Underwater target classification with optimized feature selection based on Genetic Algorithms

Rigel P. Fernandes and José A. Apolinário Jr.

***Abstract*— This paper presents an approach to target-classification optimization based on acoustic signals collected using a hydrophone, an underwater electroacoustic transducer. This study has applications to sonars or any sound-classification application. We divide the problem into three parts, namely feature extraction, feature selection, and target classification with an optimization step. Experiments were conducted using ShipsEar, a public database of raw ship noises collected using a single hydrophone located in a harbor. This dataset comprises five classes and is used to verify the performance of the approach described in this work. From raw signals, we extracted the following features: Mel-Frequency Cepstral Coefficients, Linear Predictive Coding, and Gammatone Cepstral Coefficients. All these features were evaluated using the Neighborhood Component Analysis to reduce dimensionality. We used K-Nearest Neighbors as the classifier. We adopted the leave-one-out cross-validation strategy to evaluate the classifier. Finally, we used Genetic Algorithms to optimize the features selected. We set the classifier performance as the genetic algorithm cost function and used the features selected as one individual of the first generation. This scheme optimized the performance of the classifier by 13 percentage points. In our case, the optimized feature selection algorithms reduced the dimensionality and improved classifier accuracy when compared with the same scheme using all features or a subset of features selected by Neighborhood Component Analysis. These techniques can select the most useful information from features of different ship classes.**

***Keywords*— Classification, feature selection, feature extraction, KNN, underwater acoustic signals.**

I. Introduction

Acoustic event classification is a subject of great interest in defense and law-enforcement for its capability of improving situational awareness. To recognize the environment based on audio waveforms is also a subject of great interest for civilian applications [1]. For instance, voice-controlled houses and speaker identification are some examples of civilian applications that depend on audio signal processing techniques [2]. In the healthcare industry, there are new approaches to make a diagnosis of lung diseases [3], [4], heart diseases [5], and COVID-19 [6] that use acoustics and machine learning algorithms. In both cases, the research area is the same, acoustic event classification, and the methods used are very similar: extraction of useful information from the data to make the automatic diagnosis (classification).

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Detection and classification of acoustic events are broadly used in defense, including underwater acoustic warfare or Anti-Submarine Warfare (ASW). Sonar technicians using sophisticated methods to detect and classify ships motivates efforts to produce more silent ships [7]. Target classification depends on devices that allow environmental sensing, including the hydrophone, a passive acoustic sensor with many applications [7]. This military capability also depends on the following research areas: development of acoustic sensors with higher sensitivity [8], signal enhancement techniques [9], pre-processing [10], and machine learning methods to classify [11], [12], estimate and identify [13] the signal of interest (SoI). Another application of transducers is surveillance of ports and coastal areas [14]. A preliminary and automatic classification performed for every vessel inside the sensors range is important to provide an initial indication of possible threats [15].

Hydrophones can be installed near harbors, or in patrol ships, and used in mono or multichannel systems. The utilization of sensor arrays makes it possible to use multichannel signal processing techniques, for example, spatial filtering [9]. Vessel monitoring has great significance on the military field. The noise spectrum of a remote vessel (at a distance of 1000 nautical miles, or more, from the measuring transducer) mainly distributes from 20 Hz to 500 Hz, and the peak of the power spectrum of a vessel is in the range of 100Hz to 1kHz. Thus, the upper band limit of a hydrophone should be at least 1 kHz.

Recently, some projects aim at using autonomous surface vehicles to perform the surveillance of coastal areas and other tasks [16], [14]. There is also a myriad of applications for underwater autonomous vessels, some of them can be found in [17]. Besides, warships have always depended highly on acoustic sensors [18]. Autonomous vessels are expected to continue depending on acoustic sensing and on new technologies to detect, classify, and estimate the position of targets.

For military applications, the use of active devices is avoided to maintain the low probability of interception in the field of Electronic Warfare [15] and Anti-Submarine Warfare. Thus, passive acoustic sensors are commonly used in warships.

In this work, the classification task will be done using signals from passive acoustic sensors, followed by feature extraction, feature selection, and machine learning algorithms [12]. More specifically, we improve the accuracy of an AI-based classifier and reduce feature vector dimensionality using genetic algorithms as an additional step of the feature selection algorithm. It is meant to be a contribution to the underwater target classification scenario using a single sensor collecting ship signals buried on strong background noise.

The paper is organized as follows: Section II describes techniques employed to extract and select features from acoustic signals, machine learning algorithms to classify the target, genetic algorithms to optimize the classification, and the proposed method. Section III explains the database, and shows and discusses experimental results. Section IV concludes the paper.

II. The Target Classification Problem

A. Problem statement and assumptions

The problem we try to solve is the classification of targets using signals collected by a single hydrophone. The targets in this work are classes of ships in a harbor. For the target classification problem, we assume that, during the recordings, the target was in the range of the sensor, i.e., the signals produced by the target (broadband and narrowband signals) were collected by the transducer. The signal obtained with the hydrophone, $x[k] = s[k] + n[k]$, is the noisy machinery sounds produced by the vessels. It is composed of the signal of interest, the narrowband signal, $s[k]$, emitted by the target machinery, and the background noise, $n[k]$, which corresponds to signals from other sources that are summed to the SoI, e.g., cavitational, biological, and anthropogenic noises.

B. Feature extraction

The features used in this work are Mel-Frequency Cepstral Coefficients (MFCC), Linear Prediction Coding (LPC), and Gammatone Cepstral Coefficients (GTCC) [19]. The vessel classification task depends on pieces of information that are unique to some ship or a class of ships. We depicted in Figure 1 the process used to extract features from audio signals.

Depicted in Figure 1 (a), is one audio signal collected from MSC Opera in the time domain, signal $x[k]$. Figure 1 (b) depicts the following stage, which is to select an interval of the signal with a specific size (in this example we used 1024 samples with 50% of overlap). In Figure 1 (c), it is possible to note the Hamming window that we use to reduce the amplitude of discontinuities at the boundaries for each finite sequence. In Figure 1 (d), the signal depicted is the result of the Hamming window applied to the signal previously cut. We use this process in all feature extraction methods used in this paper.

The next stages are used by the MFCC and GTCC. In Figure 1 (e), it is depicted the signal in the frequency domain; it is possible to see some peaks near 1600, 3200, 4800, and 6400 Hz. This is important information about the ship: the machinery main frequencies and its harmonics. The energy for each frequency is the first feature that could be used to train a machine-learning algorithm, the Short Time Fourier Transform (STFT). In Figure 1 (f), the same signal after the values being squared. The lower frequencies, still strong, are related to the cavitation noise.

Figure 1 (g) presents a Mel filter bank composed of 40 triangle filters, covering the first 8kHz. In Figure 1 (h), the STFT is compressed in this stage using the triangle filters. In Figure 1 (i), the iDCT is used to transform the resulting signal back into time domain which corresponds to the MFCC vector. We also use the first and second derivatives appended to the MFCC features. The first derivative is computed as the difference of the current MFCC vector and the previous MFCC vector, which is known as delta vector. The second derivative is the difference between the current delta and the previous delta vector already computed.

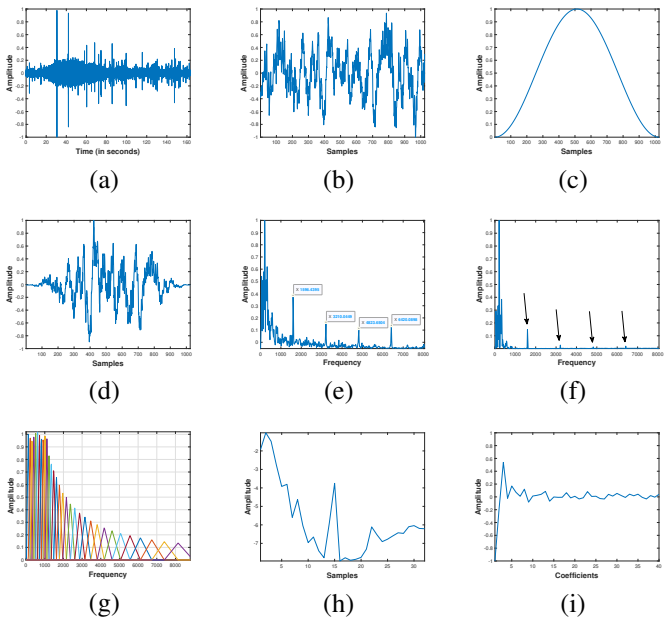

Fig. 1. MFCC and GTCC feature extraction process. (a) Signal $x[k]$ in time domain; (b) a frame with 1024 samples of this signal; (c) Hanning window; (d) windowed signal; (e) absolute values of the frame in the frequency domain; (f) squared values of the frequency domain signal; (g) Mel filter bank composed of 40 triangle filters; (h) Spectrum compressed by the Mel filter bank; and (i) features obtained after applying iDCT.

The computation scheme represented in Figure 1 is the basis for many feature extraction method. The Gammatone cepstral coefficients (GTCCs) are a biologically inspired modification of MFCC that uses this scheme. GTCC uses filters with rectangular bandwidth bands instead of Mel filter bank [20].

The Linear Predictive Coding (LPC) with order s is obtained through the following closed form solution:

$$\mathbf{LPC} = \mathbf{R}^{-1}\mathbf{p}, \tag{1}$$

where the Toeplitz matrix $\mathbf{R}$ is defined as

$$\mathbf{R} = \begin{bmatrix} r_x(0) & \dots & r_x(s-1) \\ \vdots & \ddots & \vdots \\ r_x(s-1) & \dots & r_x(0) \end{bmatrix}, \tag{2}$$

with vector $\mathbf{p}$ being given by

$$\mathbf{p} = \begin{bmatrix} r_x(1) & r_x(2) & \cdots & r_x(s) \end{bmatrix}^{\mathrm{T}}, \tag{3}$$

while $r_x(\tau)$ corresponds to

$$r_x(\tau) = \mathrm{E}\left[\ x(k)\ x(k-\tau)\ \right]. \tag{4}$$

C. The optimized feature selection

Feature selection algorithms are useful to reduce features dimensionality. In this paper we chose to use the Neighborhood Component Analysis (NCA) [21]. This method can be used to transform high-dimensional feature vectors into lower dimensional vectors for classification problems given the nearest neighbor criterion. This method takes as input a data matrix $\mathbf{X}_{N\times m} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$, comprised of a set of training vectors where $\mathbf{x}_i \in \mathbb{R}^m$ and an associated set of labels $\{y_1, y_2, \ldots, y_N\}$. In our experiments, $\mathbf{x}_i$ consists of concatenated vectors of MFCC, first and second derivatives, LPC and GTCC features and y_i indicates the ship class described by the vector. The method then learns a projection matrix $\mathbf{A}_{p\times m}$ that projects the training vectors $\mathbf{x}_i$ into a p dimensional representation, $\mathbf{z}_i = \mathbf{A}\mathbf{x}_i$, where a nearest neighbor classifier is effective at discriminating amongst the classes. Projection matrix $\mathbf{A}$ defines a distance metric that can be used by the nearest neighbor classifier in the projected space.

The output of the NCA method is a vector with the weighted m features. One threshold must be used to select the most important features (the larger feature weights) from all m possible choices. This threshold was selected experimentally to maximize the classifier accuracy. We represent the features selected as a binary vector $\mathbf{b}_{\text{NCA}}$ of size $m \times 1$ of 1's and 0's, the ones represent that the features will be used and zeros that they will not be used. The size of the vector $\mathbf{b}_{\text{NCA}}$ is m the same size of the feature vector $\mathbf{x}_i$, however the number of features selected (the ones in $\mathbf{b}_{\text{NCA}}$) is $p < m$.

However, NCA has one drawback: the non-convex optimization function, i.e., this function potentially has many local minima. Thus, a global search method can be used as a new attempt to optimize the results. In this paper, we have chosen a method from evolutionary computing, the Genetic Algorithms (GA) [22]. This evolutionary algorithm was reported [23] to improve Turkish vowels classification. GA is used to generate chromosomes of 1s and 0s, in this work the size of each chromosome $\mathbf{b}_{\text{GA}}$ is $m \times 1$. This is the same representation of the features selected previously in the NCA method (vector $\mathbf{b}_{\text{NCA}}$). This is important to allow the features selected with NCA to be used as one individual in the GA. The first generation is created randomly or known chromosomes can also be used as the first population, e.g., we can use the NCA vector of 1's and 0's. Each chromosome is evaluated according to a cost function. In this case, the cost function of the genetic algorithms is the classification accuracy obtained through one validation strategy. After we have each chromosome cost function, we run the roulette wheel selection, crossover, and mutation steps for every individual.

D. Target classification

The works that used the same dataset [24] employed different classifiers. For instance, in [25], it was proposed a method based on 1D and 2D frequency domain representation of audio signals to classify the five ship types. In [26], a novel feature extraction method for ship-radiated noise based on hierarchical entropy was evaluated using this database. In [27], a method that aims at improving the accuracy of underwater acoustic target recognition is proposed with only a small number of labeled data. This work comprises four steps, namely pre-processing, pre-trainning, fine-tuning with supervised feature separation, and recognition.

The dataset was also used to run simulations to perform localization of autonomous underwater vehicles using noise emitted by the support ship and their own noise [28]. The work presented in [29], proposes a method to classify the ship radiated noise using audio segmentation method.

In this work, we use the k-Nearest Neighbors (KNN) classifier [30]. KNN is a simple algorithm based on feature similarity that assigns, to an $\mathbf{x}_i$ vector, the class of the nearest set of previously labeled vectors, $\hat{y}_i$. KNN performance depends on the number of neighbors K, the voting criterion (for $K > 1$), and the training data size. The training step produces a very simple model, but the inference phase requires exploring the whole training set [31].

In the pre-processing step, we used a pre-emphasis filter, $h(z) = 1 - 0.97z^{-1}$, to enhance lower frequencies, extracted features using MFCC, LPC, and GTCC techniques, and selected features using NCA. We used KNN algorithm to classify each audio file, and the leave-one-out validation strategy to estimate the classifier accuracy. Finally, we applied GA to improve the classifier accuracy by selecting the most important features, we speed up the optimization step by using the features selected by NCA (vector $\mathbf{f}$) as one of the individuals of the first population.

III. Experiments and Results

A. Database

We conducted experiments using the ShipsEar database [24]. This database is available for the scientific community interested in investigating vessel classification using hydrophones; it consists of 81 recordings from 11 types of vessel. In [24], these vessels were grouped into 4 classes and 1 background noise class. In this paper we followed this approach. This database was chosen due to its availability and large number of recordings. As mentioned in [24], 12 database files were not used in order to balance the number of frames of each class. The same subset is also used in this paper (69 files).

B. Results

In this work, we compare the classification of all features extracted from each class, the features extracted using the NCA algorithm, and the features obtained through genetic algorithms.

The results obtained with all features are presented in Table I. It should be noted that, even with all information presented in the feature vectors, class 1 presented only 25% of accuracy.

It is not always that a great number of features increase the performance of a classifier. The use of NCA increased the performance of all classes by selecting the most important features. According to Table II, class 1 increased 12.5% points,

class 3 and 5 also improved their accuracy by 5.9% and 8.3%, respectively, if compared with Table I.

The best results can be seen in Table III. Except for class 3, we improved the classification accuracy by reducing the dimensionality. 27 features were collected out of 63 features available. This result was achieved after 28 generations, with 10 individuals each.

It should be mentioned that the 27 features selected after the GA stage are composed of: 6/13 features from MFCC, 7/13 MFCC first derivative, 4/13 MFCC second derivative, 5/10 LPC, and 5/14 GTCC features; which corresponds to 46% 53% 30% 50% 35% respectively. Therefore, the most discriminatory features for this classification problem was the MFCC first derivative and the second derivative was the less discriminatory one.

We calculated the overall classification accuracy by summing all the correct classifications dividing by the total number of recordings. We achieved 58.0% for all features, 60.9% for the 26 features selected by NCA algorithm, and 71.1% accuracy for the GA improved feature vector.

TABLE I
CONFUSION MATRIX WITH ALL FEATURES (63 FEATURES)

Class	1	2	3	4	5
1	4(25.0%)	1	7	4	0
2	3	9(60.0%)	3	0	0
3	3	1	12(70.6%)	1	0
4	3	0	0	6(66.6%)	0
5	0	3	0	0	9(75.0%)

TABLE II
CONFUSION MATRIX USING NCA (26 FEATURES)

Class	1	2	3	4	5
1	6(37.5%)	1	5	4	0
2	2	7(46.7%)	3	2	1
3	3	0	13(76.5%)	1	0
4	3	0	0	6(66.6%)	0
5	0	2	0	0	10(83.3%)

TABLE III
CONFUSION MATRIX USING GENETIC ALGORITHMS FEATURE VECTOR OPTIMIZATION (27 FEATURES)

Class	1	2	3	4	5
1	9(56.3%)	0	4	3	0
2	2	11(73.3%)	2	0	0
3	3	1	12(70.6%)	1	0
4	2	0	0	7(77.8%)	0
5	0	1	1	0	10(83.3%)

C. Discussion

In order to a better understanding of the misclassifications in the validation process, we depict in Figure 2 two spectrograms of classes 1 and 4. In these figures, we can easily see similarities between the two ship classes. From both signals, it is possible to note that after 80 seconds the most predominant energy of class 4 vessel is around 1600Hz. This information is very similar to the one presented in Figures 2 (a) and (b), class 1 vessel.

The data compression is very useful to reduce the bandwidth used when the features must be sent to another station. For instance, commercial applications that classify songs, they use massively cloud computing and dimensionality is a great problem when dealing with millions of users sending features through the internet. Another example is military exercises: if a new target is detected, probably the features should be sent to other ships and this should occur very fast.

Moreover, in military applications when unknown targets are detected, the classifier should be passed through another quick training phase to include new targets in its model. This can happen because during peace time, for example, many equipments and machinery can be used in a different mode or even new targets (unknown targets so far) could appear. Therefore, the solution of the feature selection algorithms presented in this paper when combined can be used as a tool to select the most important information and provide quicker training, reducing the amount of data to be processed or transmitted.

The method proposed herein can also benefit the assessment of new feature extraction methods. As we saw, the optimal results in the classification stage is not always achieved when all features are used to fit the classifier model. Thus, the use of this method can help researchers unleash the potential of new feature extraction methods.

IV. CONCLUSIONS

The results obtained with the feature selection scheme outperform the classification performance with the whole set of features, the combination of MFCC, LPC, and GTCC. Although a simple algorithm, when the KNN is combined with a good pre-processing scheme it works well with the multiclass classification problem using 4 nearest neighbors. Methods to deal with signal and feature enhancement could be considered as a future work to improve the results. The misclassification problem could be solved by analysing each signal and proposing signal enhancement for these specific set of ship classes. One example would be to enhance the higher frequencies in order to pronounce the harmonics of the class 4 vessel.

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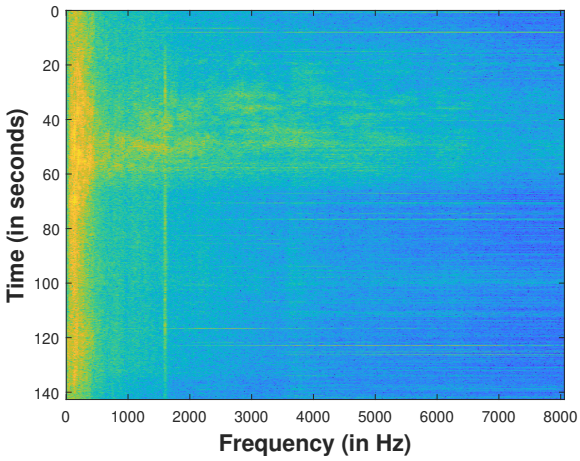
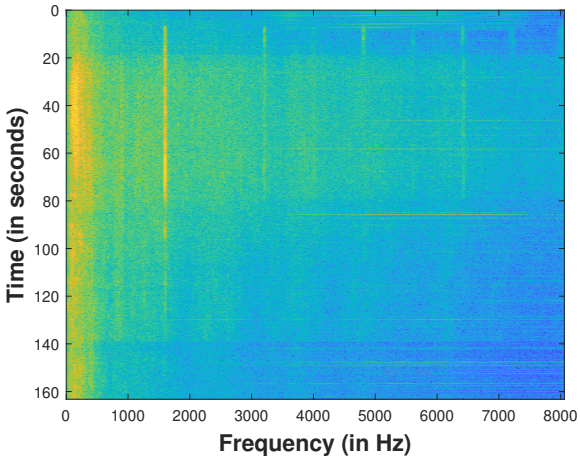


(a)



(b)

Fig. 2. Example of spectrogram from classes 1 (a) and 4 (b).

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