beam performs the processing and categorization of the target features, whereas several beams are used for signal detection. According to signal processing theory, the most effective methods for evaluating signals are LOFAR and DEMON analysis [10].

Sonar must primarily compute three distinct features, beginning with the signal in the temporal domain:

- Broadband signal or continuous spectrum;
- LOFAR signal or discrete spectrum;

- DEMON signal allows assessing whether there are intermodulation products as cavitation broadband noise, which is modulated with low frequency lines from the propeller rotation.

A broadband spectral analysis that spans the anticipated range of the controlled object noise is what LOFAR analysis is. The following is the LOFAR analysis sequence [12]:

- Choosing the direction of interest, also called "bearing";
- Applying the Hanning window to process the incoming signal;
- Applying the Fast Fourier Transform to further process the resultant signal (the FFT processing is used in order to obtain signal representation in the particular frequency domain).

Signal normalization is achieved by applying a task-specific method that includes calculating a normalized frequency interval based on the established normalization factor and assessing the amount of background noise at each spectrum. Volume and frequency. Peak equalization and the elimination of signal bias are made possible by this estimation. Conversely, DEMON analysis is a narrowband analysis that processes cavitation noise while accumulating more data from the controlled item. In terms of actual use, DEMON analysis makes it possible to determine the number of shafts, their rotation frequency, and blade rate in addition to separating the cavitation noise from the entire signal spectrum. This study is also very helpful for target detection since it offers detailed information about the target propellers. The sequence of DEMON analysis is as follows:

The steps involved in signal processing are as follows:

- Direction of interest selection (also known as "bearing");
- Additional band pass filtering to reduce the cavitation frequency range of the overall signal;
- Signal squaring (using a standard demodulation algorithm);
- Next, the normalization algorithm is implemented to reduce the background noise level and highlight the target signal peaks;
- Finally, the target signal processing is completed by using a short-time Fast Fourier Transfer to observe signal peaks in the frequency domain.

Correction of the Spectrum using an Estimate of the Background Sound

A passive sonar system is typically made from a number of building blocks (see Figure 1); described in terms of its aim and specific signal processing techniques that have been applied for signal analysis. [13]

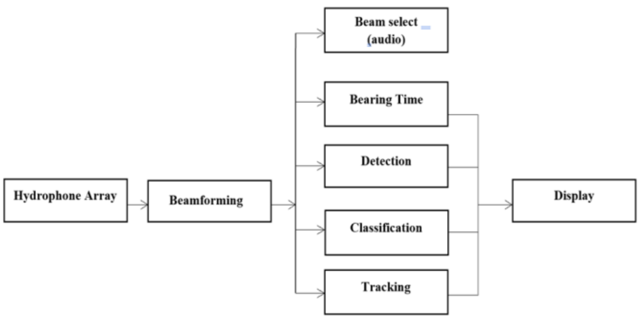

Figure 1. Process of detection and classification in passive sonar

The sound spectrum that is released includes tones that are connected to shipboard gear. These tones are recorded by SONAR and are placed on a continuous spectrum sound that is created when nearby background sounds come together. Most of the time, the spectrum is corrected by estimating the background sound and concentrating on details related to particular amplitude peaks in the spectrum [14].

Typically, the Two-Pass Split Window (TPSW) technique is used to estimate the background noise [15]. The average amplitude values are estimated using this approach. First, an estimated local average is made, with each point denoting the average of its nearest neighbors. The local average is multiplied by a constant that establishes the detection threshold. The local mean takes the place of the spectrum points that cross this threshold. A final estimate of the spectrum's background noise is obtained by performing a second convolution of this updated spectrum with a fresh window. As previously mentioned, this estimation equalizes the spectrum amplitude and eliminates spectrum bias.

A way to correct the spectrum by the background sound is specified as follows:

$$\boldsymbol{y^k} = \mathbf{log}\,(\boldsymbol{x^k}(\boldsymbol{n})) - \boldsymbol{TPSW}(\mathbf{log}\,\boldsymbol{x^k}(\boldsymbol{n}))$$

Where x(n) represents the nth spectrum of class k, and y(n), the corrected spectrum. This equation permits both correction and normalization of the spectrum.

Signal Post-Processing

In order to separate narrowband noise from broadband noise, the target signal is treated in the time-frequency domain in this stage using band-pass filters and decimation blocks. Next, in order to acquire more suitable results for LOFAR and DEMON viewing, the noise is visualized in a spectrogram that is augmented using the Two-Pass Split Window technique with precise settings chosen following laboratory trials.

Lastly, LOFARGRAM and DEMONGRAM are introduced as inputs of a CNN model into a neural network's training process. This allows the neural network to categorize any signal into any of the categories that the model has been trained in.

Experimental Setup

LOFAR Analysis: (Low Frequency Analysis & Recording)

It consists of a broadband analysis to extract propeller and auxiliary machines noises. This analysis is applied after preprocessing the target noise sound. [16]

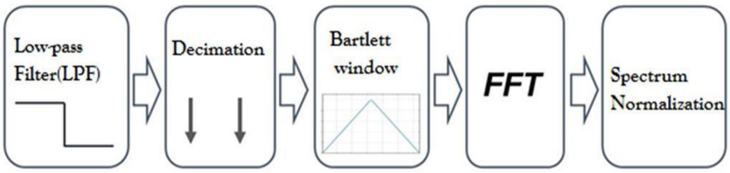

Figure 2. LOFAR analysis process

The sonars picked up a signal with a wide frequency range that goes above 40 KHz. Nonetheless, the [0-1000Hz] band is typically where the relevant frequencies are found. Following the removal of all other frequencies, we apply Nyquist-Shannon law to decimate the output signal:

$$\mathbf{Freq}_{sampling} \geq \mathbf{2} * \boldsymbol{Freq}_{max}$$

After applying a Bartlett window, we divide the signal into blocks of 1024 samples. The Fast Fourier Transform (FFT) is then used to move the blocks of samples into the frequency domain. After the spectrum analysis is finished, we compute the energy of each frequency channel [17] from those values. By comparing those energy values with the threshold, we can isolate the relevant noise. This brings us to the issue of false alarm detection. Nonetheless, a threshold that ensures a constant probability of detection and a probability of false detection is desirable for an even examination of sonar waves throughout all frequency bands. Normalizing the FFT's output is essential to resolving this problem. The standard deviation in each frequency band from a raw energy spectrum to a normalized one is calculated to achieve this. Finally, as seen in figure 3, we are left with a continuous normalized spectrum with distinct peaks.

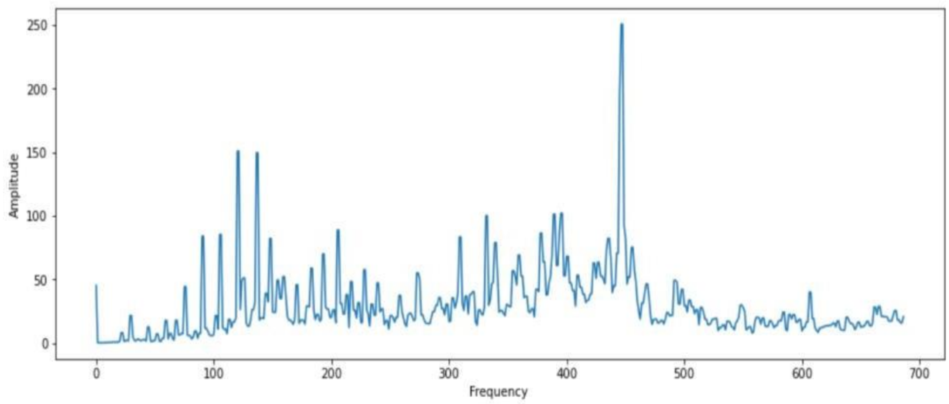

Figure 3. Form of normalized spectrum

DEMON Analysis: (Detection Envelope Modulation On Noise):

A wideband noise that has been frequency modulated can be found in some noise profiles. Thus, this analysis is referred to as "Demodulation on noise". These noises are typically associated with the propeller [18] and the cavitation noise modulation phenomenon produced by the propeller blade. There is a narrow band [19] of hundreds to thousands of Hz when cavitation noise is present. The cavitation noise band is then extracted using a band pass filter. After that, the envelope is extracted using the standard method. The DC component is then taken out. Most of the time, the sampling rate of the signal is high enough to sample the relevant frequencies at a higher resolution than is required for observation. Because of this, before using the FFT, the signal needs to be decimated.

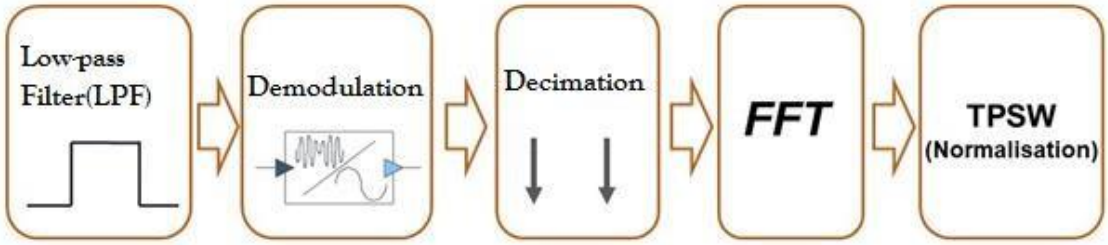

Figure 4. DEMON analysis process

3. RESULTS

The results of the suggested approach are displayed on a database that comprises pre-processing, neural network conception, learning algorithm selection, network training, and classification, as shown in Figures 2, 3, and 4.

In this study, we have conducted around one hundred records for each target category (fishing and merchant vessels) in the environmental noise of the Atlantic sea in order to test and analyze the effectiveness of the suggested method. The acquired database was utilized to learn the algorithm. Examples of ambient noise signals in the Atlantic Ocean with a sampling rate of 44 kHz and signals produced by a merchant vessel's propeller are shown in Figures 5 and 6, respectively.

The architectural model established to achieve our classification is presented in figure 7. This step consists of a signal processing of the recorded audio based on the two types of spectral analysis mentioned above, namely: LOFAR analysis and DEMON analysis

To obtain the LOFARGRAM image (Fig. 8), which relates to tonal noise (narrowband noise) radiated by the target building, and the DEMONGRAM image (Fig. 9), which is likely to take into account the propeller speed in revolutions/minute as well as the number of blades of the target.

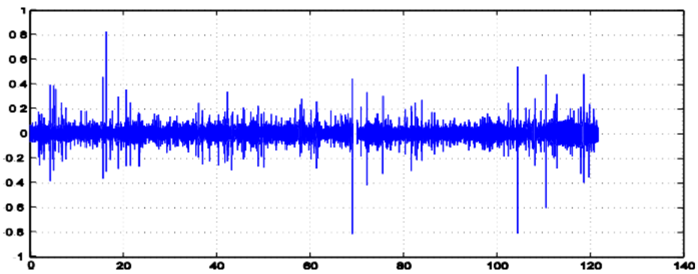

Figure 5. Sample of ambient noise in Atlantic sea with at 44 Khz

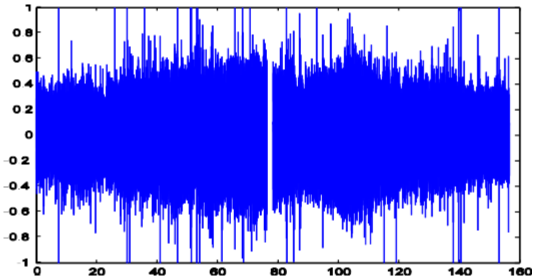

Figure 6. Propeller sound of a merchant vessel

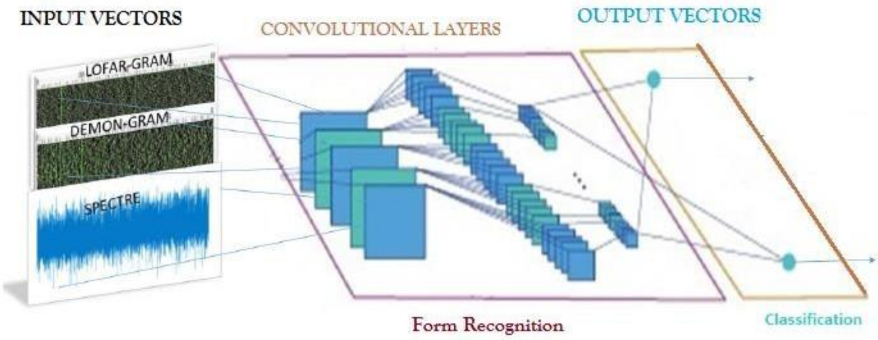

Figure 7. The architecture of Deep Learning used for classification

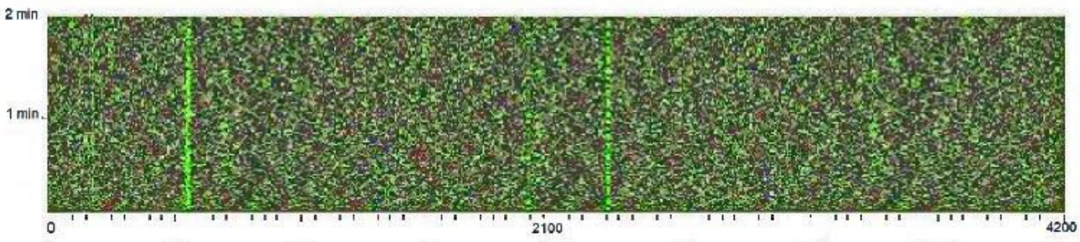

Figure 8. The LOFARGRAM from frequency 0 to 4200 hz

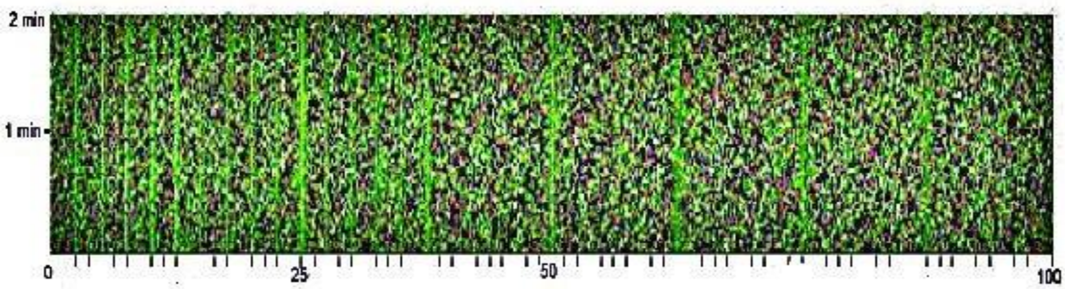

Figure 9. The DEMONGRAM from frequency 0 to 100 hz

Our proposed classification technique is predicated on a particular kind of Artificial Neural Network (ANN), which is typically used for image processing and classification. Inspired by the brain's visual cortex, this kind is known as Network Neural Convolutional.

There are two main sections to the Convolutional Neural Network (CNN), which is a multi-layered acyclic network (forward feed). An image in the form of a pixel array is supplied as input. For a grayscale image, it has two dimensions. To portray the primary colors—Red, Green, and Blue—the color is represented by a third dimension with a depth of three.

The convolutional portion of a CNN is its initial component. It functions as an extractor of image resources. A series of filters, or kernels, have been applied to a picture to produce new outputs known as a map of features. Ultimately, the map feature is concatenated and flattened to create a feature vector. In order to produce a single lengthy feature vector, we flatten the convolutional layers' output. Additionally, it is linked to the last classification model, sometimes known as an RNC code or a fully-connected layer. After the convolutional component's output, this CNN code is coupled to the input of a second part that is made up of completely connected layers (multi-layered perceptrons).

This section's job is to classify the image by combining the CNN code's features. A final layer with one neuron for each category is the result. Typically, the derived numerical values are normalized within the range of 0 to 1, resulting in a probability distribution in categories. Figure 10 depicts the network structure that was used in this article [21].

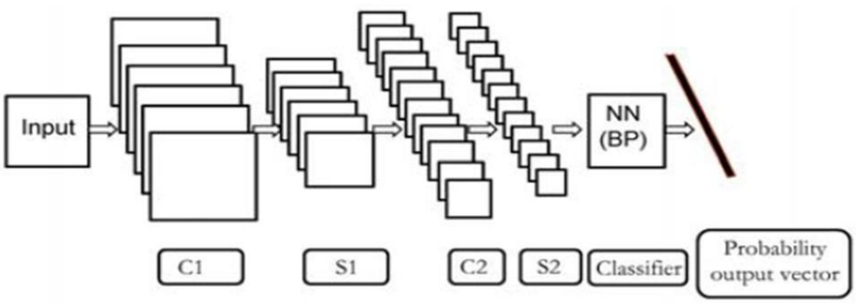

Figure 10. The architecture of CNN

The next step in CNN training is to reduce the classification error at the output by optimizing the network's coefficients after random initialization. In actuality, a gradient descent algorithm is used to modify network coefficients in order to repair the classification errors that are discovered. The term "back-propagation of the gradient" refers to the process by which these gradients are used to train neural network algorithms within the network starting at the output layer. It is true that having a collection of photographs for which we already know which category to choose is necessary in order to make use of back-propagation. Put otherwise, in order to construct the LOFAR-GRAM, DEMON-GRAM, and Propeller sounds of each recording, a variety of recordings of the acoustic noise radiated by the targets of different categories are required. Having said that, we did manage to get a number of samples from various targets across several categories.

We initially choose the training data in order to begin learning the RNC. Each sample has three photos with the appropriate category included. In addition, the maximum number of iterations that must be completed and the network's maximum learning rate must be specified. Our application captures the audio of naval targets, processes it, and outputs the LOFARGRAM, DEMONGRAM, and propeller sound, accordingly. The target can then be classified into one of the following categories: commerce vessel, warship, or fishing vessel by using the aforementioned graphs as input vectors. See Figures 11 and 12.

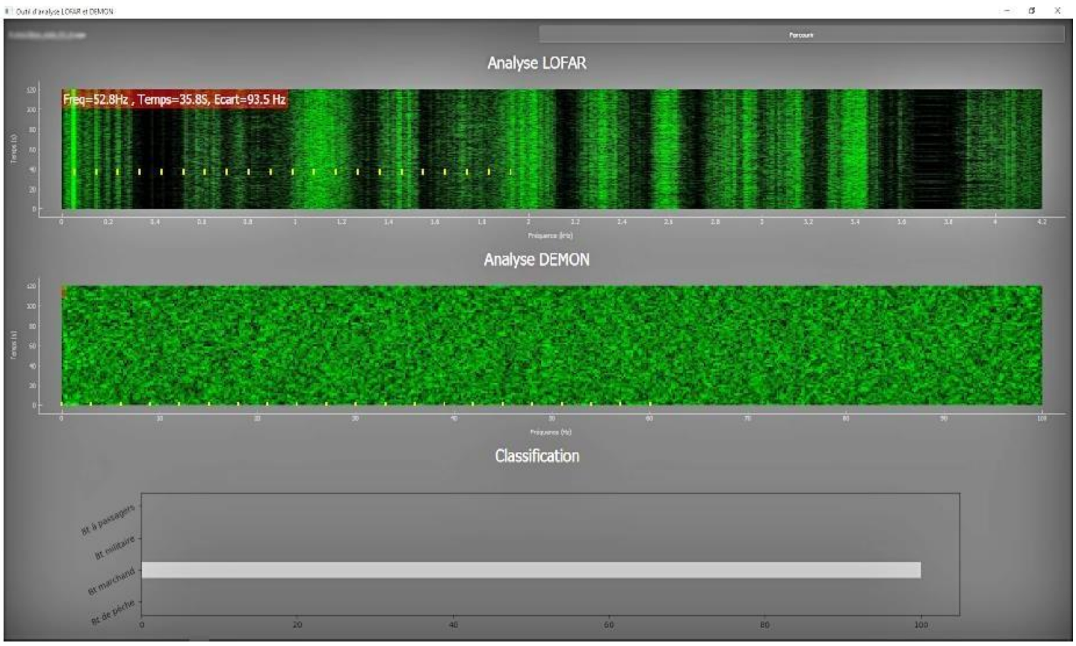

Figure 11. Classification of merchant vessel

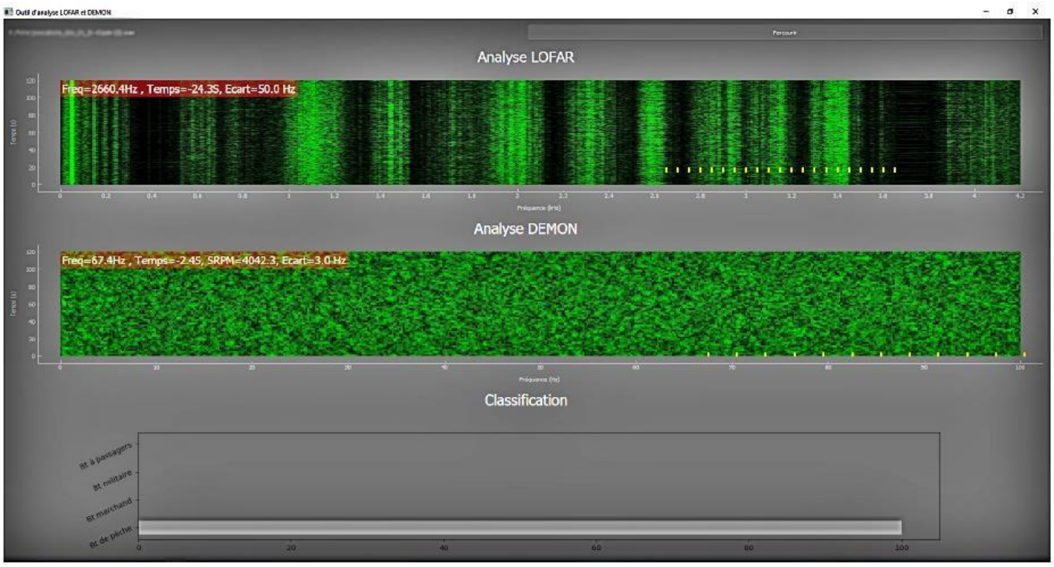

Figure 12. Classification of a fishing vessel

In the figures 13, 14 and 15, it is presented the performances in terms of Mean-Square Errors (**MSE**), which is the squared difference of the inputs and the outputs of the network. Results show that the error is more optimized in term of the Iterations Numbers "**It**", the momentum "**mom**" ,and the number of hiden neurons "**nhn**" with a step of 0.1.

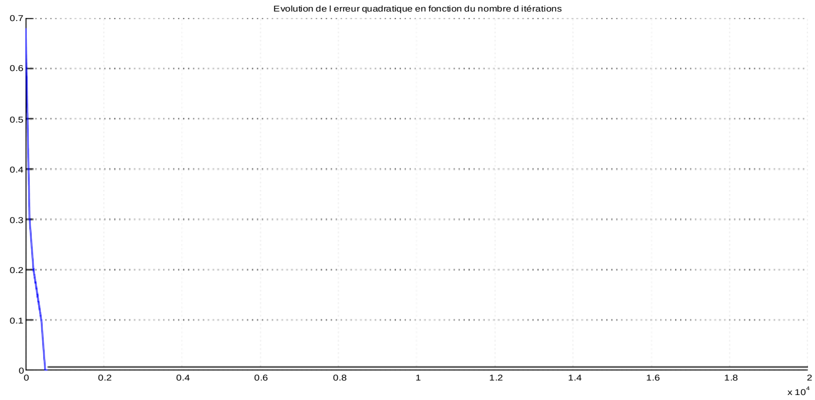

Figure 13. Mean square error(It=20000, mom=0,997, nhn=4, err=2.07726e-007)

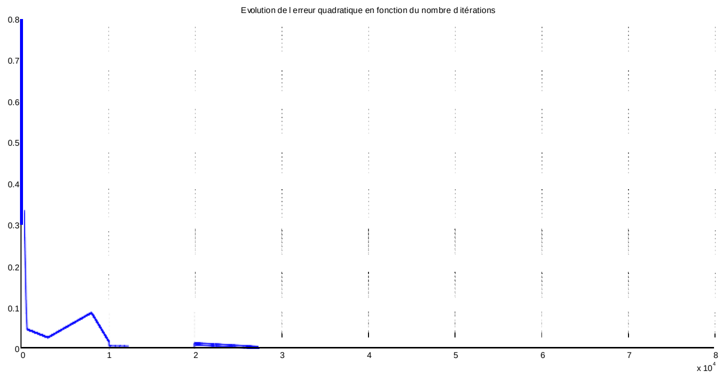

Figure 14. Mean square error(It=80000, mom=0,997, nhn=4, err=1.1802e-025)

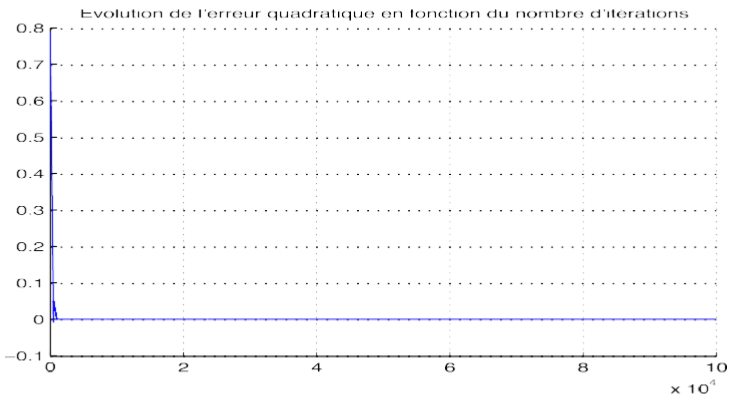

Figure 15. Mean square error(It=100000, mom=0,999, nhn=4, err=2.1506e-004)

The deep learning method can achieve significantly better results and a higher accuracy with 93.75% when recognizing the underwater targets by using acoustical recordings.

4. DISCUSSION AND CONCLUSIONS

The primary goal of this study was to create a neural network that could recognize a passive sonar target's acoustic signature. We took these simple actions in order to do this. Initially, we divided the signal from the numerous recorded propeller noises into two groups: "fishing vessel" and "merchant vessel." After that, we developed a program that could produce the propeller sound, LOFARGRAM, and DEMONGRAM for each category. The images were then saved in two files with the same names as the categories. In order to train a CNN model to identify the target's signature, another software is developed. After training was finished, we tested the neural network scheme by giving it fresh target samples, which enabled us to assess the CNN model's performance.

The following processes can be observed by a neural network to identify an audio signature, according to the results. First off, training a neural network can take a very long time. However, we can shorten this process by optimizing the dataset, modifying the learning parameters, and selecting the right threshold function. We also discovered that we could greatly improve the CNN model's overall performance by selecting the optimal neural network design and utilizing the optimal set of training data. Finally, we observed that neural networks are not infallible. Under certain circumstances, a target may be mistaken for another target. Retraining the model with an improved and larger dataset will help to improve this restriction. Additionally, the neural network's performance can be specified by preparing the input data using the proper signal processing techniques to increase the signal-to-noise ratio. As a result, neural networks can be useful in scenarios where human pattern recognition skills are needed; this technology is a good way to advance sonar systems. To identify various types of ships, the program will incorporate more vessel categories. Additionally, to enhance passive sonar target classification, several statistically based signal processing algorithms, like convolutive blind separation [23] and nonnegative matrix factorization [22], may be used. These elements will be covered in future project.

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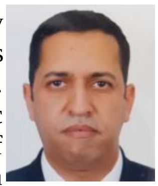

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