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Technical note

ShipsEar: An underwater vessel noise database

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ABSTRACT

There is a manifest shortage of audio databases available to underwater acoustics researchers. With the aim of palliating this situation, ShipsEar, a database of underwater recordings of ship and boat sounds, has been made available to the research community at http://atlanttic.uvigo.es/underwaternoise/. The database is currently composed of 90 records representing sounds from 11 vessel types. It includes detailed information on technical aspects of the recordings and environmental and other conditions during acquisition. To demonstrate the usefulness of ShipsEar, a vessel classifier was developed, based on cepstral coefficients and Gaussian mixture models. It was tested on a subset of ShipsEar database in which the original 11 vessel types were merged into 4 vessel size classes. The system yielded an overall classification rate of 75.4%, and 100% accuracy in detecting vessel presence. ShipsEar is potentially useful for the development and testing of applications based on processing underwater vessel sound.

1. Introduction

Interest in the sound vessels make underwater arose with the invention of sonar [1], a system that uses underwater sound to detect, locate, identify and control objects in the sea. Sonar has been used primarily for military purposes, but interest is growing in non-military use, for instance, in maritime traffic management, fishing and protection of the marine environment.

Analysis of the sound characteristics of vessels is useful to improve ship design to make them quieter or more efficient, to assess environmental impact and to develop models to predict and simulate vessel noise. This type of study no longer focuses on warships – see [2] for one of the few studies of warships – and research vessels, which are purposely designed to be quiet [3–5]. As Patterson et al. [6] point out, growing social and institutional concerns about noise pollution at sea is promoting studies of underwater noise produced by all types of vessels, including freighters [7,8], icebreakers [5] and jet skis [9], to name just a few.

Detecting, classifying and tracking vessels from their sound can be useful for monitoring maritime traffic [10–12] and for identifying the source of noise in underwater environmental monitoring systems. In the last 15 years, interest in this type of application has fostered research aimed at developing algorithms to classify vessels from their sound. The task is challenging, due to the ongoing evolution in engine design, the complexity of sound propagation in the sea (especially in shallow waters) and the frequent presence of high background noise in the sensor. Researchers have applied various signal processing strategies to address these problems: Das et al. [13] used spectral characteristics and cepstral coefficients, Wang et al. [14] used a bark-wavelet analysis combined with Hilbert-Huang transform, Bao et al. [15] exploited the nonlinear features of radiated sound through empirical mode decomposition, Zak [2] used Kohonen neural networks, Yang et al. [16] proposed fractal approaches and Lennartsson et al. [17] fused sound and electromagnetic signatures for classification purposes.

All such studies require real data in the form of underwater noise recordings made using hydrophones. Numerous recordings made in military installations are not available for use by researchers and companies. Each research team usually has to record and create their own database of underwater sounds, either by installing their own recording equipment or by moving targeted vessels to fixed recording installations. The logical outcome is a costly investment in human resources, equipment, time and logistics. Consequently, available recordings cannot always guarantee the robustness and generality of the results of the developed systems – all the more so when it is borne in mind that recorded sound depends on many variables, among them, the engine regime and mode of operation, the recording environment, the propagation characteristics of the sea and environmental conditions. Examples of databases employed by researchers are: McKenna et al. [8], who used data recorded opportunistically from 29 freighters via an autonomous recording device installed under the Santa Barbara Channel (California, USA); Arveson and Vendittis [7], who analysed the noise of a single freighter from good quality recordings made in

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AUTEC (Bahamas); Erbe [9], who recorded 66 jet ski pass-bys to characterize their sound; Roth et al. [5], who characterized the noise of an icebreaker under the ice of the Arctic Ocean with a sonobuoy that provided hours of recording before it exited the range of the radio link; Lennartsson et al. [17], who used hydroacoustic and electromagnetic signatures to create a database of 15 vessels; Das et al. [13], who trained a classifier by completing the recorded sound of 6 boats with synthetic data; Bao et al. [15], who used recordings of 6 boats to train a classifier; and Yang et al. [16] and Zak [2], who trained a neural network with sounds from 5 Polish Navy ships. Many of these authors expressed the desirability of having better databases for their research, but to date no database of recordings has been made available to the research community.

In other areas where detection, classification and recognition techniques are more advanced, databases – of images, music and speech [18–20], for instance – are available to researchers to facilitate the development of algorithms and the comparison of solutions provided by the research community. The underwater field, however, has a clear shortage of such resources, although worth mentioning is DOSITS [21]. The European Commission has recently approved funding for several projects aimed at reducing the impact of noise from seagoing vessels on the marine environment, including SILENV, a database of acoustic signatures for 171 vessels that has only recently been made public, and SONIC, as yet incomplete, which aims to eventually publish an online database of underwater vessel noise.

To make up for this lack of data for underwater researchers, during 2012 and 2013 the sounds of many different vessels were recorded on the Spanish Atlantic coast and were included in the ShipsEar database (available at http://atlanttic.uvigo.es/underwaternoise/). In what follows, Section 2 describes the ShipsEar database and Section 3 describes a vessel classifier based on Gaussian mixture models (GMMs), developed to demonstrate the usefulness of the Shipsear database.

2. Shipsear: an underwater vessel noise database

Sound recordings were made during autumn 2012 and summer 2013 in different parts of the Spanish Atlantic coast in northwest Spain. Most recordings were made in or near the port of Vigo (42°14.5′N 008°43.4′W) located within the Ria de Vigo, a drowned river valley, 35 km long, 10 km at its widest point and with a maximum depth of under 45 m. It is one of the largest fishing ports in the world and also has heavy traffic in goods and passengers. Taking advantage of the intensity and variety of port traffic, it was possible to make recordings of many different types of vessels from the docks, including fishing boats, ocean liners, ferries of various sizes, container, ro-ros, tugs, pilot boats, yachts, small sail boats, etc.

2.1. Recording system and methodology

The recordings were made with autonomous acoustic digitalHyd SR-1 recorders, manufactured by MarSensing Lda (Faro, Portugal). This compact recorder includes a hydrophone with a nominal sensitivity of −193.5 dB re 1V/1 uPa and a flat response in the 1 Hz–28 kHz frequency range. The amplifier chain consists of a preamplifier with a high-pass cutoff frequency of 100 Hz (which minimizes ambient noise in shallow waters), followed by a programmable gain amplifier that can be adjusted before use according to expected sound levels. The device also includes a 24-bit A/D sigma-delta converter with a sampling rate of 52,734 Hz. The data are stored in *wav* format files of 5 min duration on a 16-GB SD card.

The hydrophones were bottom-moored, and attached to a submerged buoy to ensure verticality and a surface buoy for recovery (Fig. 1). Hydrophones height over the bottom was selected according to water depth at the mooring point. Whenever possible, 3 hydrophones at different depths and with different gains were used to maximize the dynamic range of the recording. In very shallow areas (depths under 10 m), recordings were made with 1 or 2 hydrophones.

All recording sessions were documented in a log completed with data that included date and time, type of noise, GPS position of the recording point, height of the hydrophones, an approximation of the hydrophone-vessel horizontal distance, channel depth and hydrophone gain. Targeted vessels were visually identified at the time of recording. Most recording sessions were also documented by means of annotated videos.

Additional equipment used during the recording sessions included an "underwater ear" (made of an electret capsule connected to a minidisc), designed to detect unexpected sources of noise before hydrophone deployment, and also an underwater source consisting of a small horn with a remote control, used in order to add 2 kHz beeps as markers for events when video recording was not available for synchronization with vessel pass-bys.

2.2. Database structure

The recordings are of real vessel sounds captured in a real environment. Both anthropogenic and natural background noise is therefore present, and also occasional vocalizations by marine mammals. For each recording, the hydrophone was located so as to capture the sound of the targeted vessel with the best possible quality, that is, trying to minimize the noise generated by other vessels that inevitably passed through this high-traffic area.

ShipsEar was populated with recordings made by hydrophones deployed from docks to capture different vessel speed noises as well as cavitation noises corresponding to docking or undocking manoeuvres. Frequently audible is high background noise, explained by waves crashing against the port infrastructure.

ShipsEar was also populated with recordings of vessels under normal operational conditions. Selected were 3 recording sites in the middle of the Ria de Vigo, near entry routes to the port of Vigo and other nearby ports. An auxiliary vessel was used to deploy the hydrophones and recordings were scheduled according to vessel movement information obtained from the port authority and the Automatic Identification System (AIS) for vessels. Other vessel sounds were recorded opportunistically. The database also includes the sound of a suction dredge operating in La Coruña's outer harbour.

Recordings were also made of background noise resulting from natural phenomena, given that this kind of recording is useful for training vessel classifiers and detectors. Equipment was installed at the Intecmar meteorological station (www.intecmar.org) – located outside the Ria de Vigo and away from major traffic routes – during several days of heavy weather. Included in the database are 4 recordings of wind, rain, waves and current noises, acquired with a view to subsequently characterizing these sources of natural background noise.

Given uncertainty about the level of sound present at each recording point, several hydrophones with different gains were deployed whenever possible. In these cases, the recording with the highest sound level before clipping was selected for inclusion in the database.

The recordings were segmented with wide margins to preserve information from the beginning to the end of the event or pass-by. Recordings with excessive sensor background noise, clipping or misleading or ambiguous information on vessel noise sources were eliminated. The final database included 90 recordings in

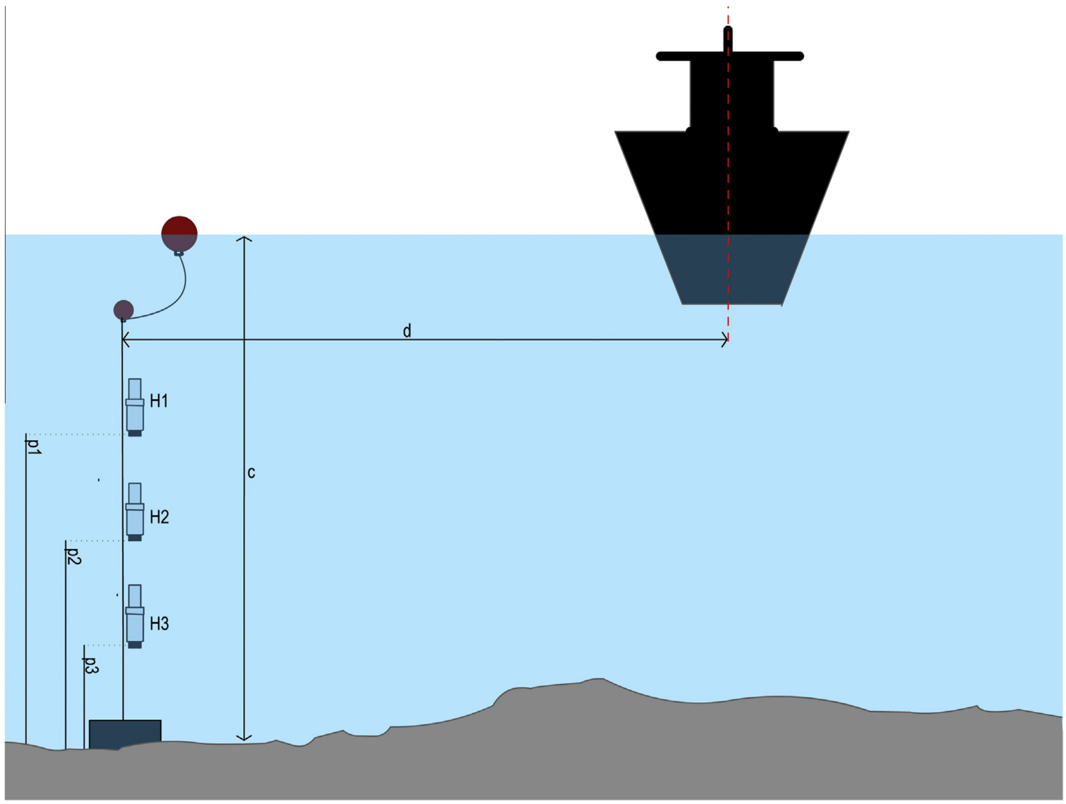

Fig. 1. Hydrophone setup for underwater recordings of vessel noise.

wav-format lasting from 15 s to 10 min. Each audio file and its corresponding data form a single record in the ShipsEar database with information fields as follows:

- 'id': Numerical identifier for each record.
- 'name': The name of the recording, usually the name of a vessel, except for recordings of unknown vessels or of natural background noise.
- 'type': Vessel category/background noise. Possible values for this field are: fishing boat, trawler, mussel boat, pilot ship, tugboat, dredger, ro-ro, ocean liner, passenger ferry, sailboat, motorboat, and background noise (wind, rain, waves and current).
- 'pic': Link to a picture of the vessel.
- 'location': GPS position of the recording equipment shown in a Google Map.
- 'date': Time and date of the recording in the YYYY–MM–DD HH:MM:SS format. If no exact information is available, the recorded time is 00:00:00.
- 'H_G_D': Gains and depths of the hydrophones, organized by the number of hydrophones (maximum 3), hydrophone gains and hydrophone depths, measured as distance to the seafloor (*p1, p2, p3* in Fig. 1). For instance, H_G_D = (1,2)(16,32)(5,7.5) means that hydrophones 1 and 2 were used for the recording, and that gains were 16× and 32×, and distances from the seafloor were 5 m and 7.5 m, respectively.
- 'audio': Link to the audio file and a streaming player to listen to the recording.
- 'video': Whether or not a video documents the recording.
- 'channeldepth': Sea height (m) at the hydrophone position (*c* in Fig. 1).
- 'wind': Wind speed (km/h) measured in situ.
- 'ais link': Link to the vessel AIS, when available.
- 'distance': Approximate distance between the vessel and the vertical of the hydrophone (*d* in Fig. 1),which, if unknown, is recorded in one of 4 intervals: <50 m, 50–100 m, 100–150 m and >150 m.
- 'atmospheric and oceanographic data': Temperature, humidity, wind speed and rain data obtained from nearby meteorological stations.
- 'duration': Duration of the recording
- 'notes': Information obtained during recording or from the video file not entered in the other fields.

Fig. 2 shows a snapshot of the online interface of the ShipsEar database. It was built with PHP/MySQL, a standard open source software combination of server-side scripting (PHP) and relational database management (MySQL) for web development. Data is presented in a table, with each row representing a single record. The field names head each column. Records can be sorted by any field and can be searched for using the information of 1 or 2 fields.

3. Vessel detection and classification experiments

The usefulness of ShipsEar is illustrated below through a simple experiment of vessel detection and vessel classification by size. For this purpose, the 11 vessel types listed in Section 2.2 were merged into 4 experimental classes (based on vessel size) and 1 background noise class, as follows:

Class A: fishing boats, trawlers, mussel boats, tugboats and dredgers
Class B: motorboats, pilot boats and sailboats
Class C: passenger ferries
Class D: ocean liners and ro-ro vessels
Class E: background noise recordings.

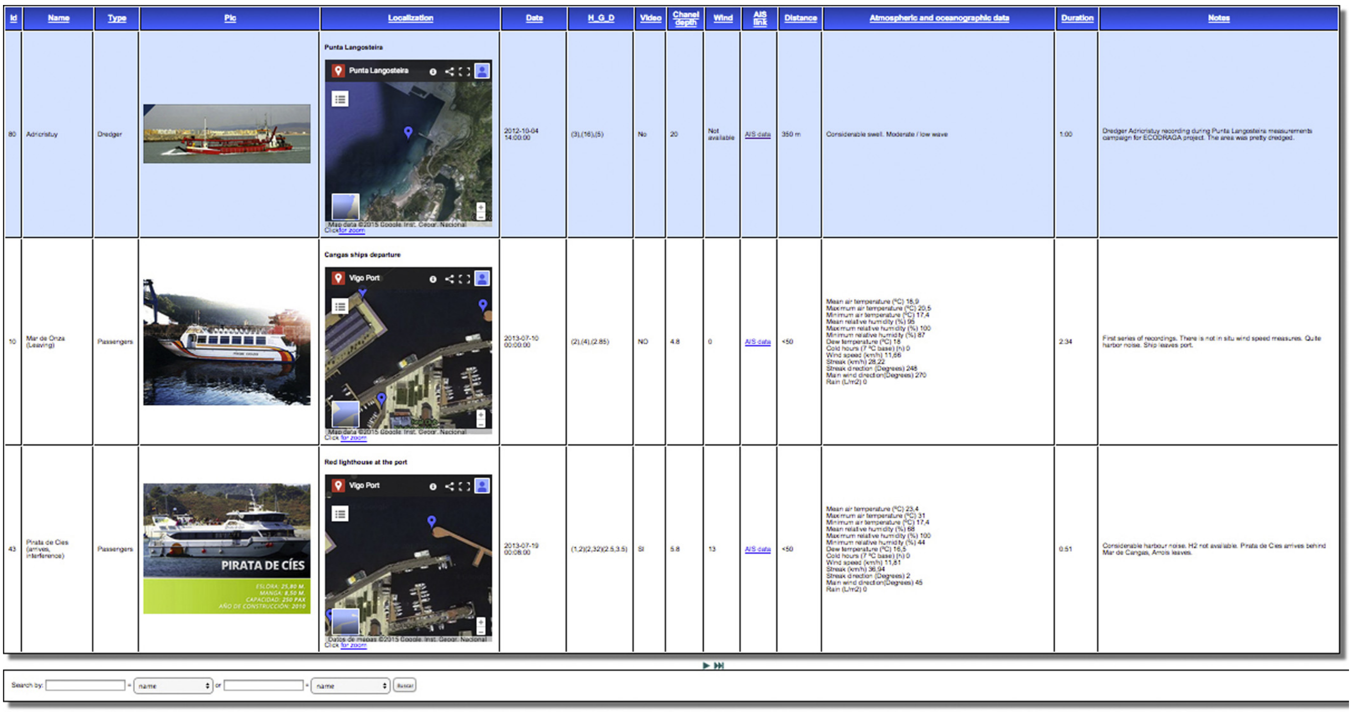

Fig. 2. Screenshot of entries in the online ShipsEar database (http://atlanttic.uvigo.es/underwaternoise/).

To obtain a balanced amount of material for each class, 12 database files were excluded, resulting in the subset composition described in Table 1. This ShipsEar database subset is just one of several possibilities for conducting a simple classification experiment with ShipsEar.

3.1. Classifier overview

The most popular approach to the classification problem is a parametrization stage followed by a statistical classification stage (see [2,22,23] for examples). The classifier used for this experiment, which followed this general structure, was derived from a detection and classification system for marine mammals described in detail in [24]. Parametrization was based on cepstral coefficients [25] and statistical classification was based on Gaussian mixture models (GMMs) [26]. Other examples of GMMs and cepstral coefficients applied to this particular problem may be found in the literature (for example, [22,23]). Several alternative algorithms have been tested in this scenario, both for the parametrization and the statistical classification stages. In [2], for example, parametrization was computed directly using the discrete Fourier transform (DFT), while in [22,14] it was computed using Mel-frequency cepstral coefficients (MFCCs) and a combination of a Hilbert-Huang transform followed by bark-wavelet analysis, respectively. As for the classification stage, hidden Markov models [23], neural networks [2,22] and support vector machines [14] are some alternatives tested with some success.

Table 1
Database composition for a ShipsEar classification experiment. ShipsEar noise types merged into 4 vessel classes (A–D) and a background noise class (E). Each cell shows recording duration in seconds and the number of files (in brackets).

		Class				
		A	B	C	D	E
Database material	Total	1729 s (16)	1435 s (17)	4054 s (27)	2041 s (9)	923 s (12)
	Experimental	1729 s (16)	1228 s (15)	1098 s (17)	2041 s (9)	923 s (12)

3.2. Parametrization

Fig. 3 depicts the classification system. The acoustic signal was framed using a 90 ms hamming window with 50% overlap. The sampling rate was 52,734 Hz although, only the first 8 kHz turned out to be useful for the best classification rate.

The procedure for obtaining the cepstral coefficients commenced by applying to the acoustic signal a filter bank comprised of a set of triangular filters with 50% overlap. The next step was to compute the energy of the output from each filter. The resulting vector was transformed to the cepstral domain using a logarithm followed by an inverse discrete cosine transform. To capture some of the dynamic behaviour of the coefficients, the parametrization was completed by appending the first and second time-derivatives of the cepstral parameters.

The number, bandwidth and distribution of the filters were selected experimentally. The baseline design was based on studies by Arveson and Vendittis [7], Gloza [27] and Okeanos [28], which

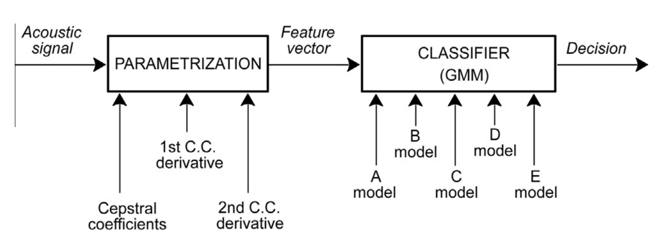

Fig. 3. Methodology flowchart. The first block represents the parametrization stage with cepstrum coefficients (CC) that include first and second derivatives. The second block represents the statistical classification stage, based on Gaussian mixture models (GMMs). Classes A–D correspond to vessel sounds and E to background noise.

Table 2
Configuration of the baseline filter bank used to obtain the cepstral coefficients. All filters are triangular, with 50% overlap.

Channel number	1–7	8–19	20–22	23–32	33–41
Bandwidth	50 Hz	100 Hz	200 Hz	400 Hz	1 kHz
Centre frequency	25, 50, ..., 175 Hz	200, 250, ..., 750 Hz	800, 900, 1000 Hz	1.2, 1.4, ..., 3 kHz	3.5, 4,..., 7.5 kHz

Table 3
Confusion matrix for best classifier performance. Each cell shows the number and percentage of vessels for the classes in the rows classified in the classes in the columns. The diagonal indicates the number of correctly classified utterances. Each utterance is an audio file containing a recording of a single vessel. Classes A–D refer to 4 vessel classes and class E refers to background noise.

		Predicted sound				
		A	B	C	D	E
Actual sound	A	10 (62.5%)	1 (6.2%)	3 (18.7%)	2 (12.5%)	0 (0%)
	B	2 (13.3%)	12 (80%)	1 (6.6%)	0 (0%)	0 (0%)
	C	4 (23.5%)	0 (0%)	13 (76.4%)	0 (0%)	0 (0%)
	D	3 (33.3%)	0 (0%)	1 (11.1%)	5 (55.5%)	0 (0%)
	E	0 (0%)	0 (0%)	0 (0%)	0 (0%)	12 (100%)

show how the signature of the noise produced by vessel engines is mostly contained below 1 kHz. The reference filter bank was designed with more resolution in lower frequencies than in higher frequencies. The best results were obtained using the baseline filter bank described in Table 2. Note that the filter bank uses 40 channels (filters) covering the first 8 kHz only. No further improvements were obtained by extending cover beyond this bandwidth. However, we observed an increase of 5 absolute points when the filter with centre frequency of 75 Hz was discarded and the channels with centres in 50 Hz and 100 Hz were modified to cover 25 Hz–100 Hz and 50 Hz–125 Hz, respectively. The first and second derivatives provided an increase of 3 absolute points on classification rate.

3.3. Classification

A GMM-based classifier was used for the identification task, with different Gaussian models trained for each of the five sound classes described at the beginning of Section 3. The standard expectation maximization (EM) algorithm [29] was used for training purposes. The classification was obtained by parametrizing each audio file and computing its global likelihood with each class model. The model with highest likelihood was selected as the final class.

Training was performed using shared full covariance matrices. Using diagonal covariance matrices, the classification rate dropped more than 20 absolute points. Given the size of the database and the length of the parameter vector, it was necessary to use shared matrices to ensure convergence of the EM algorithm. Using unshared matrices, the algorithm only converged when the number of mixtures was reduced to one, with the classification rate dropping by 4.5 absolute points.

The number of mixtures per model was selected experimentally, with the best performance obtained with 6 mixtures per model.

The leave-one-out cross-validation procedure was used to test the classifier, trained using the whole database except for 1 audio file, which was then used to test the classifier. This procedure was repeated for each audio file.

3.4. Experimental results

Classifier performance was measured using the classification rate, defined as the percentage of correctly classified utterances. The best classification rate for the described classifier was 75.4%.

Table 3 shows the confusion matrix for this experiment. The ability of this system to identify the presence/absence of vessels is indicated by the fact that there was no confusion between background noise class E and the 4 vessel classes A–D.

The vessel classes with the best results were B (motorboats, pilot boats and sailboats) and C (passenger ferries), with classification rates of 80.0% and 76.4%, respectively. The poorest results were obtained for D (ocean liners and ro-ro vessels), the class with the fewest audio files for training.

4. Conclusions

ShipsEar is a database of underwater marine sounds aimed at providing researchers with sound recordings of vessels of various types and natural background noise. The sounds were recorded in shallow waters and in real conditions, so the recordings contain both natural and anthropogenic background noise. The aim is to provide a database of real sounds that researchers could use, for example, to train vessel detectors and classifiers or to monitor maritime traffic. Recordings are accompanied by information that includes type of vessel, place and date of the recording, hydrophone depth and weather conditions. This database is available at http://atlanttic.uvigo.es/underwaternoise/.

This paper also describes a methodology for recording sounds and gathering additional information, aimed at facilitating the use of this database and future additions to the dataset by any researcher.

We developed a vessel classifier based on cepstral coefficients and GMMs to demonstrate ShipsEar's capacity to successfully identify vessels. For 4 vessel size classes defined from the database recordings, our classifier was able to detect vessel presence with 100% accuracy, despite high background noise in shallow-water recordings. Our classifier was able to classify each of the four vessel classes with an overall classification rate of over 75%.

Although both the parametrization and classification stages were studied in some depth, plenty of room for improvement remains. A more sophisticated state-of-the-art algorithm for the classifier – based on support vector machines or neural networks, for instance – would likely yield better results. Furthermore, the inclusion of more recordings to the database, especially of less well represented vessel types, would allow the development of classifiers with larger number of vessel classes. ShipsEar, as a database tool useful for detection, classification, identification and tracking applications based on processing underwater vessel sounds, is freely available to researchers, who are invited to contribute to its growth.

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