Comparison of seabed classification using unsupervised and supervised learning on ship noise spectrograms

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***Abstract*—Applications of supervised machine learning to ocean acoustics is often limited by the lack of labeled measured data. To overcome this, synthetic data can be used for training. This paper explores the potential for unsupervised learning to provide labels for measured data. Specifically, a comparison is made between seabed classification from supervised learning and labels inferred from unsupervised learning. Both networks are trained on synthetic ship noise spectrograms. Six CNN-based supervised learning methods were trained using synthetic data labeled by seabed class. The trained networks were applied to 69 measured spectrograms from the Seabed Characterization Experiment 2017. The results show a distinct preference for seabeds with softer top layer (water-sediment sound speed ratios less than one). The unsupervised ML method, k-means clustering, is applied to same synthetic dataset, and the resulting clusters are evaluated based on the characteristics of the synthetic data samples placed into each cluster. The measured ship noise spectrograms are then passed through the trained clustering model, and the characteristics of the assigned clusters are evaluated. Of the 69 measured data samples, 70% are placed in clusters showing a distinct preference for seabed classes similar to those obtained from the CNN-based classifiers. Other measured data samples are placed in clusters that contain synthetic data samples from short ranges. This work illustrates the potential for using clustering to assign preliminary labels to unlabeled data.**

***Index Terms*—machine learning, unsupervised learning, ocean acoustics, ship noise, spectrograms, k-means clustering, seabed classification**

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I. Introduction

Potential applications of machine learning in ocean acoustics are often hampered by the lack of labels for measured data. The lack of labeled data means that supervised machine learning algorithms are often trained on labeled synthetic data. Another way to find labels for unlabeled data is by clustering the data using an unsupervised learning method. The potential for unsupervised learning to provide labels for measured data is explored in this paper by comparing the results of unsupervised clustering to the seabed classification results from supervised models. Both the unsupervised and supervised models are trained on synthetic data and then applied to measured ship-of-opportunity (SOO) spectrograms measured during the Seabed Characterization Experiments (SBCEX) conducted in the New England Mudpatch in Spring 2017.

Closely related to the current work are studies that use SOO noise and supervised learning. Van Komen *et al.* [1] used a CNN to obtain ranges and ship speed predictions on synthetic spectrograms while also providing an estimate of basic seabed type. The difference between the type of input data were investigated: complex spectral density, the magnitude of the spectral density squared, and spectral density levels. They found that the complex spectral density input was better for estimating the range to the closest-point-of-approach (CPA) and the spectral density levels were best for seabed classification. While this study only considered four representative seabed types, a subsequent study by Escobar *et al.* [2] applied five different convolutional neural networks (CNNs) and one residual CNN (ResNet) to classify between 34 seabeds and applied the trained networks to spectrograms of noise from ships-of-opportunity (SOO) measured during Seabed Characterization Experiment 2017. This work found that ResNet-18 gave the most consistent results because of the skip connections [3]. The catalog of 34 seabeds was selected using the Pearson correlation of broadband transmission loss over range, as described in Forman *et al.* [4]. All of these studies used a single hydrophone in the middle of the water column, similar to what is used in this paper. Concurrent work is looking at the benefits of using multiple receivers and differences between using a catalog of 34 seabeds and 12 seabeds [5].

This paper compares a seabed classification approach using supervised and unsupervised learning on SOO spectrograms. The unsupervised ML method is k-means clustering. This method assumes that a set of unlabeled data can be grouped into k number of clusters based on similar features. This investigation is carried out by training the clustering algorithm on unlabeled synthetic data and then evaluating the characteristics of the data samples placed into the same cluster. Measured ship noise spectrograms are then passed through the trained clustering model and the characteristics of the assigned clusters are considered to see if the clustering can provide seabed classification. The focus in this paper is to look at the distribution of seabed types corresponding to the synthetic data samples placed in the same clusters as the measured data samples. These seabed distributions are then compared to the seabed classification results from the ResNet-18 models. This work illustrates the potential for using clustering to assign preliminary labels to unlabeled data.

II. Methods

Machine learning comes in two main flavors: supervised and unsupervised learning. Supervised learning relies on labeled data samples, whereas unsupervised learning operates on unlabeled data. In both cases, a machine learning model is trained with a training dataset. In the case of supervised learning, the model learns how to predict the target labels associated with the input data. The primary goal of supervised learning is to be able to predict the target labels for new data. With a clustering-based unsupervised learning approach, the trained model learns how to assign input data to clusters. When a new data sample is passed through the trained model, the data sample is assigned to a cluster and likely has similar properties as the training data assigned to that cluster. Thus, if you know the properties of the training data, you can infer something about the new data samples. This inference process is not as powerful as actually predicting the labels via supervised learning, but when faced with a large amount of unlabeled data, it is important to consider the potential for unsupervised learning to provide approximate labels.

Unlabeled data are common in ocean acoustics, because often the source location, track, and level are unknown and the ocean's environmental labels are not easily defined. While it is possible to estimate some environmental labels with the help of GPS data and ocean databases, the use of ML methods on unlabeled ocean acoustical data has had significant benefits. Some commonly known unsupervised methods include principal component analysis (PCA), which has been used for acoustic mapping, [6] and dictionary learning, which has been used to improve resolution of sound speed profiles (SSPs) [7], [8]. Additional studies in ocean acoustics have utilized unsupervised learning methods in passive sonar target recognition using a deep belief network [9] and coral reef bioacoustics using deep embedded clustering [10].

In unsupervised learning and often in supervised learning, features are extracted from the data and then the feature vectors are used as input to the machine learning algorithms. Some examples are shown in recent papers about classifying ship noise [11], [12]. A different approach is taken here. Instead of deciding *a priori* which features should be extracted via preprocessing, spectrograms are sent directly into the machine learning algorithms, which minimizes the number of decisions that must be made and, thus, reduces potential biases introduced by the preprocessing. This approach works well for convolutional neural networks (CNN), which are designed to find patterns in multidimensional data. Unsupervised learning method, however, do not look for patterns but expect the same features to be in the same order, which means misalignment in time or frequency can impact the results.

A. Synthetic Ship Noise Spectrograms

The difference between supervised and unsupervised learning is tested for a specific application in ocean acoustics. The task is seabed classification using ship noise spectrograms. A catalog of 34 seabeds was created, and synthetic data were generated using a range-independent normal mode model, ORCA [13], and an empirical source spectrum for the ship noise [14] (Details about how the 34 seabeds were selected can be found in [2], [15], and [4].) These 34 seabeds and a wide range of source parameters (as shown in Table I) were used to generate labeled synthetic spectrograms. The synthetic spectrogram generation process is explained more fully in both [1] and [2]. The resulting spectrograms contain spectral density levels at 241 time steps over 20 minutes (with 5 sec spacing) and 123 frequencies in the 360-1100 Hz band. Because of the unknown source level, each data sample is scaled by its standard deviation in squared pressure. These synthetic data samples are used to train both the supervised and unsupervised models.

B. Measured Data Samples

The main goal of the SBCEX 2017 was to gain a better understanding of the physical mechanisms that control acoustic propagation in fine-grained sediments. The experiment took place 95 km south of Martha's Vineyard, MA, USA, an area known as the New England Mudpatch, in approximately 75 m

TABLE I
SOURCE PARAMETER BOUNDS FOR THE SYNTHETIC TRAINING DATASET. RECEIVER DEPTH WAS CONSTANT AT $z_r = 42\ m$, AND WATER DEPTH IS 75 M, THE MEAN WATER DEPTH IN THE AREA OF SBCEX 2017.

	S_0 (dB)	z_s (m)	CPA (km)	Speed (kt)
Bounds	230-240	6-12	0.5-15	8-20
No. Fixed	0	0	5	3
No. Random	1	3	10	6

of water as shown in Fig. 1 of [16]. The seabed label names with the suffix "_sbc", from Table 3 in [2], originated from published geoacoustic inversions results using SBCEX 2017 data, as described in Howarth *et al.* [15]. For the 34 seabed catalog, the seabeds are ordered by the sound speed at the top of the sediment layer; seabed types 0-15 had sound speed ratios across the sediment-water interface less than one, as expected in this area at the time of the experiment.

The measured data were collected by three VLAs: VLA1 and VLA2, deployed by the Marine Physical Laboratory, Scripps Institution of Oceanography, and VLA3 deployed by the University of Delaware. These VLAs were deployed during the SBCEX 2017 as shown in Fig. 1 of [2] at the locations specified in their Table 1. The data from one channel on each VLA was used (approximate depth 42 m). The Automatic Identification System (AIS) [17] data were used to identify ships recorded during the deployment of these VLAs. A total of 69 measured data samples were obtained between Julian days 67-96 in 2017. These data samples are listed in Table II along with their CPA range and speed.

The spectrograms were computer using a Fast Fourier transform with the following parameters. To create each ship noise spectrogram, the CPA time was determine and then 20 min of data were selected with CPA in the center. These data, recorded with a sampling frequency of 25 kHz, were downsampled to a sampling frequency was 12.5 Hz. The Fast Fourier Transform was performed using MATLAB's fft command with $N = 2048$ and a Hamming window, which produced a frequency resolution of 6.1035 Hz. The data were time averaged over 10 sec with 50% overlap such that there are 5 sec between the time steps in the resulting spectrogram.

C. k-Means Clustering

A simple and popular unsupervised learning algorithm is k-means clustering. The k-means algorithm requires users to choose a value for k representing the number of resulting clusters. This value is then used for selecting k data samples from the training set to act as the initial cluster centers known as centroids. For each iteration, the algorithm goes through each data sample (i.e., spectrogram) in the training dataset and assigns it to a cluster with the smallest Euclidean distance between the data sample and the centroids. After each data sample is assigned to a cluster, the centroids are changed to be the mean of the data samples in their cluster. The goal of k-means clustering is to minimize the sum of squared distances between each data sample and its assigned centroid. Multiple iterations are completed until the centroids converge or the stopping criterion is met.

Because the original k-means algorithm takes the time to go through the whole training set for a single iteration, we use a method called *minibatch* k-means. The centroids are updated more frequently, after each batch of 100 samples instead of after the entire dataset. This reduction in computation time comes at the cost of lower cluster quality [18], but the resulting clusters are sufficient for the current work.

D. Convolutional Neural Networks

Escobar *et al.* [2] compared six different convolutional neural network (CNN) architectures for seabed classification. The models used in that study were two 3-layer CNNs, three 5-layer CNNs, and one 18-layer residual CNN called ResNet-18. Details about the model architectures are provided in [2]. For each architecture, five-fold cross-validation produces five models trained with different random initializations and train/test splits of the synthetic data samples. During training, the data samples were labeled only by the seabed type, even though a variety of source parameters were used to generate the training data. The models were trained for classification between 34 seabeds with a softmax loss function.

III. RESULTS

After the k-means clustering and the CNN-based models were trained on synthetic spectrograms, the 69 measured data samples were passed through the networks. The classifier output from the CNN-based models relates to the probability that the data sample comes from a certain seabed class. The seabed with the highest classifier output was identified as the selected seabed. The selected seabeds for all 69 data samples from the six CNN-based architectures, which each had five trained models, are shown in Fig. 1. The histogram contains 2070 predictions: The most commonly predicted seabeds have a sound speed ratio less than one across the sediment–water interface, with seabeds 3-6 having the largest number of predictions. This results is important since physical measurements were made in an area where seabed classification is for a fine-grained sediment [19] and overall the analyses for SBCEXP points towards a ratio less than unity [16]

While the supervised learning methods yield classification output that correspond directly to the seabed classes, the interpretation of the unsupervised learning results is more subtle. To assess how the clustering of synthetic data could be used to infer features from measured data samples, the clusters of a trained k-means model were analyzed to find trends in the properties of the synthetic ship spectrograms placed into each cluster. Each measured data sample is then input to the trained clustering model and assigned a cluster. The characteristics of the synthetic data samples in each of the assigned clusters are then evaluated. The focus in this paper is to look at the distribution of seabed types corresponding to the synthetic data samples placed in the same clusters as the measured data samples. These seabed distributions are then

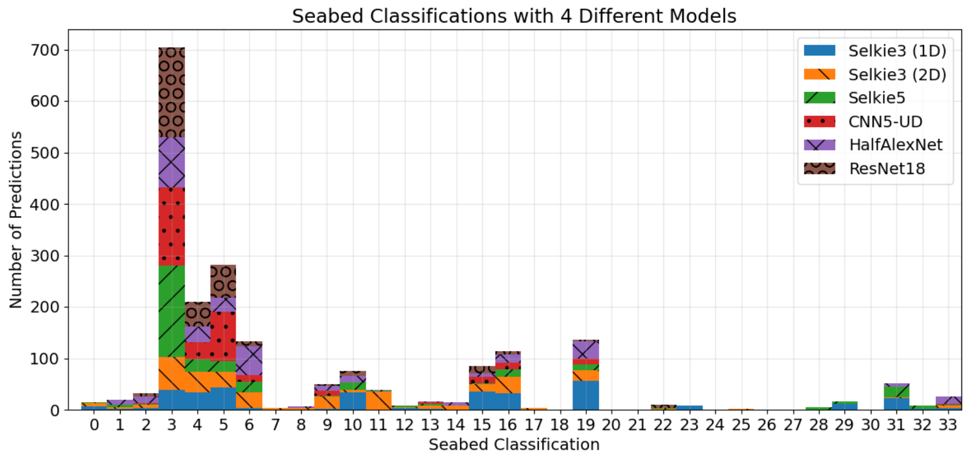

Fig. 1. Selected seabeds from the six CNN-based supervised learning models. Five models of each architecture were trained and then applied to the 69 measured data samples. Thus, 2070 predictions are contained in this histogram.

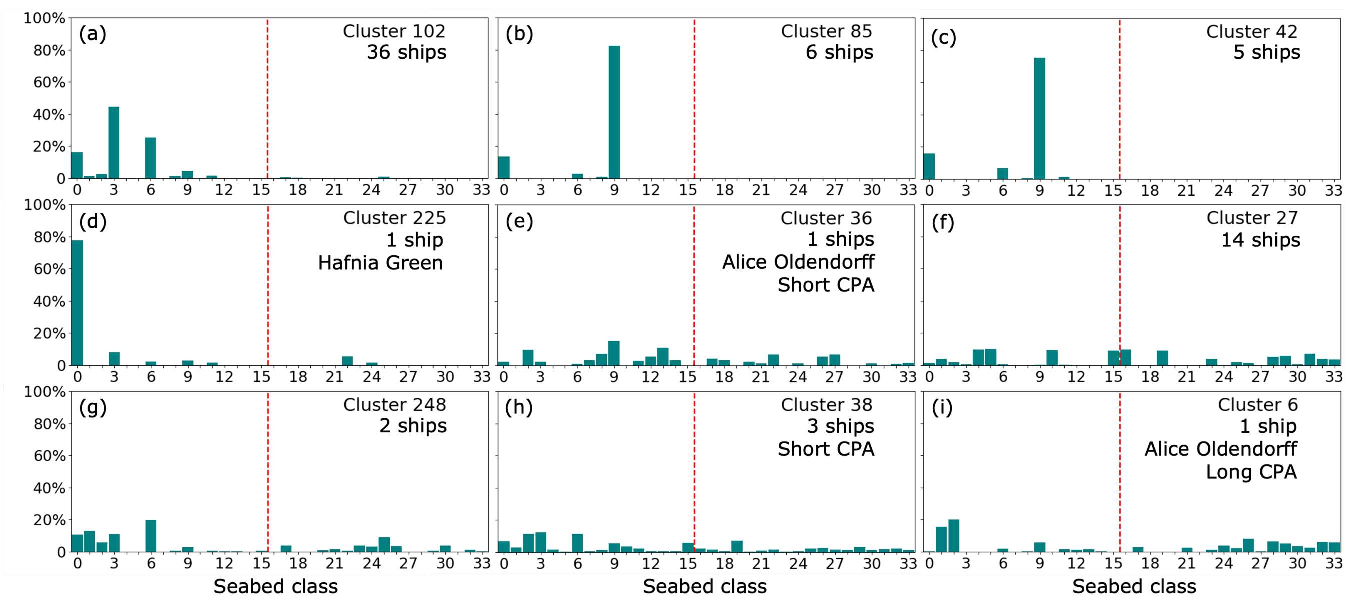

Fig. 2. Seabed probability distribution plots of the synthetic data samples assigned to the same cluster as the 69 measured data samples using the k = 250 model. The cluster assignments are listed in Table II.

compared to the seabed classification results from the ResNet-18 models.

When the 69 measured data samples (i.e., ship spectrograms from the VLAs) are individually passed through the trained k-means clustering model, they are each assigned to a cluster. The assigned cluster numbers are listed in Table II. The 69 data samples where assigned to only nine of the $k = 250$ clusters. While the cluster number is not significant, the properties of the synthetic data samples assigned to that cluster are important because they can provide insights into appropriate labels for the measured data samples. Specifically, the corresponding seabed distributions associated with the assigned clusters assigned (based on the synthetic data samples in the same cluster) are shown in Fig. 2. Plots of the seabed and CPA range for the synthetic data samples in each cluster are shown in Fig. 3.

Consider first the seabed distribution plots in Fig. 2. Of the 69 measured data samples, 48 are placed into clusters that contain synthetic data samples primarily from seabeds 0, 3, 6, and 9. These 48 data samples could reasonably be assigned a specific seabed label using the most common seabed in the cluster, or the distribution of seabeds could be used to estimate the probability that the data sample was measured in an area with different effective seabeds. Thus, for 70% of the measured data samples, the unsupervised method can yield an approximate seabed label.

The remaining 21 samples are placed into clusters with no distinct seabed associations in Fig. 2. Of these 21, five had extraneous noise in the spectrograms and four had low signal-to-noise ratio (SNR). A limitation is expected with regards to low SNR because no extra background noise was added in the training in the unsupervised clustering model. Also, because the entire spectrogram is input to the k-means algorithm, any misalignment of CPA would potentially affect the ability to assign reasonable clusters to the data samples.

With regards to the main goal of providing labels for the measured data, the seabed is not the only property associated with the synthetic data samples. For example, the single ship placed into cluster 36 has a CPA of only 0.6 km and the three ships assigned to cluster 38 have CPA ranges 2.9-3.3 km. The synthetic data samples in clusters 36 and 38 all have short CPA ranges, as shown in Fig. 3. For these clusters, the close CPA range dominates the features in the spectrograms to train the clustering algorithm. While there is no seabed class information for these clusters, a label of "short CPA range" could be applied to these four unlabeled data samples using this approach.

IV. Conclusions

This paper has shown that an unsupervised clustering method, such as k-means, has the potential to supply approximate labels for unlabeled datasets. This has been demonstrated for seabed classification labels on ship noise spectrograms.

Six different CNN-based seabed classifiers were trained on synthetic data and then applied to 69 measured data samples from SBCEX 2017. The predicted seabeds tend to have a sediment-water sound speed ratio less than one, as is expected in the New England Mudpatch area.

A k-means clustering algorithm was also trained on synthetic data, and the properties of the data samples assigned to each cluster were evaluated. The 69 measured data samples were assigned to nine clusters: 38 of them assigned to four clusters that were related with just a few seabeds (i.e., the synthetic data samples in the cluster came from seabeds 0,3,6,9). These seabeds were similar to those selected by the CNN-based seabed classifiers. Four of the measured data samples were assigned to clusters with short CPA ranges.

This work provides an example of how an unsupervised clustering approach can be used to estimate labels for unlabeled datasets and opens the way for further applications of machine learning to ocean acoustics.

References

[1] D. F. Van Komen, T. B. Neilsen, D. B. Mortenson, M. C. Acree, D. P. Knobles, M. Badiey, and W. S. Hodgkiss, "Seabed type and source parameters predictions using ship spectrograms in convolutional neural networks," *The Journal of the Acoustical Society of America*, vol. 149, no. 2, pp. 1198–1210, 2021.

[2] C. D. Escobar-Amado, T. B. Neilsen, J. A. Castro-Correa, D. F. Van Komen, M. Badiey, D. P. Knobles, and W. S. Hodgkiss, "Seabed classification from merchant ship-radiated noise using a physics-based ensemble of deep learning algorithms," *The Journal of the Acoustical Society of America*, vol. 150, no. 2, pp. 1434–1447, 2021.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," 2015.

[4] D. J. Forman, T. B. Neilsen, D. F. Van Komen, and D. P. Knobles, "Validating deep learning seabed classification via acoustic similarity. (accepted for publication)," *The Journal of the Acoustical Society of America. Express Letters*, vol. 1, no. 4, 2021.

[5] G. Lau, T. B. Neilsen, D. P. Knobles, and W. S. Hodgkiss, "Seabed classification with resnet-18 using multichannel ship noise spectrograms," *IEEE Journal of Oceanic Engineering*, submitted 2023.

[6] D. Li, C. Tang, C. Xia, and H. Zhang, "Acoustic mapping and classification of benthic habitat using unsupervised learning in artificial reef water," *Estuarine, Coastal and Shelf Science*, vol. 185, pp. 11–21, 2017.

[7] M. Bianco and P. Gerstoft, "Dictionary learning of sound speed profiles," *The Journal of the Acoustical Society of America*, vol. 141, no. 3, pp. 1749–1758, 2017.

[8] J. A. Castro-Correa, S. A. Arnett, T. B. Neilsen, L. Wan, and M. Badiey, "Supervised classification of sound speed profiles via dictionary learning," *Journal of Atmospheric and Oceanic Technology*, 2022.

[9] S. Kamal, S. K. Mohammed, P. R. S. Pillai, and M. H. Supriya, "Deep learning architectures for underwater target recognition," in *2013 Ocean Electronics (SYMPOL)*, 2013, pp. 48–54.

[10] E. Ozanich, A. Thode, P. Gerstoft, L. A. Freeman, and S. Freeman, "Deep embedded clustering of coral reef bioacoustics," *The Journal of the Acoustical Society of America*, vol. 149, no. 4, pp. 2587–2601, 2021.

[11] S. Yang, L. Xue, X. Hong, and X. Zeng, "A lightweight network model based on an attention mechanism for ship-radiated noise classification," *Journal of Marine Science and Engineering*, vol. 11, no. 2, p. 432, 2023.

[12] Q. Sun and K. Wang, "Underwater single-channel acoustic signal multitarget recognition using convolutional neural networks," *The Journal of the Acoustical Society of America*, vol. 151, no. 3, pp. 2245–2254, 2022.

[13] E. K. Westwood, C. T. Tindle, and N. R. Chapman, "A normal mode model for acousto-elastic ocean environments," *J. Acoust. Soc. Am.*, vol. 100, no. 6, pp. 3631–3645, 1996.

[14] S. C. Wales and R. M. Heitmeyer, "An ensemble source spectra model for merchant ship-radiated noise," *J. Acoust. Soc. Am.*, vol. 111, no. 3, pp. 1211–1231, 2002.

[15] K. Howarth, T. B. Neilsen, D. F. Van Komen, and D. P. Knobles, "Seabed classification using a convolutional neural network on explosive sounds," *IEEE Journal of Oceanic Engineering*, pp. 1–10, 2021.

[16] P. S. Wilson, D. P. Knobles, and T. B. Neilsen, "Guest editorial an overview of the seabed characterization experiment," *IEEE Journal of Oceanic Engineering*, vol. 45, no. 1, pp. 1–13, 2020.

[17] S. Mao, E. Tu, G. Zhang, L. Rachmawati, E. Rajabally, and G.-B. Huang, "An automatic identification system (ais) database for maritime trajectory prediction and data mining," in *Proceedings of ELM-2016*. Springer, 2018, pp. 241–257.

[18] J. Béjar Alonso, "K-means vs mini batch k-means: A comparison," *Universitat Politècnica de Catalunya, Departament de Llenguatges i Sistemes Informàtics*, 2013, https://upcommons.upc.edu/bitstream/handle/2117/23414/R13-8.pdf [Accessed on May 9, 2022].

[19] J. D. Chaytor, M. S. Ballard, B. J. Buczkowski, J. A. Goff, K. M. Lee, A. H. Reed, and A. A. Boggess, "Measurements of geologic characteristics and geophysical properties of sediments from the new england mud patch," *IEEE Journal of Oceanic Engineering*, vol. 47, no. 3, pp. 503–530, 2021.

[20] "Bureau of Ocean Energy Management (BOEM) and National Oceanic and Atmospheric Administration (NOAA). MarineCadastre.gov. [AIS_2017_03_Zone19 and AIS_2017_04_Zone19]. Retrieved [August 07, 2020] from." [Online]. Available: https://marinecadastre.gov/ais/

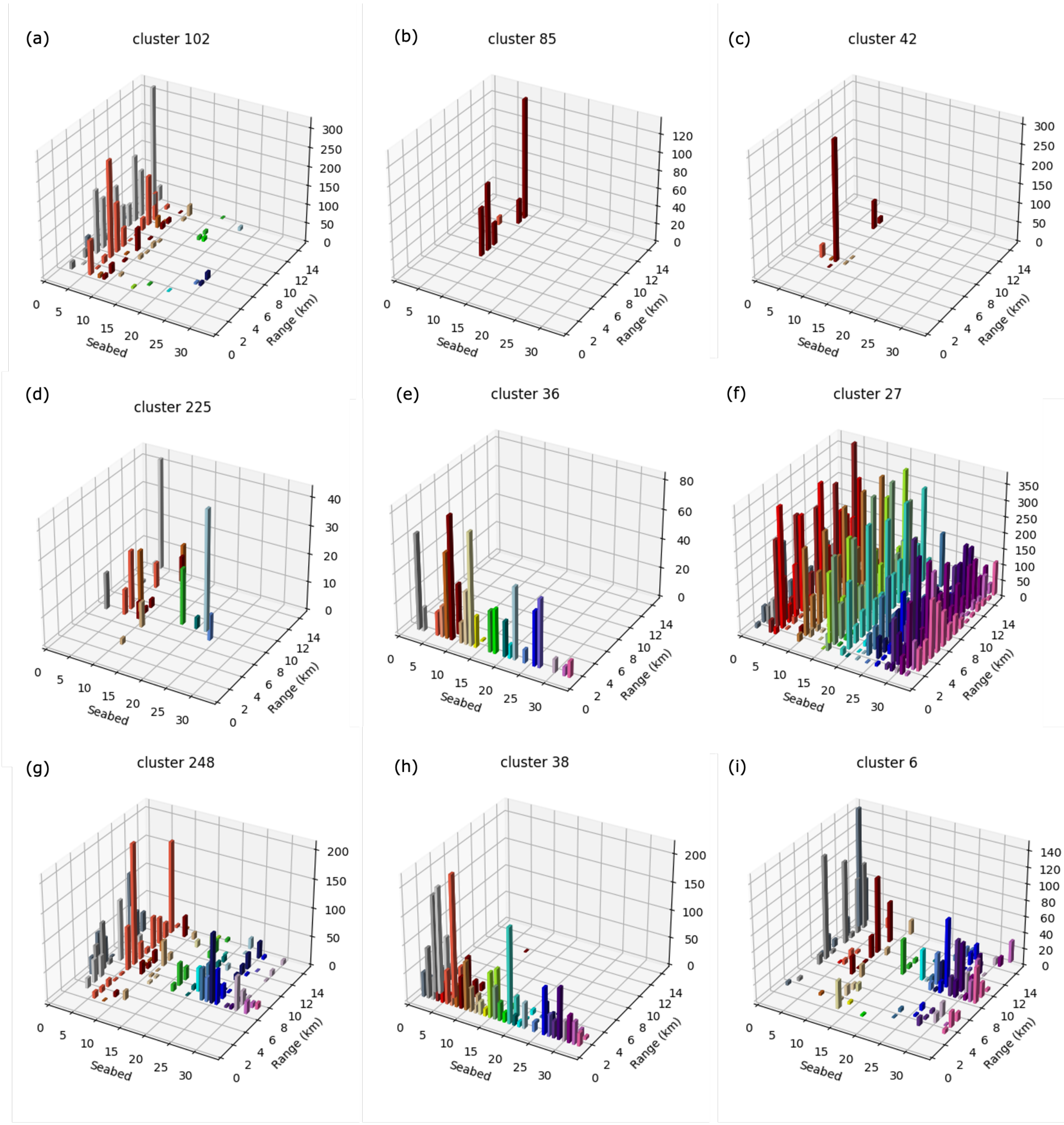

Fig. 3. Histogram showing the number of synthetic data samples with different seabed types and CPA ranges for nine clusters using the $k = 250$ model. The 69 measured data samples were assigned to these nine clusters as listed in Table II.

TABLE II

LIST OF SHIPS RECORDED DURING THE SBCEX 2017. THE SHIPS ARE NUMBERED 1-51; SOME OF THEM WERE DETECTED ON MULTIPLE VLAS TO YIELD 69 MEASURED DATA SAMPLES. THE SECOND COLUMN INDICATES SHIP NAME AND THE THIRD COLUMN WHICH VLA THE DATA SAMPLE CAME FROM: (1) VLA1-MPL, (2) VLA2-MPL AND (3) VLA-UD. THE FOURTH COLUMN IS THE CLUSTER ASSIGNED TO THE DATA SAMPLES BY THE k-MEANS CLUSTERING. THE FIFTH AND SIXTH COLUMNS CONTAIN THE CLOSEST-POINT-OF-APPROACH (CPA) RANGE IS GIVEN IN KM, AND THE SPEED OF THE SHIP, v_{sh} IN KNOTS FROM AIS DATA [20]. SYMBOLS NEXT TO THE CPA RANGE INDICATE A QUALITATIVE DESCRIPTION OF THE SIGNAL. SUPERSCRIPTS $+$ AND $-$ INDICATE THAT THE SOO SPECTROGRAM HAS HIGH OR LOW SNR, RESPECTIVELY. SUBSCRIPT $*$ REPRESENTS THAT A LOUD NOISE EVENT DIFFERENT THAN THE BROADBAND NOISE GENERATED BY THE SHIP WAS PRESENT. THE SHIPS ARE ORDERED BASED ON TIME OF THE RECORDINGS, WHICH COVERED JULIAN DAY 67 TO 96, AS LISTED IN TABLE 2 IN [2].

#	Ship name	VLA	Cluster	CPA	v_{sh}		#	Ship name	VLA	Cluster	CPA	v_{sh}
1	MATAQUITO	3	27	9.5^{+}_{*}	19.4		29	BRITISH TRANQUILLITY	3	102	9.8^{-}_{*}	13.5
2	ALICE OLDENDORFF	3	36	0.6^{+}	8.3		30	CPO BALTIMORE	1	102	9.3^{+}_{*}	14.7
3	PAGNA	3	27	13.3^{+}_{*}	17.5		31	TORM SAONE	1	27	8.6^{-}	13.0
4	JIA SHENG SHAN	3	27	9.1^{+}_{*}	11.2		32	ARDMORE SEAVANTAGE	3	102	5.0^{+}	15.4
5	EVER LIVING	3	102	5.8^{+}	18.4		33	LEOPARD	3	102	10.2^{+}	13.2
6	ZIM QINGDAO	3	102	8.8^{-}_{*}	11.3		34	CMA CGM MOLIERE	3	27	9.8^{-}	15.9
7	STI CLAPHAM	3	102	4.6^{+}_{*}	11.8		35	HAFNIA GREEN	2	85	2.8^{+}	10.9
8	NYK RUMINA	3	102	5.0^{+}	19.8		35	HAFNIA GREEN	3	225	4.8^{+}_{*}	10.9
9	BARBARA	3	102	5.7^{+}_{*}	19.9		36	MSC NERISSA	1	102	8.7^{+}	15.6
10	MSC BREMEN	3	102	10.0^{+}_{*}	18.4		36	MSC NERISSA	3	102	9.8^{+}	15.6
11	OREGON HIGHWAY	3	85	0.7^{+}_{*}	15.3	z	37	VIKING BRAVERY	1	38	3.3^{+}	14.7
12	MSC LAUSANNE	3	102	5.5^{-}	12.0		37	VIKING BRAVERY	2	42	3.1^{+}	14.7
13	NYK RIGEL	3	85	5.2^{+}_{*}	19.9		37	VIKING BRAVERY	3	38	2.9^{+}	14.7
14	ZIM SHANGHAI	3	42	5.3^{+}_{*}	17.9		38	MAERSK MATSUYAMA	1	102	7.2^{+}	11.6
15	TRANSPORT	3	102	1.5^{+}	8.4		38	MAERSK MATSUYAMA	2	102	4.6^{+}	11.6
16	BOW PIONEER	3	102	4.7^{+}_{*}	11.9		38	MAERSK MATSUYAMA	3	102	6.6^{-}_{*}	11.6
17	DISCOVERY BAY	3	102	5.9^{+}	13.3		39	TOMBARRA	1	102	6.4^{+}	16.3
18	MSC ESTHI	3	102	11.1^{-}_{*}	17.8		39	TOMBARRA	2	42	3.2^{+}	16.3
19	ATLANTIC CONVEYOR	1	102	9.0^{+}	16.1		40	ATLANTIC SEA	1	27	9.3^{+}	17.6
19	ATLANTIC CONVEYOR	2	248	12.2^{+}	16.1		40	ATLANTIC SEA	2	27	2.7^{+}	17.6
19	ATLANTIC CONVEYOR	3	102	10.2^{+}	16.1		40	ATLANTIC SEA	3	102	10.6^{+}	17.6
20	MSC ANIELLO	2	27	3.6^{+}	14.3		41	KAZDANGA	2	27	1.9^{+}_{*}	9.2
21	MSC KALAMATA	1	102	5.9^{+}	16.7		42	NYK DIANA	1	102	8.6^{+}_{*}	18.9
21	MSC KALAMATA	2	38	3.1^{+}	16.7		42	NYK DIANA	1	42	9.8^{+}_{*}	18.9
21	MSC KALAMATA	3	27	4.9^{+}	16.7		43	CHEMICAL PIONEER	1	102	8.5^{+}	16.2
22	CORRIDO	2	27	4.0^{+}	14.6		44	DENAK VOYAGER	1	102	6.7^{+}_{*}	10.3
23	YM UNANIMITY	2	102	3.8^{+}	9.1		44	DENAK VOYAGER	3	102	5.5^{+}_{*}	10.3
24	MINERVA ZOE	1	102	8.6^{-}	12.3		45	ARCTIC BREEZE	1	248	8.2^{+}	14.3
25	BBC TENNESSEE	1	42	7.4^{-}_{*}	8.3		46	PAGANELLA	3	85	4.8^{+}_{*}	14.9
25	BBC TENNESSEE	2	85	4.2^{+}_{*}	8.3		47	MSC KOLKATA	3	102	4.7^{+}_{*}	9.6
26	CHEM VENUS	1	102	9.3^{-}	12.9		48	ALICE OLDENDORFF	3	6	10.3^{+}	10.7
27	MSC GISELLE	3	102	6.5^{+}	18.3		49	MSC AMERICA	3	102	6.6^{+}_{*}	16.0
28	FEDOR	1	27	8.6^{-}	11.6		50	CSCL AMERICA	3	102	10^{+}_{*}	21.2
29	BRITISH TRANQUILLITY	1	27	8.5^{-}	13.5		51	STEALTH BERANA	3	85	5.2^{+}_{*}	13.7
29	BRITISH TRANQUILLITY	2	27	12.0^{-}	13.5							