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Cite as: JASA Express Lett. **1**, 071201 (2021); https://doi.org/10.1121/10.0005512
Submitted: 10 March 2021 . Accepted: 07 June 2021 . Published Online: 13 July 2021

Jennifer L. K. McCullough, Anne E. Simonis, Taiki Sakai, Erin M. Oleson, et al.

JASA EXPRESS LETTERS ARTICLE asa.scitation.org/journal/jel

Acoustic classification of false killer whales in the Hawaiian islands based on comprehensive vocal repertoire

Jennifer L. K. McCullough,[1,a)] Anne E. Simonis,[2] Taiki Sakai,[3] and Erin M. Oleson[4]
[1]Joint Institute for Marine and Atmospheric Research, University of Hawai'i at Mānoa, Honolulu, Hawai'i 96822, USA
[2]Ocean Associates for Pacific Islands Fisheries Science Center, Arlington, Virginia 22207, USA
[3]Environmental Assessment Services, LLC for Southwest Fisheries Science Center, Richland, Washington 99354, USA
[4]Pacific Islands Fisheries Science Center, National Oceanic and Atmospheric Administration Fisheries, Honolulu, Hawai'i 96818, USA

jennifer.mccullough@noaa.gov, anne.simonis@noaa.gov, taiki.sakai@noaa.gov, erin.oleson@noaa.gov

Abstract: Use of underwater passive acoustic datasets for species-specific inference requires robust classification systems to identify encounters to species from characteristics of detected sounds. A suite of routines designed to efficiently detect cetacean sounds, extract features, and classify the detection to species is described using ship-based, visually verified detections of false killer whales (*Pseudorca crassidens*). The best-performing model included features from clicks, whistles, and burst pulses, which correctly classified 99.6% of events. This case study illustrates use of these tools to build classifiers for any group of cetacean species and assess classification confidence when visual confirmation is not available.

[Editor: Charles C. Church] https://doi.org/10.1121/10.0005512

Received: 10 March 2021 **Accepted:** 7 June 2021 **Published Online:** 13 July 2021

1. Introduction

Use of passive acoustic datasets to assess various elements of cetacean occurrence, population structure, and abundance is increasing (Baumann-Pickering *et al.*, 2014; Baumann-Pickering *et al.*, 2015; Barlow *et al.*, 2021; Barlow and Taylor, 2005). Although the sounds of some species are well characterized, recognizable by trained researchers, or unique enough for simple detection/classification routines (Backus and Schevill, 1966; Baumann-Pickering *et al.*, 2013; Zimmer *et al.*, 2005), the assignment of species identity to a detected vocal group is not a trivial task for many species. Ship-based surveys with concurrent visual and acoustic efforts provide acoustic detection datasets with visual species confirmation (Hill *et al.*, 2020; Rankin *et al.*, 2008; Yano *et al.*, 2018), allowing for examination of cetacean sound characteristics (Keating *et al.*, 2016; Rankin *et al.*, 2017) that can be used to classify acoustic detections without accompanying visual identity (Keating *et al.*, 2018).

A 2017 joint visual and acoustic ship-based survey of Hawaiian waters [Hawaiian Islands Cetacean and Ecosystem Assessment Survey (HICEAS)] (Yano *et al.*, 2018) provides a dataset with which classification tools can be developed and performance tested. This dataset, collected with two simultaneously surveying ships across the entire Hawaiian Exclusive Economic Zone (EEZ) throughout the summer and fall, contains 766 acoustic detections of 23 cetacean species with vocal groups verified by a team of experienced visual observers. The survey provides a large species-confirmed dataset with ample data to evaluate classifier performance for multiple species.

In waters surrounding the Hawaiian Islands, there are three distinct populations of false killer whales [*Pseudorca crassidens* (PC)] known as the Northwestern Hawaiian Islands insular, Main Hawaiian Islands (MHI) insular, and pelagic populations (Baird *et al.*, 2008; Baird *et al.*, 2010; Baird *et al.*, 2013; Chivers *et al.*, 2007). The resident MHI insular population is listed as endangered under the United States Endangered Species Act[1] due to its small population size and large decline over several decades in the late 1990s (Oleson *et al.*, 2010). Furthermore, the pelagic population is taken as bycatch in the Hawaii-based tuna longline fishery (Forney *et al.*, 2011). The management concerns surrounding these stocks have made them a focus of many Hawaii survey efforts due to the need for robust occurrence and abundance data when examining population status and potential management measures (Bradford *et al.*, 2017; Bradford *et al.*, 2018; Bradford *et al.*, 2021). Abundance estimates for these populations are available from visual-based sighting surveys, and to date there have not been adequate classifiers that can provide a species-level classification score for each encounter, independent of the

[a)]Also at: Pacific Islands Fisheries Science Center, National Oceanic and Atmospheric Administration Fisheries, Honolulu, Hawai'i 96818, USA. Author to whom correspondence should be addressed.

type of calls detected, that would allow for quantitative evaluation of acoustic detections that do not have visual species confirmation (Barlow and Rankin, 2007; Bradford *et al.*, 2021).

Highly vocal false killer whales produce echolocation clicks, whistles, and burst pulses (Oswald *et al.*, 2007; Oswald *et al.*, 2008; Rankin *et al.*, 2008). This behavior has allowed researchers to identify the possible vocal activity of false killer whales in towed hydrophone array recordings before the initial visual sighting of the species during ship-based surveys (Yano *et al.*, 2018). Classification models with high correct classification rates (>80%) have been developed to identify false killer whales through whistles (Oswald *et al.*, 2007) and echolocation clicks (Baumann-Pickering *et al.*, 2015) separately, but these models do not incorporate their entire vocal repertoire. Accurate and automated classification of false killer whales would provide the opportunity to incorporate acoustic detections from ship-based surveys into abundance assessments and provide an efficient means for examining other autonomous passive acoustic datasets for false killer whale occurrence.

A compound classification model known as "bio-acoustic event classifier" (BANTER) has been developed using the entire repertoire of detected sounds, including echolocation clicks, whistles, and burst pulses (Rankin *et al.*, 2017). The BANTER model developed by Rankin *et al.* (2017) achieved an overall correct classification score of 84% across five dolphin species in the California Current and was able to distinguish short and long-beaked common dolphins (*Delphinus capensis* and *Delphinus delphis*, respectively). In previous classification efforts, the two species of common dolphins could not be differentiated (Oswald *et al.*, 2007), and including call characteristics from three different sound types allowed for a more accurate discrimination between species. BANTER models evaluate characteristics of acoustic detections from known species both individually and collectively (in events) to build a model that can be applied to novel data for classification of species (Rankin *et al.*, 2017). Additionally, it provides classification confidence scores for defined species or groups based on the available testing and training dataset. Together with a new data extraction and aggregation tool (PAMpal; Sakai, 2020), we demonstrate the workflow and ultimate performance of the BANTER classifier for false killer whales in the Hawaiian Islands. This case study can be modified for use toward any other single or multi-species detection and classification problem.

2. Methods

The methods framework breaks down into three sections: process recordings, extract features, and build classifier (Fig. 1). Each section break represents a modular joint where researchers can package data for various analyses.

2.1 Process recordings

All acoustic recordings were collected as part of HICEAS in 2017 (Yano *et al.*, 2018). This large-scale survey for cetaceans and seabirds took place in July–December using two research vessels, which systematically surveyed the Hawaiian EEZ. On both vessels, the towed hydrophone array components and data acquisition systems were designed to be as similar as possible to produce comparable data. Acoustic recordings were collected from multi-channel towed hydrophone arrays using a 500 kHz sampling rate and a high pass filter at 1.6 kHz to reduce ship and flow noise. The visual and passive acoustic observers worked independently in the field; the passive acoustics observers received information on visual sightings in near real-time; however, passive acoustic detection information was not shared with the visual observers until the group had passed beyond the beam of the array. More details on the HICEAS survey, including data collection methods, the technical specifications of the towed array, and a summary of all acoustic and visual observations from the survey, are available from Yano *et al.* (2018).[2]

Automated detectors within the PAMGuard software (version 2.00.16e; Gillespie *et al.*, 2009) were used to identify echolocation clicks, whistles, and burst pulses. To increase the speed and resolution of data processing, the data were decimated to 250 kHz for click detection and 75 kHz for whistle and burst pulse detection. Echolocation clicks were detected using the Click Detector module, which incorporated a fourth order IIR Butterworth high-pass filter with a 4 kHz corner frequency to reduce false triggering on low-frequency sounds. A 14 dB signal-to-noise ratio (SNR) threshold was required for all click detections. A suite of PAMGuard click classifiers (Keating and Barlow, 2013) was used to categorically label click detections based on the presence of energy in various frequency bands. Within BANTER, these labeled detections were treated as distinct click detectors, which allow the model to distinguish contributions from each detector to different classes or species. Whistles were detected from spectrograms (1024 point FFT Hanning window) using the PAMGuard Whistle and Moan Detector module. Whistle contours were saved if they were between 2 and 28 kHz and had a minimum duration of 546 ms. Burst pulses were detected through a multi-step process utilizing the same spectrogram used in whistle detection, as well as the PAMGuard Cepstrum module. In signal processing, the cepstrum is used to identify periodic structures within the spectrum (Bogert *et al.*, 1963). In our case, the cepstrum captures the harmonic nature of burst pulses in a spectrogram, and the y axis of the cepstrum can be interpreted as the inter-click interval (ICI) of burst pulses. To detect burst pulses, the Whistle and Moan Detector module identified cepstral contours with a minimum duration of 68 ms between 2 and 37 kHz. A frequency range of 2–37 kHz in the cepstral space corresponds to an ICI between 0.36 and 6.7 ms or equivalently harmonics separated by 150–2750 Hz. Detections of echolocation clicks, whistles, and burst pulses were then grouped into acoustic events.

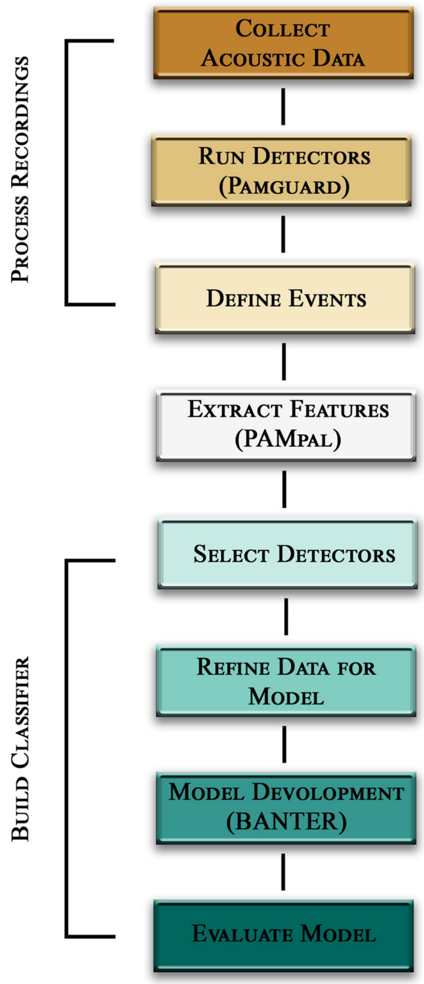

Fig. 1. Development flow chart for species classification model.

All acoustic events were labeled with a species code based on concurrent visual observations, with the exception of beaked whale (Ziphiidae) and sperm whale (*Physeter macrocephalus*) events, which were labeled based on the species-specific spectral and temporal characteristics of detected clicks (Backus and Schevill, 1966; Baumann-Pickering *et al.*, 2013; Zimmer *et al.*, 2005). Any acoustic events that were not classified to the species level (e.g., "Unidentified small delphinid") were not included in the model training dataset. All mixed-species events and overlapping events (those visually or acoustically localized within 3 nmi of another event) were also omitted. The start and end times of acoustic events were initially defined by analysts in the field based on localization and verified in post-processing. The start and end times are the respective first and last call times detected by the PAMGuard detectors or through aural monitoring.

2.2 Extract features

A suite of spectral and temporal features was calculated from a single channel for all click, whistle, and burst pulse detections using the open-source PAMpal package within the R software (R Core Team, 2020; Sakai, 2020). The full list of features calculated by PAMpal is available in the R package documentation[3]; these features were chosen based on those that have proven important in previous species classification efforts using echolocation clicks (Baumann-Pickering *etal.*, 2010; Griffiths *et al.*, 2020) and whistles (Oswald *et al.*, 2007). For echolocation clicks, a high pass filter at 1.6 kHz was applied before extracting features using a window length of 250 ms. Click detections were omitted if they contained peak frequencies outside of the expected range for each detector (e.g., 2–15, 15–30, 30–50, and 50–80 kHz). Because acoustic events were defined by start and end time encompassing all click detections in that time window, we evaluated model performance with additional noise-removal steps. Click detections with peak frequencies below 5 kHz or greater than 80 kHz, 10 dB bandwidth less than 5 kHz, and durations less than 2 μs or greater than 1000 μs contained temporal and spectral properties that suggested they were noise (including echosounder pulses used throughout the survey); therefore, these signals were discarded using a custom script in R.

2.3 Build classifier

We used the two-step, random forest BANTER modeling framework described by Rankin *et al.*, (2017) and available in the R package "banter," in which call classifiers (step 1) are used to develop an event-level classifier (step 2). Defining the "best model" is an iterative process. Multiple detector types were considered in the model development, including the whistle, burst pulse, and five click detectors described earlier. Because BANTER uses generalized detectors with the intent of capturing a broad diversity of those signals that are present, any given detector included in the model development was required to contain detections from at least two species for functionality. We varied the number of trees and sample size of calls or events used to train the respective call (step 1) and event classifiers (step 2) to both minimize and stabilize error within the model.

Because random forest algorithms sample the data and randomize the variables, they are in principle robust to overfitting (Hastie *et al.*, 2009) and do not require separate training and testing datasets. Variable importance and model performance were visualized using the rfPermute package (Archer, 2020). We evaluated models trained on multiple potential species labels (e.g., false killer whales, sperm whales, rough-toothed dolphins) as well as a two-case scenario where all species besides false killer whales "PC" were considered under an aggregated label "OTHER." OTHER species consist of spotted dolphin (*Stenella attenuata*), striped dolphin (*Stenella coeruleoalba*), rough-toothed dolphin (*Steno bredanensis*), Risso's dolphin (*Grampus griseus*), Fraser's dolphin (*Lagenodelphis hosei*), melon-headed whale (*Peponocephala electra*), pygmy killer whale (*Feresa attenuata*), short-finned pilot whale (*Globicephala macrorhynchus*), and sperm whale (*Physeter macrocephalus*). The model provides a classification score for each candidate species within each acoustic event, with each species score ranging from 0 to 1. The species (or grouping, in the case of the PC versus OTHER model) with the greatest score is the assigned species for each event.

3. Results

Approximately 2400 h of recordings were collected during HICEAS 2017, including 766 acoustic events of cetaceans. After removing baleen whales, unidentified dolphins, mixed-species, and overlapping acoustic events, 230 cetacean acoustic encounters from 10 species were used to build BANTER models. A preliminary review of beaked whale acoustic encounters indicated that our noise removal steps were not sufficient to eliminate false noise detections within beaked whale events such that false detections dominated these encounters. Therefore, all beaked whale events were excluded from the models. For all species included in the models, the event duration and the number of echolocation click, whistle, and burst pulse detections are described in Table 1.

For the final models, the first step of random forest BANTER modeling consisted of 2000 trees and 15 individual calls per species for each detector. These values result in 105 calls per tree in the multi-species model and 30 calls per tree in the two-case model. The second step for event classification of the multi-species model used 30 000 trees and 8 events per species to build each tree, whereas the two-case was built with 10 000 trees and 15 events per species to build each

Table 1. Acoustic detection data used to build classification models. Detection counts are represented as an average number of each signal type detected per event ± standard deviation, with the total number of that signal type noted in parentheses.

Species		Events		Detection counts			
Scientific name	Common name	Count	Duration (min)	Clicks	Whistles	Burst pulses	Total
Stenella attenuata	Spotted dolphin	16	36 ± 22 (570)	4888 ± 8032 (78 207)	135 ± 181 (2027)	78 ± 204 (1014)	81 248
Stenella coeruleoalba	Striped dolphin	19	117 ± 326 (2220)	273 ± 734 (5182)	106 ± 156 (2007)	21 ± 57 (278)	7467
Steno bredanensis	Rough-toothed dolphin	12	37 ± 32 (449)	8119 ± 10 552 (97 432)	113 ± 115 (1020)	93 ± 186 (1023)	99 475
Grampus griseus	Risso's dolphin	9	40 ± 36 (361)	5763 ± 5524 (51 868)	52 ± 29 (259)	205 ± 193 (1643)	53 770
Lagenodelphis hosei	Fraser's dolphin	2	62 ± 14 (124)	204 ± 54 (408)	472 ± 234 (945)	16 ± 8 (32)	1385
Peponocephala electra	Melon-headed whale	2	51 ± 22 (103)	7476 ± 1621 (14 952)	422 ± 1 (843)	1079 ± 482 (2158)	17 953
Feresa attenuata	Pygmy killer whale	3	18 ± 8 (55)	1275 ± 1376 (3824)	2 ± 1 (5)	28 ± 43 (83)	3912
Pseudorca crassidens	False killer whale	20	150 ± 101 (3004)	17 879 ± 29 252 (357 574)	2651 ± 2359 (53 011)	122 ± 146 (2436)	413 021
Globicephala macrorhynchus	Short-finned pilot whale	20	62 ± 46 (1248)	4579 ± 5849 (91 577)	259 ± 308 (4914)	506 ± 687 (8602)	105 093
Physeter macrocephalus	Sperm whale	127	46 ± 49 (5793)	1697 ± 6357 (201 925)	27 ± 28 (557)	7 ± 15 (658)	203 140

Table 2. Confusion matrix for the multi-species model. Classification scores are shown as percent correct with 95% confidence interval in parentheses. Prior percentage represents the chance of correct classification based solely on the total number of events possible (Archer *et al.*, 2017). Species code is based on the first letter of the genus and species shown in Table 1. NA, not applicable.

	SC	SB	SA	GG	PC	GM	PM	Correct (%)	Prior (%)
SC	17	0	2	0	0	0	0	89.47 (66.68, 98.70)	8.52
SB	0	7	1	1	0	1	2	58.33 (27.67, 84.83)	5.38
SA	3	1	10	1	1	0	0	62.50 (35.43, 84.80)	7.17
GG	0	0	1	7	0	0	1	77.78 (39.99, 97.19)	4.04
PC	0	0	0	0	20	0	0	100.00 (83.16, 100.00)	8.97
GM	2	1	0	1	1	14	1	70.00 (45.72, 88.11)	8.97
PM	7	1	2	3	2	2	110	86.61 (79.44, 92.00)	56.95
Overall	NA	NA	NA	NA	NA	NA	NA	82.96 (77.37, 87.65)	35.74

tree. This results in 56 events per tree for the multi-species model and 30 events per tree in two-case model. All remaining events in step 2 for both models were assigned to an out-of-bag (OOB).

The multi-species BANTER model produced a 100% correct classification rate for false PC, but only an 82.96% overall correct classification across all species (Table 2). Even though all the PC events were correctly classified, four events from other species were misclassified as PC within close proximity of the main cluster [Fig. 2(A)]. Model output was stable when the number of trees versus error no longer varied for more than 2500 trees, reached at the 20 000 mark [Fig. 2(B)]. In addition, the multi-species model dropped three species (Fraser's dolphin, melon-headed whale, pygmy killer whale) due to their low event count based on the selected value of events per species. If the value of events per species had been one, the multi-species model would have produced an overall correct classification of 59.13%, and those species could have been included. The best performing BANTER model that included all ten species was the two-case model producing a

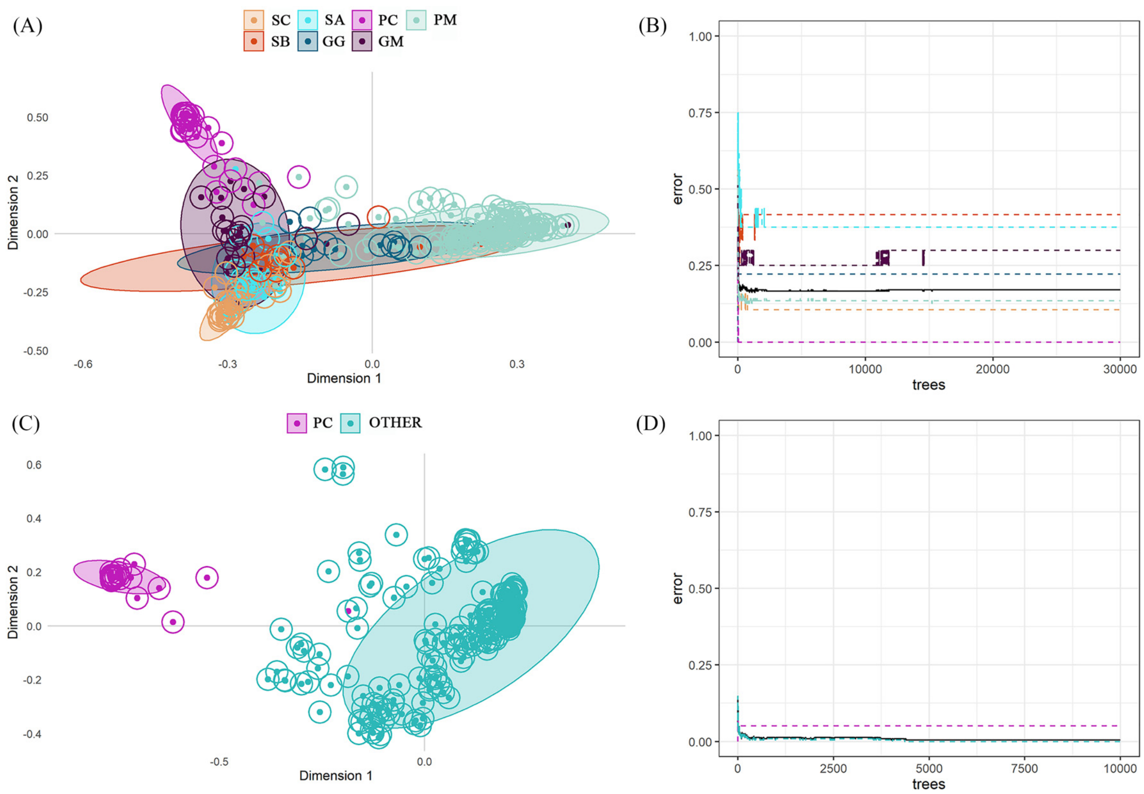

Fig. 2. Proximity plots [(A), (C)] and random forest event classification error rates versus the number of trees [(B), (D)] applied in the classification model. Dots on the proximity plot represent acoustic events color-coded by the true species surrounded by a ring indicating species classification from model. Error rates for species classification are represented as dashed lines and OOB as solid black. Output from the multi-species model [(A), (B)] is shown versus single-species focused model [(C), (D)].

Table 3. Confusion matrix for the two-case model representing PC versus remaining species (OTHER). Classification scores are shown as percent correct with 95% confidence interval in parentheses. Prior percentage represents the chance of correct classification based solely on the number of events possible (Archer *et al.*, 2017). NA, not applicable.

	PC	OTHER	Correct (%)	Prior (%)
PC	19	1	95.00 (75.13, 99.87)	8.70
OTHER	0	210	100.00 (98.26, 100.00)	91.30
Overall	NA	NA	99.57 (97.60, 99.99)	84.12

99.57% overall correct classification (Table 3). Model output was stable when the number of trees reached the 7500 mark [Fig. 2(D)]. All OTHER events classified correctly, and the one misclassified PC event was in close proximity to a cluster of OTHER events [Fig. 2(C)].

4. Discussion

The two-case BANTER model (PC versus OTHER) was able to correctly predict species labels for 99% of all cases, providing a robust classifier for false killer whale acoustic events. Though the multi-species model only reached 83% correct classification, it showed that the cluster of false killer whale events was highly distinguishable from the other species [Fig. 2(A)]. The strength of these classification models is likely based on the expansiveness of the dataset. Acoustic data collection spanned numerous months, two vessels with varying noise profiles, and over large geographic areas. These training data captured a variety of social groups and behavioral contexts within acoustic events from each species.

The two-case classification model has several applied strengths with some limitations. Some uses of passive acoustic datasets toward addressing current conservation and management issues for false killer whales require only reliable identification of false killer whale acoustic events, with little need for understanding the presence of other species detected within the dataset. Improving classifier performance for false killer whales by aggregating detections of all others in a single category is beneficial in this use-case. A similar approach (one versus the rest) could be applied to other species or ensembles of species, though doing so clearly precludes the ability to identify other priority species, at least within the same classifier set. Further, this approach may not be as successful for less vocal species or species with fewer distinct species-specific features.

The ten species of odontocetes in the two-case classification model represent the majority of odontocetes species present in the Hawaii region. Other known species in the region are killer whale (*Orcinus orca*), spinner dolphin (*Stenella longirostris*), bottlenose dolphin (*Tursiops truncatus*), ginkgo-toothed beaked whale (*Mesoplodon ginkgodens*), dwarf sperm whale (*Kogia sima*), and pygmy sperm whale (*Kogia breviceps*), but they were not acoustically detected during HICEAS and, therefore, were not included in this initial model. As additional data become available, species can be added to the model for future analyses. Future studies may also consider additional data from other seasons or other geographic regions to evaluate whether such variation impacts classifier performance.

Until now, there were no tools to classify acoustic detections of false killer whales automatically using their entire vocal repertoire. Manual evaluation of acoustic characteristics has been the primary method for analyses (Bayless *et al.*, 2017; Thode *et al.*, 2016). Depending on the specific questions to be addressed, either the multi-species or the two-case BANTER model will provide automatic classification and metrics for evaluating the classification confidence of false killer whale detections with no visual confirmation. All of the detection, feature extraction, and classification tools are open-source, and the methods we demonstrate here can easily be applied to other regions, taxa, and call types.

Acknowledgments

We thank the officers and crew of the National Oceanic and Atmospheric Administration (NOAA) ship *Oscar Elton Sette* and NOAA ship *Rueben Lasker* for assistance and support throughout the HICEAS 2017 survey. We thank the additional acoustics team members from both ships for exceptional data collection (Shannon Coates, Ann Allen, Ali Bayless, Arial Brewer, Jessica Crance, Rory Driskell, Erik Norris, Megan Slack, and Jenny Trickey). Thanks to the extensive visual team during HICEAS 2017 for species identification. Additional thanks to Shannon Rankin and Eric Archer for advice and guidance with the BANTER model. Support for data analyses was provided by the National Marine Fisheries Service (NMFS) Pacific Islands Fisheries Science Center.

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