Automated detection and tracking of marine mammals: a novel sonar tool for monitoring effects of marine industry.

Gordon D. Hastie[1*], Gi-Mick Wu[1, 2], Simon Moss[1], Pauline Jepp[3], Jamie MacAulay[1], Arthur Lee[4], Carol Sparling[5], Clair Evers [1, 6], and Doug Gillespie[1].

1. *Sea Mammal Research Unit, Scottish Oceans Institute, University of St Andrews, St Andrews, Fife, KY16 8LB. UK*
2. *DEVELOP, Helmholtz Centre for Environmental Research, Permoserstraße 15, 04318 Leipzig, DE*
3. *Tritech International Ltd, Peregrine Road, Westhill Business Park, Westhill, Aberdeenshire, AB32 6JL. UK*
4. *SMRU Consulting Asia Pacific, 1802 One Midtown, 11 Hoi Shing Road, Tseun Wan West, Hong Kong SAR*
5. *SMRU Consulting Europe, New Technology Centre, North Haugh, St Andrews, Fife, KY16 9SR. UK*
6. *Fisheries and Oceans Canada, Bedford Institute of Oceanography, 1 Challenger Drive, Dartmouth, Nova Scotia, B2Y 4A2. Canada*

Abstract

1. Many marine industries may pose acute risks to marine wildlife. For example, tidal turbines have the potential to injure or kill marine mammals through collisions with turbine blades. However, the quantification of collision risk is currently limited by a lack of suitable technologies to collect long-term data on marine mammal behaviour around tidal turbines.
2. Sonar provides a potential means of tracking marine mammals around tidal turbines. However, its effectiveness for long-term data collection is hindered by the large data volumes and the need for manual validation of detections. Therefore, the aim here was to develop and test automated classification algorithms for marine mammals in sonar data.
3. Data on the movements of harbour seals were collected in a tidally energetic environment using a high-frequency multibeam sonar mounted on a custom designed seabed mounted platform. The study area was monitored by observers to provide visual validation of seals and other targets detected by the sonar.
4. A total of 65 confirmed seals and 96 other targets were detected by the sonar. Movement and shape parameters associated with each target were extracted and used to develop a series of classification algorithms. Kernel Support Vector Machines (SVM) were used to classify targets (seal vs non-seal) and a series of cross-validation analyses were carried out to quantify classifier efficiency.
5. The best-fit kernel SVM correctly classified all the confirmed seals but misclassified a small percentage of non-seal targets (~8%) as seals. Shape and non-spectral movement parameters were considered to be the most important in achieving successful classification.
6. Results indicate that sonar is an effective method for detecting and tracking seals in tidal environments and the automated classification approach developed here provides a key

tool that could be applied to collecting long term behavioural data around anthropogenic activities such as tidal turbines.

KEYWORDS: ocean, monitoring, new techniques, behaviour, mammals, renewable energy

1. Introduction

Most marine environments have experienced growing industrialisation over the past several decades with increases in marine transportation, oil and gas exploration and extraction, and fisheries (Smith, 2000). Many of the activities associated with these industries pose acute risks to marine wildlife; for example, marine mammals can be injured or killed as a result of vessel collisions (Vanderlaan & Taggart, 2007), fisheries gear entanglement (van der Hoop, Corkeron, & Moore, 2017), and fisheries bycatch (Read, Drinker, & Northridge, 2006). In many cases, the nature and extent of these interactions can have important consequences for the demographics of affected populations and endanger the existence of some species (Read et al., 2006).

More recently, a number of novel technologies are being deployed in the marine environment that have the potential to cause injury or mortality to marine species. For example, tidal stream energy extraction is being rapidly developed in a number of countries; this is typically carried out using subsurface turbines that extract energy from tidally-driven moving water. Although there are a wide range of different tidal turbine designs, the majority have moving horizontal axis rotors that operate in a similar fashion to wind turbines. Concerns derive primarily from the potential for physical injury to marine mammals through direct contact with moving structures or parts of the devices (Wilson, Batty, Daunt, & Carter, 2007). However, at present there is a paucity of data on the 'fine-scale' movements of marine mammals around potentially high-risk activities or structures such as tidal turbines to quantify the true nature of the risks associated with potential interactions (Hastie et al., 2017).

One of the major challenges with collecting these data are the inherent difficulties associated with accurately measuring the movements of marine mammals underwater. However, accelerated development of active sonar systems for the sub-sea monitoring of potential security threats for the defence sector, and for fisheries research and management, provide a basis for tracking animal movements and monitoring avoidance or evasion behaviour of animals around tidal turbines (Hastie et al., 2014). The fundamentals of all active sonar systems are essentially the same; pulses of sound ('pings') are produced electronically underwater using a sonar projector and the system then monitors for echoes of these pulses as they reflect off objects using a series of hydrophones (Hastie et al., 2014). Active sonar has been used extensively in studies of marine mammal behaviour underwater (e.g. Benoit-Bird & Au, 2003a; Doksæter, Godo, Olsen, Nottestad, & Patel, 2009; Gonzalez-Socoloske & Olivera-Gomez, 2012; Nøttestad, Ferno, & Axelsen, 2002; Pyć, Geoffrey, & Knudsen, 2016) to track the movements of individual animals in a range of different habitats, and has provided insights into studies of diving behaviour, foraging mechanisms, and habitat selection. For example, Nøttestad et al (2002) used a 95 kHz Simrad SA 950 multibeam sonar to measure the behaviour of fin whales (*Balaenoptera physalus*) foraging on herring schools, and Benoit-Bird & Au (2003a) used a 200 kHz Kongsberg SM2000 to locate and track spinner dolphins (*Stenella longirostris*) in the water column in Hawaii. Further, West Indian manatee (*Trichechus manatus*) behaviour was measured in waters with very poor visibility (due to turbidity and sediment load) using a range of side-scan sonar systems (Gonzalez-Socoloske, Olievera-Gomez, & Ford, 2009; Gonzalez-Socoloske & Olivera-Gomez, 2012), and bottlenose dolphin (*Tursiops truncatus*) movements were tracked in high tidal flows using a 455 kHz Reson Seabat 6012 (Ridoux et al., 1997).

Whilst sonar has been used effectively for behavioural studies of marine mammals, these have tended to be relatively short term in nature and interpretations of the sonar data can be validated with concurrent visual observations at the surface (e.g. Benoit-Bird & Au, 2003a; Benoit-Bird & Au, 2003b). To be effective as a long-term behavioural monitoring tool, a number of potential limitations need to be overcome (Pyć et al., 2016). Specifically, by their nature, encounters between anthropogenic sources (such as tidal turbines) and marine mammals are expected to be infrequent so long time-series of data would likely be required to meaningfully analyse risk. However, data volumes from sonar systems are generally very high making it impractical to store data in the long term, and it is likely to be highly inefficient to manually review data post hoc to identify animals. An effective means of automatically identifying marine mammals and effectively reducing data volumes to a manageable size is therefore required for sonar to be efficient as a long term behavioural monitoring tool.

In the current study, the potential of high-frequency multibeam sonar as a means of remotely collecting high resolution movement data for marine mammals is investigated. Specifically, a series of sonar data of wild seals is collected to quantify the detection probability of seals and how this varies with range from the sonar. A seabed mounted sonar system is then designed and built to collect a series of movement data for seals in tidally energetic environments; the temporal and spatial granularity of these movement data are then measured to determine their suitability for measuring the 'fine scale' movement behaviour of seals in close proximity to anthropogenic activities such as tidal turbines. Further, the data were used as the basis for the development and validation of automated classification algorithms for seals. The implications of the results for using sonar as a long term monitoring tool around anthropogenic activities, in particular tidal turbines, are discussed.

2. Methods

Sonar system

Data on the movements of individual seals were collected using a high-frequency multibeam sonar system (Tritech Gemini 720id: Tritech International Ltd, Westhill, Aberdeenshire, UK). This is a forward looking multibeam sonar which provides information on sonar targets in the X-Y plane; it has a fundamental frequency of 720 kHz, a temporal resolution of approximately 10 Hz (when imaging up to ranges of 60 m), an angular resolution of 0.5°, and a range resolution of 0.8 cm. The horizontal swath width of the Gemini is 120° and the vertical beam is 20° (-3dB with a 10° downward tilt) (Parsons et al., 2017). The sonar emits an acoustic signal approximately 70 μs in duration and has a source level of approximately 200 dB re 1μPa (broadband) with a main lobe at 720 kHz (Parsons et al., 2017); for further details on the characteristics of the acoustic signal, see Electronic Supporting Information.

Multibeam sonar data is processed and displayed using the Tritech Gemini software (http://www.tritech.co.uk/support-software/gemini-software-v12000). This provides a display interface for data recording/ playback, screen capture, and range and gain control. Further, an automated target detection and tracking module (SeaTec) allows for the recording of information related to discrete objects in the sonar data that are within user-defined size and persistence bounds. This uses a flood-fill algorithm approach (e.g. Law, 2013) to summarise the shape and intensity patterns exhibited by each target and, if the target is within the user-defined specifications, it records basic information to *.txt files on timings (hh-mm-ss), locations (X-Y coordinates), ranges from the sonar (m), and kinematic information (speed and trajectory in the X and Y planes) for all mobile targets detected in the data (Parsons et al., 2017).

Detection of seals using sonar

To measure the detection probability of seals with the SeaTec sonar target detection and tracking software (see Sonar system section), a series of sonar data of wild grey seals (*Halichoerus grypus*) were collected between the 6th and 20th of June, 2011, in waters adjacent to a haul out site on the east coast of Scotland (Tay Estuary: 56° 26' 43.95'' N, 2° 47' 28.48'' W) where up to 1,000 grey seals regularly haul out (around 100 were present during data collection). Data were collected using a sonar deployed on a custom-built sonar mount from the side of a 7.5 m aluminium vessel and data were stored to external hard drives using a laptop PC located in the cabin of the boat. The boat was anchored approximately 200 m offshore and seals were imaged as they passed between the haul out and the open sea. The water was relatively shallow (3-5 m) with a sandy seabed and tidal currents ranged from approximately 0.5-1.5 ms^{-1}. Grey seals were imaged on the sonar appearing as distinct targets which were temporally persistent, and had highly localised patterns of high intensity pixels in the sonar images.

The range (m) of each seal was manually measured in the sonar image data at one second intervals and the probability of detection was modelled with respect to range from the sonar. This was achieved using a Generalised Linear Model (GLM) with binomial errors and a logit link function. The candidate predictor variable was mean range (m) of the seal from the sonar and the response variable was a categorical variable specifying whether the seal was detected by the SeaTec software (Yes=1, No=0). GLM analyses were carried out using the *stats* package in R (R Core Team, 2012) and model diagnostics were assessed using the package *car* (Fox & Weisberg, 2011). Model selection was carried out using a Wald's Test (Hardin & Hilbe, 2003) to determine the covariates' significance.

Classification of seals in sonar data

To develop and test classification algorithms for seals in sonar data, sonar data were collected in a narrow, tidally energetic channel on the west coast of Scotland (Kyle Rhea: 57°14'8.10"N, 5°39'15.25"W). The channel is approximately 4 km long, and 450 m wide (Hastie et al., 2017); water depths within the channel are generally less than 30 m and tidal currents can reach over 4 ms^{-1} (Wilson, Benjamins, & Elliott, 2013). Between April and September, over 100 harbour seals (*Phoca vitulina*) routinely haul out on intertidal rocks along the sides of the channel and forage within the channel (Hastie et al., 2016).

The sonar was mounted on a custom designed High Current Underwater Platform (HiCUP). This has a low profile tripod design (0.5 m high and 1.8 m from platform centre to end of each leg) and was based on calculations of turning moments and stability for a structure in a high tidal current. The HiCUP was fabricated in box steel beams with 400 kg of lead ballast inside each of the legs, and had an overall weight of approximately 1,500 kg. Overall, the HiCUP was designed to be stable on uneven seabed terrain and in tidal currents of up to 4 ms^{-1}. It was also designed to be deployable, to and from the seabed, by a relatively small non-specialist, vessel. The sonar was mounted in the centre of the HiCUP on a custom built sonar mount. This provided a secure mount for the sonar and, in the event that the HiCUP was deployed on uneven seabed terrain, allowed the sonar orientation to be manually adjusted in the pitch and roll axes to ensure that it was level (Figure 1).

The sonar HiCUP was deployed from 1st to 5th of August, 2015, on the seabed (rocky with small boulders) towards the western shore of Kyle Rhea at a depth of approximately 15 m (relative to Admiralty chart datum) using the survey vessel MV Toohey (Figure 1). A diver manually adjusted the pitch and roll of the sonar using a levelling bubble as reference immediately after deployment to ensure the sonar was level with respect to these axes. The HiCUP was attached to a small surface marker buoy so that its location could be determined by visual observers during data collection. A secondary 1,000 kg anchor was connected to the HiCUP via a chain running along the seabed and was located approximately 30 m inshore from the HiCUP. A polysteel rope riser from the secondary anchor was connected to two subsurface mooring buoys (to ensure that the sonar cables were kept clear of the HiCUP and seabed, and reduce potential damage as a result of chafing) and to a surface mooring buoy where a 7.5 m aluminium vessel could be moored to collect data (Figure 2). The sonar was connected to a 150 m power and communications cable with wet-mate terminations at each end. The cable was attached to the chain from the HiCUP, the secondary anchor, and the rope riser using cable ties; these could be connected to the topside electronics of the sonar (Gemini 72V VDSL Adapter) and a laptop PC on the vessel for data collection.

The data collection vessel was moored to the secondary anchor and data were collected during daylight flood tides, as seals in this area are most abundant during this time (Hastie et al., 2016). Sonar data were recorded continuously to the laptop PC. Concurrent visual observations of seals and other targets at the surface (birds, seaweed, and hydrographic features) were made from the vessel to provide validation for sonar targets. In practice, two observers on the vessel maintained a constant visual watch and the noted the timings (hh:mm:ss) and the estimated range (m) and bearing (degrees) of targets from the surface mooring buoy (assumed to be representative of the sonar location) on datasheets. A third observer monitored the sonar images and noted the timings (hh:mm:ss), and relative range (m) and bearing (degrees) of targets using a marker tool in the sonar software. It should be noted that the sonar and visual observers were not blind to either dataset, and communication between the teams was maintained throughout to confirm the identity of targets observed on the sonar. This ensured a high degree of certainty in the matching of observations.

Data were collected over most of the flood tide period on each of the data collection days; however, at peak flow (>3 ms^{-1}) difficulties associated with maintaining the vessel on the mooring in the high current meant that there were short breaks (around 90 mins) in monitoring over these periods. A total of 574 min (265 files: 76 GB) of sonar data were collected for further analyses.

To provide the data for the development and validation of classification algorithms for seals, a series of parameters were derived for mobile targets detected within the sonar data. These were based on the standard outputs of the SeaTec software (see Sonar system section). Further, the SeaTec outputs were customized for this study to provide detailed information on the size and shape of each detection; these were recorded as a series of target intensity matrices of the detected target within a defined bounding box which were saved as *.txt files (e.g. Figure 3).

A total of 161 targets detected by the SeaTec software were used for the classification algorithm development; based on temporal and spatial matching between the sonar data and visual observations, 65 of these were confirmed to be seals and 96 were non-seals. Non-seal targets were generally small scale turbulent hydrographic features and items of debris (e.g. seaweed). Each confirmed seal and non-seal target was summarised in terms of mean horizontal speed over ground (ms^{-1}) and mean distance (m) from the sonar. Further, to determine whether the tracks of seals produced by the detection and tracking software are of sufficient temporal and spatial granularity to measure the 'fine-scale' movement behaviour of seals in close proximity to anthropogenic activities such as tidal turbines, the time (ms) and distance (m) between consecutive detections of seals in the XY plane was measured for all confirmed seal tracks and non-seal targets.

Based on the summary kinematic information and the target intensity matrix information for each target, a total of 110 candidate features of the targets were extracted to be used in the classification algorithm development. This included the temporal persistence of the target, summary statistics on the movement of the target (distance travelled, angle of movement, and proportion of static frames), the shape of the target (length, area, perimeter length, and their respective ratios), and pixel intensity of the targets. Shape features were extracted from the intensity matrices using the R package *raster* (version 2.4-15). The mean, median, standard deviation, minimum, and maximum was computed for each feature. In addition, spectral properties of all features, except persistence, were derived (spectral density, frequency and amplitude of the first and second peaks). The spectral properties describe changes of the features through time, and are extracted from spectrograms generated by Fourier transforms of the features (Cryer & Chan, 2013). For instance, the shape of a seal in the sonar data may change cyclically as it swims; this would appear as one peak frequency in the spectrogram of one or more shape features. Spectral features were extracted using the R package *stats* (version 3.2.1). Finally, features with near-zero variance and those that were highly correlated to other features ($r>0.9$) were filtered out using the R package *caret* (version 6.0.64). Eighty-three features remained and were scaled prior to use in the analysis.

A kernel Support Vector Machine (SVM) (Hastie, Tibshirani, & Friedman, 2009) was fitted to the data to classify targets using the R package *kernlab* (version 0.9-22). SVMs have been applied to a wide range of pattern classification and function approximation applications in biology (Yang, 2004). In the current study, it was used to classify the sonar targets into one of two classes (seal vs non-seal).

Inputs to the classifier (features) are determined so that they represent each class well or so that data belonging to different classes are well separated in the input space (Abe, 2006). SVMs fit boundaries (support vectors) between classes in 2D space (pairs of features). The number of support vectors can be increased by increasing the parameter "C" (cost of misclassification) to yield a better fit to the data. However, using too many support vectors can result in over-fitting to the data and loss of generality.

To avoid potential over-fitting, the parameter "C" was chosen to minimise cross-validation error. A 20-fold cross-validation was performed for each parameter value: the data were split into 20 sub-samples, after which the algorithm was fitted using 19 sub-samples and validated using the remaining one. This was repeated 20 times using each sub-sample in turn for validation. The cross-validation error was thus the mean error rate in the 20 validation sub-samples. The algorithm was fitted with parameter "C" of $10^{(-1 \text{ to } 6)}$, and 100 times with each parameter value to estimate the uncertainty of the cross-validation error rate. As there were more non-seal targets than seal targets, a balanced sample was generated using the sampling algorithm *SMOTE* (Chawla, 2002). A new sample was generated using the R package *unbalanced* (version 2.0) for each of the 100 iterations. The algorithm that had the lowest mean cross-validation error was chosen as the best fitting model.

The importance of individual features in the classifier can be challenging to extract because kernels are fitted in multi-dimensional space (combinations of features). However, to determine which features are important, we compared the performance of classifiers fitted to different groups of features: all, only spectral, all except spectral, only pixel intensity, only shape, and only movement.

3. Results

Detection of seals using sonar

A total of 62 grey seals were successfully imaged at ranges of between 5.0 and 80.0 m from the sonar. Mean range of each of the individual seals varied from 15.5 to 79.0 m from the sonar.

The SeaTec software detected a total of 31 (50%) of the grey seals in the sonar data. In general, the seals that were detected were closer to the sonar than those not detected; the mean range of seals detected varied from 15.5 to 56.0 m from the sonar, and the mean range of seals not detected varied from 21.0 to 79.0.

The results of the model of detection probability of seals in the sonar data showed that there was a significant negative relationship between the mean range of seals from the sonar and the probability of detection (χ^2_1 = 59.9, P<0.0001). Inspection of the model predictions showed that the mean probability of the detection and tracking module successfully detecting a seal was greater than 0.95 for ranges up to approximately 33 m from the sonar; it then declined markedly to 0.5 at approximately 47 m and to below 0.05 at ranges greater than 59 m (Figure 4).

Classification of seals in sonar data

Multibeam sonar data were collected successfully from the seabed mounted HiCUP in the tidally energetic channel. The HiCUP maintained position on the seabed and the sonar was stable on its mount throughout the data collection period.

Seals (confirmed through the visual observations) were successfully imaged using the sonar; mean distance of seals from the sonar HiCUP ranged from 15.3 to 59.8 m and peaked between 40 and 45 m. A range of other targets confirmed through the visual observations were also imaged; these included hydrographic features such as eddies, and drifting seaweed. When expressed as a number of targets per minute of sonar data analysed, there were markedly fewer seals (0.11 min^{-1}) than non-seal (1.48 min^{-1}) targets. The mean distance of non-seal targets ranged from 16.1 to 58.5 m and peaked between 15 and 20 m (Figure 5 and 6). The mean velocity of confirmed seals ranged from 0.6 to 4.7 ms^{-1} and peaked between 2 and 2.5 ms^{-1}. The mean velocity of other targets ranged from 0.3 to 4.5 ms^{-1} and peaked between 1 and 1.5 ms^{-1} (Figure 5 and 6). It should be highlighted that these results do not account for the underlying water current speeds and therefore represent velocities over-ground rather than true speeds through the water.

The majority (99.9%) of consecutive detections of seals within a track were less than or equal to 1 second apart and all were less than 2 seconds apart. The distance between consecutive detections of seals within a track was generally low; the majority (81%) of consecutive detections were less than 0.5 m apart and 95% of all consecutive detections were less than 0.9 m apart.

Results of the classification algorithm development and validation showed that the best fitting algorithm from the SVM had the parameter "C" = 1000; it yielded a mean cross-validation error of just under 6% using 110 support vectors. The classification accuracy for the entire dataset based on the chosen algorithm was 100% for confirmed seal targets and 92% for non-seal targets (Table 2), with an overall accuracy of 95% (SD=1.6%). A comparison of classification accuracy between classifiers fitted to different groups of features shows that the shape and non-spectral movement features result in the lowest cross validation error (Table 3).

4. Discussion

This paper presents the results of a study which investigated the efficiency of a high frequency multibeam sonar system for the automated detection and tracking of seals. Results show that seals can be reliably detected out to a range of several tens of metres and tracked with a high degree of spatial and temporal resolution. Further, through the development of a series of classification algorithms, seals can be efficiently discriminated from other mobile targets in tidally energetic environments.

The results of the analysis of detection probability of seals shows that the multibeam sonar is highly effective for detecting seals out to ranges of at least 33 m. Beyond this range, the mean detection probability decreased markedly to below 0.5 at a range of 47 m, and below 0.05 at ranges beyond 59 m. This shows that the tracking of seals using high frequency multibeam sonar should be effective up to ranges of at least 30-40 m. However, it should be highlighted that the detection probability tests were carried out in a relatively shallow environment and, although efforts were made to ensure the sonar transducer did not move during the calibration trials, it was deployed from a boat and automatic detection ranges and probabilities may have been compromised by seabed-induced acoustic clutter and transducer movement. For example, interactions between the sonar signals and the seabed (through reflections and absorption) could potentially influence acoustic signal-noise ratios and reduce the probability of detecting targets in shallow waters (Ona & Mitson, 1996). Given the orientation of the sonar and the water depth in the current study, acoustic signals would likely interact with the seabed at ranges beyond approximately 8-14 m from the sonar and detection probability of seals may have been compromised to a degree beyond this. Although it would therefore seem reasonable to assume that stable deployments in deeper environments, would yield greater automatic detection efficiency, it is important to highlight that the high frequency characteristics (720 kHz) of the sonar system tested here are likely to have fundamentally limited the detection of seals to tens of metres due to the absorption of high frequency sound in seawater (Fisher & Simmons, 1977). From this perspective, further investigation of the detection efficiency of seals using other sonar systems (with different acoustic characteristics) in a range of different habitats and conditions may prove useful.

In terms of the practicalities associated with collecting sonar data remotely from a seabed platform, the design of the HiCUP proved effective and confirms that marine mammal data can be collected reliably from a multibeam sonar on a remote seabed platform in a tidally energetic environment. The spatial and temporal resolution of seal locations measured by the sonar on the HiCUP was relatively high with the majority of consecutive detections less than 1 s and less than 1 m apart, independent of range from the sonar. This shows that seals can be tracked in the X-Y plane in tidal currents up to approximately 3 ms^{-1} with sub-metre spatial resolution. However, it is important to highlight that the multibeam sonar used here only provides information on seal movements in the X-Y plane. It is likely that information on the locations of the seal in 3D (X-Y-Depth) may be desirable in a range of different applications. To address this, recent research has shown that the combination of the two multibeam sonars orientated in the same horizontal angle but offset vertically can provide an effective means of determining depth of seals and may be an effective means of tracking seals in 3D (Hastie et al., In press).

The results of the classification analyses show that it is possible to effectively discriminate between seals and non-seals in multibeam sonar data with a relatively high degree of accuracy. The kernel SVM algorithm developed here correctly classified all the confirmed seal targets but misclassified a relatively small percentage of non-seal targets (~8%) as seals. If this result holds with future datasets, the analytical approach appears to be an effective means of detecting, classifying, and tracking seals. However, it should be highlighted that the classification analyses here were carried out on a dataset from a single location and tidal phase and, although this is likely to represent a relatively challenging dataset for the classification of seals (i.e. it was collected in a highly mobile environment with numerous mobile targets), it is unclear how the classifiers would perform in markedly different habitats or oceanographic conditions. It would therefore be useful to expand the data collection and classification validation to a range of different sites and conditions. It is also important to highlight that the density of seals present in the study area is relatively high compared to most coastal habitats (Hastie et al., 2016); it is therefore likely that, in most applications, the number of non-seal targets will be far greater than the number of true seals targets. Therefore, an 8% misclassification of non-seal targets has the potential to result in a relatively high number of false positive classifications and, in practical terms, relatively high levels of post hoc manual validation of targets. Nevertheless, the aim here was to improve the data reduction without significantly reducing the probability of detecting marine mammals and, from this perspective, the approach appears successful.

Further development of the classifiers (with more validated targets) could potentially increase the accuracy and further reduce the potential for false positive detections. Although comparison of the classifiers using different subsets of features suggests that simple summary statistics about the movement of targets may be sufficient to classify seals, additional target information may also help in the classification process. For example, depth information and movement in the depth plane of targets may significantly improve the accuracy; this is based on the supposition that seals, unlike objects moving passively with the water current, regularly exhibit vertical movement in the water column whilst diving (Hastie et al., In press). Classification accuracy may also be improved through the integration of other sensor systems on the platform. For example, passive acoustic monitoring (PAM) has proven to be highly effective for the detection and classification of vocally predictable marine mammals. Dolphins and porpoises in particular produce echolocation clicks for navigation and finding prey and PAM has been used extensively to detect and classify these species (Chappell, Leaper, & Gordon, 1996; Gillespie et al., 2008). The combination of multibeam sonar and PAM systems would appear to be highly complementary and would potentially provide an effective means of differentiating seals from dolphins and porpoises in sonar data.

In the current study, the classification algorithms were based a series of target geometry (size and shape) and kinematic metrics produced using a specific multibeam sonar system; however, there are increasing numbers of active sonar systems commercially available (Hastie, 2012) which could, in theory, also measure these metrics. Despite this, the wide range of acoustic signal characteristics and processing approaches by different sonar systems would likely mean that further work would be required to provide geometry and kinematic metrics analogous to those collected in the current study. It would therefore be useful to collect further marine mammal data with a range of other sonar systems and formally evaluate the effectiveness of the classification approach with these data.

Overall, the hardware design and the detection and classification results are positive from the perspective of monitoring seals around tidal turbines over extended periods and suggests that sonar mounted on a platform in the vicinity of a turbine could be used to efficiently collect data on seal movements. The HiCUP proved to be stable during the data collection in current speeds estimated up to approximately 3 ms^{-1} which is similar to the higher current speeds anticipated at proposed tidal energy development sites (Goddijn-Murphy, Woolf, & Easton, 2013; Wilson et al., 2013). Further, seals were automatically detected to ranges of several tens of metres from the HiCUP and recorded locations with sub-metre resolution. From the perspective of tracking seals in close vicinity to operational tidal turbines, this would appear to be of sufficient accuracy to determine whether a turbine blade and seal were in the same place at the same time. However, it is important to consider potential issues related to tracking seals in close vicinity to a tidal turbine; for example, acoustic reflections or shadowing from the turbine structure may influence detection and classification probabilities, particularly for targets at close range to the rotors. The most effective configuration is likely to be a sonar mounted on a platform located at approximately 30 m from the turbine which would maximise the vertical sonar coverage whilst ensuring that detection probability remains high. Although likely dependent upon turbine design and location, it would seem most efficient to locate the sonar perpendicular to the tidal flow direction and oriented so the turbine is approximately mid-frame. This would effectively provide the best coverage of the turbine and the water column in both the upstream and downstream directions and would likely maximise the data available for effective detection, classification, and tracking. More widely, such an approach would complement the range of available technologies for detecting and tracking other species such as fish or seabirds and extends the capacity for multi-species environmental monitoring around tidal turbines (Joslin, Polagye, & Parker-Stetter, 2014; Viehman & Zydlewski, 2017; Williamson et al., 2016; Williamson et al., 2017). The application of these technologies alongside operational tidal turbines is clearly now required to provide information on the movements of seals around tidal turbines and quantify the true environmental risks posed by tidal turbine developments.

The results presented here also provide the basis for a monitoring tool in a range of other research or conservation applications where information on the presence and numbers of seals at discrete locations of interest is required. For example, management of potential impacts of seals foraging on salmonid species in rivers requires information on the temporal variation in presence and numbers of seals within river systems over long periods (Graham, Harris, Matejusová, & Middlemas, 2011). Further, behavioural research into high resolution swimming kinematics and dive behaviour of seals could benefit greatly from the kinds of detection and tracking information collected using sonar systems such as the one tested here (e.g. Hastie et al., In press). There is also the potential that the approach could be used to increase the efficiency of mitigation around high-risk activities. For example, fish predation by seals at marine aquaculture sites is often perceived as problematic from a commercial perspective (Quick, Middlemas, & Armstrong, 2004). This has led to the use of Acoustic Deterrent Devices (ADDs) in an effort to deter seals from fish cages; however, the increasing use of these devices has led to concerns about long terms effects on non-target species such as cetaceans (Findlay et al., 2018; Nowacek, Thorne, Johnston, & Tyack Peter, 2007). In theory, the detection and classification capabilities of multibeam sonar shown in the current study provide the basis to target ADD use to times when seals were detected, thereby reducing unnecessary acoustic emissions. In practice, for such real-time monitoring and mitigation, the effective integration of the sonar, processing PC, and ADD technologies would be required, together with a series of software developments such that the classification algorithms could be run in real time and the results used to trigger the ADD when a seal was detected.

5. Conclusions

The results presented here showed that high-frequency multibeam sonar is highly effective for detecting seals out to ranges of several tens of metres, and that post-hoc classification analyses are highly effective at identifying seals but misclassified a small percentage of non-seal targets (~8%) as seals. This makes it an efficient means for reducing data volumes to manageable sizes and provides the basis of an efficient long-term monitoring tool for identifying and tracking individual seals in discrete locations. From a conservation and management perspective, the approach shows promise for monitoring marine mammal movements around potentially high risk anthropogenic activities or structures such as tidal turbines.

Acknowledgements

The work was funded under the Scottish Government Demonstration Strategy (Project no. USA/010/14) and as part of the Department of Energy and Climate Change's Offshore Energy Strategic Environmental Assessment programme, with additional resources from the Natural Environment Research Council (grant numbers: NE/R014639/1 and SMRU1001). We wish to thank Elaine Tait at Marine Scotland Planning and Policy for project guidance and the loan of the sonar equipment used during the study. We would also like to thank the Editor, Guest Editor, and two anonymous reviewers whose comments greatly improved the manuscript. All authors declare that they have no conflicts of interest to disclose.

References

Abe, S. (2006). *Support Vector Machines for Pattern Classification* (Second Edition ed.): Springer-Verlag London Limited.

Benoit-Bird, K. J., & Au, W. (2003a). Hawaiian spinner dolphins aggregate midwater food resources through cooperative foraging. *Journal of the Acoustical Society of America,* 114, 2300.

Benoit-Bird, K. J., & Au, W. L. (2003b). Prey dynamics affect foraging by a pelagic predator (*Stenella longirostris*) over a range of spatial and temporal scales. *Behavioral Ecology and Sociobiology,* 53, 364-373.

Chappell, O., Leaper, R., & Gordon, J. (1996). Development and performance of an automated harbour porpoise click detector. *Reports of the International Whaling Commission,* 46, 587-594.

Chawla, N. V. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research,* 16(1), 321-357.

Cryer, J. D., & Chan, K. S. (2013). Time Series Analysis With Applications in R. In S. F. G. Casella, and I. Olkin (Ed.), *Springer Texts in Statistics*: Springer.

Doksæter, L., Godo, O. R., Olsen, E., Nottestad, L., & Patel, R. (2009). Ecological studies of marine mammals using a seabed-mounted echosounder. *ICES Journal of Marine Science,* 66, 1029-1036.

Findlay, C. R., Ripple, H. D., Coomber, F., Froud, K., Harries, O., van Geel, N. C. F., . . . Wilson, B. (2018). Mapping widespread and increasing underwater noise pollution from acoustic deterrent devices. *Marine Pollution Bulletin,* 135, 1042-1050. doi:https://doi.org/10.1016/j.marpolbul.2018.08.042

Fisher, F. H., & Simmons, V. P. (1977). Sound absorption in sea water. *The Journal of the Acoustical Society of America.,* 62, 558-564. doi:doi: 10.1121/1.381574

Fox, J., & Weisberg, S. (2011). *An R Companion to Applied Regression* (Second Ed.). Thousand Oaks, CA. USA: Sage.

Gillespie, D., Mellinger, D. K., Gordon, J., McLaren, D., Redmond, P., McHugh, R., . . . Thode, A. (2008). PAMGUARD: Semiautomated, open source software for real-time acoustic detection and localisation of cetaceans. *Proceedings of the Institute of Acoustics,* 30, 67-75.

Goddijn-Murphy, L., Woolf, D. K., & Easton, M. C. (2013). Current Patterns in the Inner Sound (Pentland Firth) from Underway ADCP Data. *Journal of Atmospheric and Oceanic Technology,* 30, 96-111. doi:DOI: 10.1175/JTECH-D-11-00223.1

Gonzalez-Socoloske, D., Olievera-Gomez, L. D., & Ford, R. E. (2009). Detection of free-ranging West Indian manatees *Trichechus manatus* using side-scan sonar. *Endangered Species Research,* 8, 249-257.

Gonzalez-Socoloske, D., & Olivera-Gomez, L. D. (2012). Gentle Giants in Dark Waters: Using Side-Scan Sonar for Manatee Research. *The Open Remote Sensing Journal,* 5, 1-14.

Graham, I. M., Harris, R. N., Matejusová, I., & Middlemas, S. J. (2011). Do 'rogue' seals exist? Implications for seal conservation in the UK. *Animal Conservation,* 14(6), 587-598.

Hardin, J. W., & Hilbe, J. M. (2003). *Generalized estimating equations*. London, UK.: Chapman and Hall/CRC Press.

Hastie, G. D. (2012). Tracking marine mammals around marine renewable energy devices using active sonar. *SMRU Ltd report URN:12D/328 to the Department of Energy and Climate Change. September 2012 (unpublished).*

Hastie, G. D., Bivins, M., Coram, A., Gillespie, D., Gordon, J., Jepp, P., . . . Sparling, C. E. (In press). Three-dimensional movements of harbour seals in a tidally energetic channel: application of a novel sonar tracking system *Aquatic Conservation: Marine Freshwater Ecosystems*.

Hastie, G. D., Gillespie, D., Gordon, J. C. D., Macaulay, J., McConnell, B., & Sparling, C. E. (2014). Tracking Technologies for Quantifying Marine Mammal Interactions with Tidal Turbines: Pitfalls and Possibilities. In M. A. Shields. & A. I. L. Payne (Eds.), *Marine*

Renewable Energy Technology and Environmental Interactions, Humanity and the Sea. Dordrecht: Springer Science+Business Media.

Hastie, G. D., Russell, D. J. F., Benjamins, S., Moss, S., Wilson, B., & Thompson, D. (2016). Dynamic habitat corridors for marine predators; intensive use of a coastal channel by harbour seals is modulated by tidal currents *Behavioural Ecology and Sociobiology,* 70, 2161-2174. doi:DOI: 10.1007/s00265-016-2219-7

Hastie, G. D., Russell, D. J. F., Lepper, P., Elliot, J., Wilson, B., Benjamins, S., & Thompson, D. (2017). Harbour seals avoid tidal turbine noise: implications for collision risk. *Journal of Applied Ecology*.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (2nd edition ed.): Springer.

Joslin, J., Polagye, B., & Parker-Stetter. (2014). Development of a stereo-optical camera system for monitoring tidal turbines. *Journal of Applied Remote Sensing,* 8(1), 083633. doi:https://doi.org/10.1117/1.JRS.8.083633

Law, G. (2013). Quantitative Comparison of Flood Fill and Modified Flood Fill Algorithms. *International Journal of Computer Theory and Engineering,* 53(3), 503-508.

Nøttestad, L., Ferno, A., & Axelsen, B. E. (2002). Digging in the deep: killer whale's advanced hunting tactic. *Polar Biology,* 25, 939-941.

Nøttestad, L., Ferno, A., Mackinson, S., Pitcher, T., & Misund, O. A. (2002). How whales influence herring school dynamics in a cold-front area of the Norwegian Sea. *Ices Journal of Marine Science,* 59(2), 393-400.

Nowacek, D. P., Thorne, L. H., Johnston, D. W., & Tyack Peter, L. (2007). Responses of cetaceans to anthropogenic noise. *Mammal Review,* 37(2), 81-115. doi:https://doi.org/10.1111/j.1365-2907.2007.00104.x

Ona, E., & Mitson, R. B. (1996). Acoustic sampling and signal processing near the seabed: the deadzone revisited. *ICES Journal of Marine Science,* 53(677-690).

Parsons, M. J. G., Fenny, E., Lucke, K., Osterrieder, S., Jenkins, G., Saunders, B. J., . . . Parnum, I. M. (2017). Imaging Marine Fauna with a Tritech Gemini 720i Sonar. *Acoustics Australia,* 45(1), 41-49.

Pyć, C. D., Geoffrey, M., & Knudsen, F. R. (2016). An evaluation of active acoustic methods for detection ofmarine mammals in the Canadian Beaufort Sea. *Marine Mammal Science,* 32(1), 202-219.

Quick, N. J., Middlemas, S. J., & Armstrong, J. D. (2004). A survey of antipredator controls at marine salmon farms in Scotland. *Aquaculture,* 230(1-4), 169-180. doi:https://doi.org/10.1016/S0044-8486(03)00428-9

R Core Team. (2012). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. URL http://www.R-project.org/. Retrieved from URL http://www.R-project.org/

Read, A. J., Drinker, P., & Northridge, S. (2006). Bycatch of Marine Mammals in U.S. and Global Fisheries. *Conservation Biology,* 20(1), 163-169. doi:DOI: 10.1111/j.1523-1739.2006.00338.x

Ridoux, V., Guinet, C., Liret, C., Creton, P., Steenstrup, R., & Beauplet, G. (1997). A video sonar as a new tool to study marine mammals in the wild: Measurements of dolphin swimming speed. *Marine Mammal Science,* 13(2), 196-206.

Smith, H. D. (2000). The industrialisation of the world ocean. *Ocean & Coastal Management,* 43(1), 11-28. doi:https://doi.org/10.1016/S0964-5691(00)00028-4

van der Hoop, J., Corkeron, P., & Moore, M. (2017). Entanglement is a costly life-history stage in large whales. *Ecology and Evolution,* 7(1), 92-106. doi:10.1002/ece3.2615

Vanderlaan, A. S. M., & Taggart, C. T. (2007). Vessel collisions with whales: The probability of lethal injury based on vessel speed. *Marine Mammal Science,* 32(1), 144-156. doi:DOI: 10.1111/j.1748-7692.2006.00098.x

Viehman, H. A., & Zydlewski, G. B. (2017). Multi-scale temporal patterns in fish presence in a high-velocity tidal channel. *PLos ONE,* 12(5), e0176405. doi:https://doi.org/10.1371/journal.pone.0176405

Williamson, B. J., Blondel, P., Armstrong, E., Bell, P. S., Hall, C. B., Waggitt, J. J., & Scott, B. (2016). A Self-Contained Subsea Platform for Acoustic Monitoring of the Environment Around Marine Renewable Energy Devices–Field Deployments at Wave and Tidal Energy Sites in Orkney, Scotland *IEEE journal of oceanic engineering,* 41(1), 67-81.

Williamson, B. J., Fraser, F., Blondel, P., Bell, P. S., Waggitt, J. J., & Scott, B. E. (2017). Multisensor Acoustic Tracking of Fish and Seabird Behavior Around Tidal Turbine Structures in Scotland. *IEEE journal of oceanic engineering,* 42(4), 948-965.

Wilson, B., Batty, R. S., Daunt, F., & Carter, C. (2007). Collision risks between marine renewable energy devices and mammals, fish and diving birds. *Report to the Scottish Executive*.

Wilson, B., Benjamins, S., & Elliott, J. (2013). Using drifting passive echolocation loggers to study harbour porpoises in tidal-stream habitats. *Endangered Species Research,* 22, 125-143.

Yang, Z. R. (2004). Biological applications of support vector machines. *Briefings in bioinformatics,* 5(4), 328-338. doi:https://doi.org/10.1093/bib/5.4.328

Tables

Table 1: Fitting the parameter "C" for the kernel Support Vector Machine algorithm. Values for the cross-validation (20-fold) and the number of support vectors are the mean and SD for 100 iterations. The selected model is shown in bold.

	Cross-validation error		Number of support vectors	
Parameter "C"	Mean	(SD)	Mean	(SD)
0.1	0.610	(0.016)	260	(0)
1	0.120	(0.018)	166	(6.4)
10	0.067	(0.014)	119	(6.0)
100	0.059	(0.012)	111	(6.9)
1000	**0.057**	**(0.012)**	**110**	**(5.9)**
10000	0.059	(0.012)	110	(6.8)
100000	0.059	(0.012)	111	(6.4)
1000000	0.058	(0.012)	112	(6.1)

Table 2: Classification of the entire dataset (161 targets) using the fitted kernel Support Vector Machine algorithm. Values in the confusion matrix are mean (SD) frequencies of the 100 iterations.

	Classified Seal	Classified Non-seal
Confirmed seals (N=65)	65 (0)	0 (0)
Non-seal targets (N=96)	7.7 (2.5)	88.3 (2.5)

Table 3. Performance of kernel Support Vector Machine classifiers fitted with different subsets of features. Cross-validation error is the proportion of incorrect classifications (mean and SD of 20-fold cross-validation error over 100 iterations). N is the number of features included in each classifier after excluding near-zero variance and highly correlated features. The mean (SD) number of support vectors is also shown to indicate the complexity of the classifier.

		Cross-validation error		Number of support vectors	
Features	N	Mean	(SD)	Mean	(SD)
All	83	0.057	(0.012)	110	(5.9)
Non-spectral	26	0.073	(0.014)	101	(5.5)
Spectral only	57	0.180	(0.013)	129	(7.3)
Pixel intensity	23	0.179	(0.030)	158	(7.9)
Shape	36	0.091	(0.017)	100	(5.8)
Movement	23	0.072	(0.015)	93	(5.0)
- spectral	13	0.242	(0.016)	139	(4.4)
- non-spectral	15	0.086	(0.015)	104	(4.8)

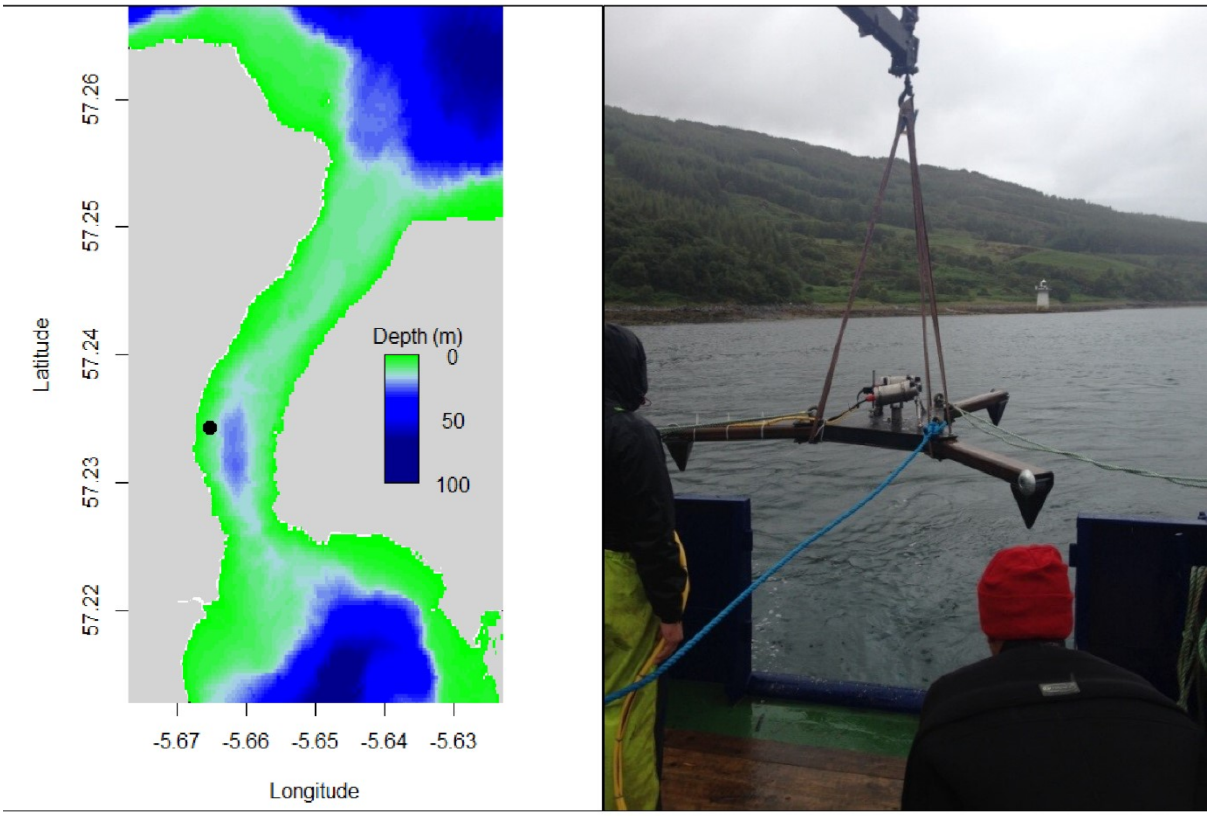


Figure 1: The left panel shows a map of the coastal channel with the location (black point) of the High Current Underwater Platform (HiCUP); the map is colour coded to illustrate water depth. The right panel shows a photograph of the deployment of the HiCUP from the stern of the survey vessel.

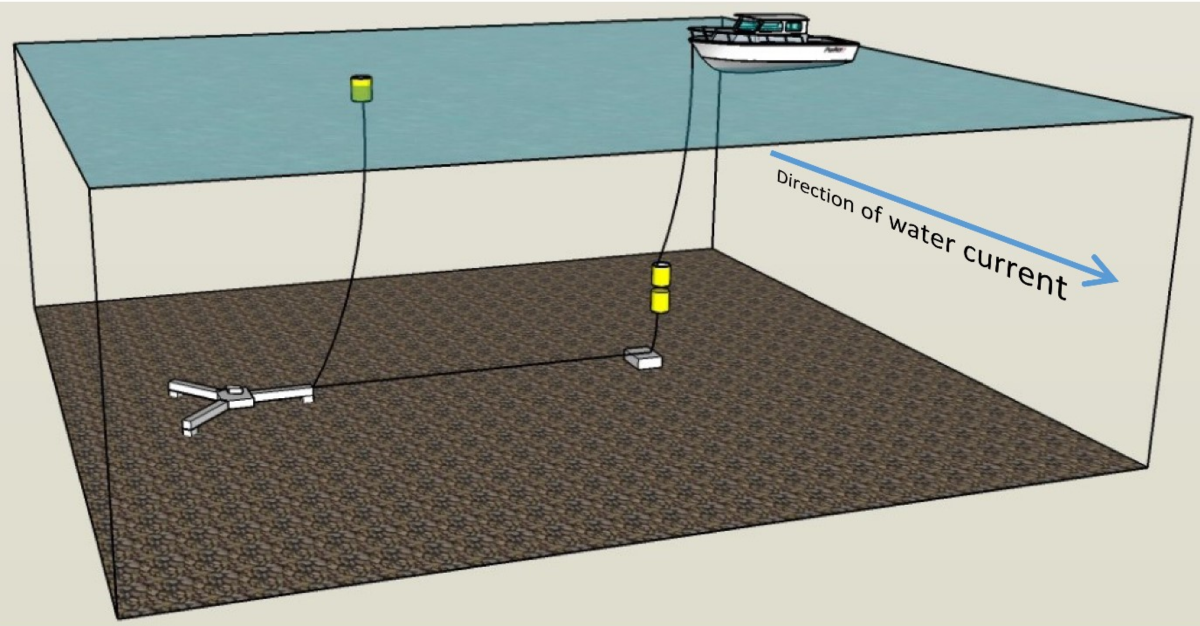
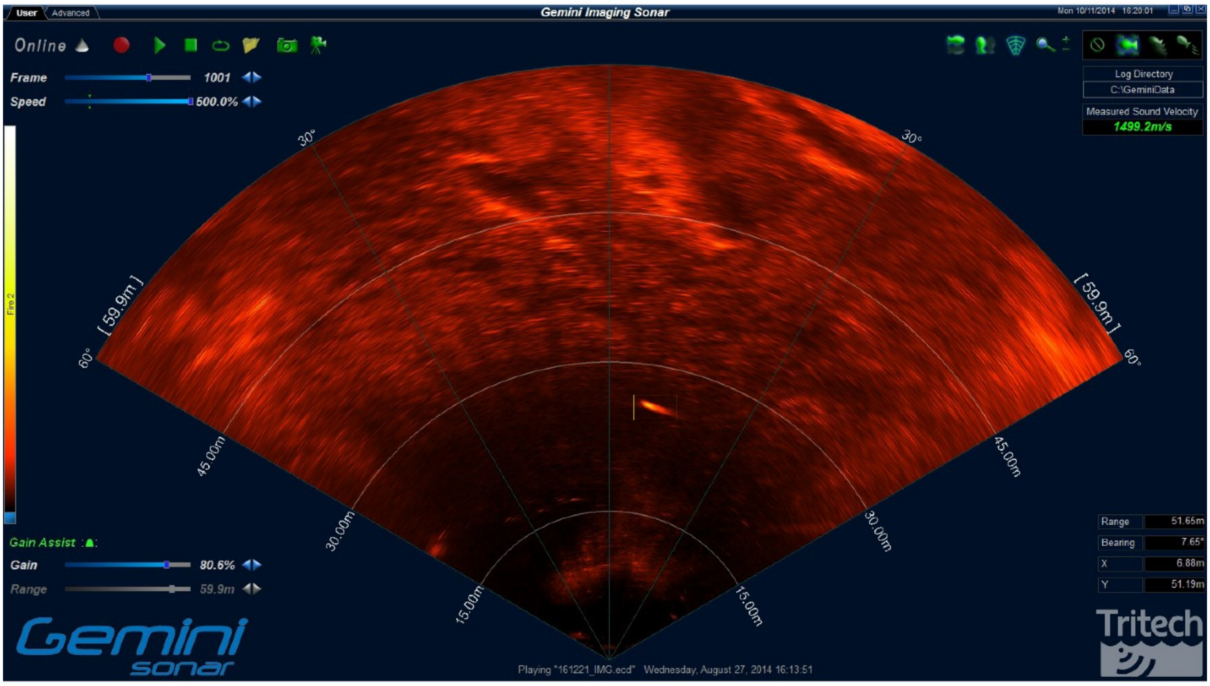
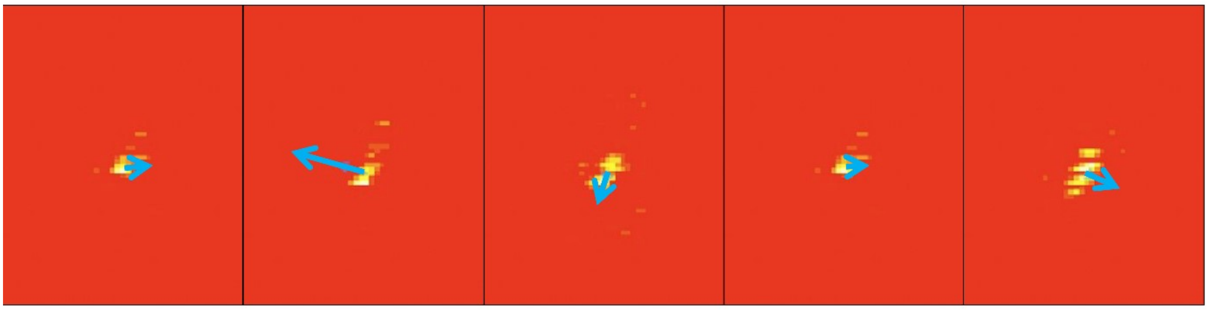


Figure 2: Schematic of the sonar mounted on the High Current Underwater Platform (HiCUP) mooring deployed in a tidally energetic channel. The figure shows the seabed mounted HiCUP, the secondary anchor with dual subsurface floats, the small HiCUP locating surface buoy, and the data collection vessel. The arrow indicates the general flow direction of the water current.

(A)



(B)



(C)

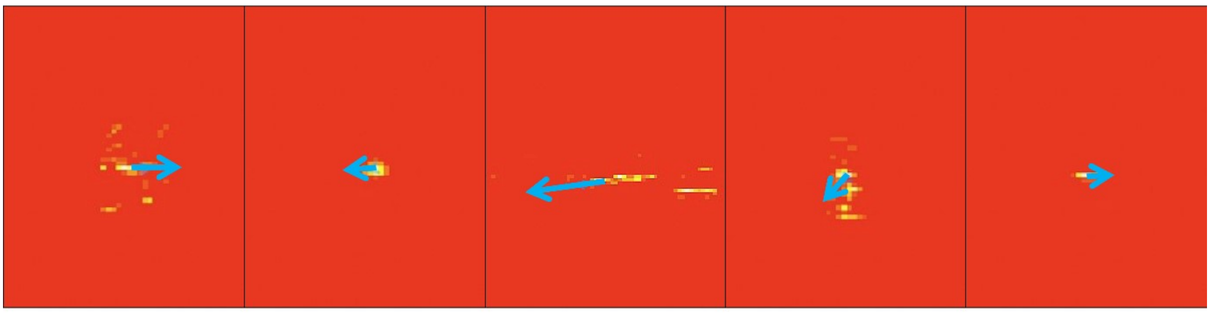


Figure 3: (A) Example of the data from the seabed mounted Tritech Gemini in a tidally energetic channel showing a harbour seal in the yellow bounding box (confirmed through concurrent visual observations). Examples of the target intensity matrices produced as part of the target detection process for a sequence of detections for one confirmed seal over 5 consecutive frames (B) and sample images from five different non-seal targets (C). The matrices are colour coded by relative pixel intensity and the blue arrows represent the velocity of moving targets.

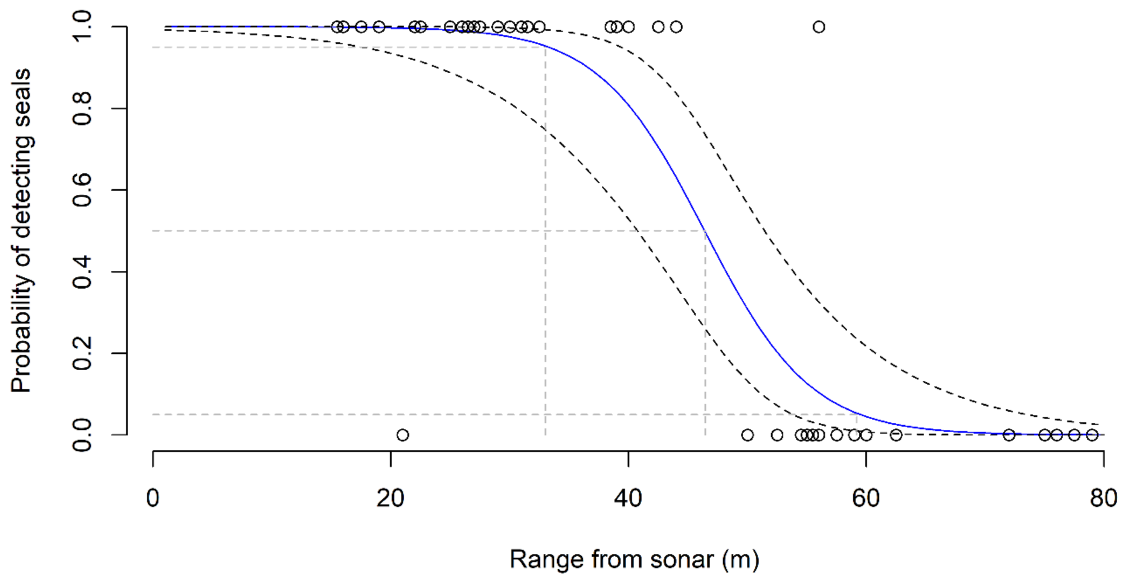


Figure 4: The probability of the detection and tracking module (SeaTec) successfully detecting seals. The figure shows the predicted relationship between range (m) and the mean probability (± 95% CIs) of detection from the binomial Generalised Linear Model. The mean probability was greater than 0.95 for ranges up to approximately 33 metres, 0.5 at approximately 47m and less than 0.05 at ranges greater than 59 metres. The grey dashed lines illustrate these associated ranges (m) at a 0.95, 0.5, and 0.05 mean probability of detection

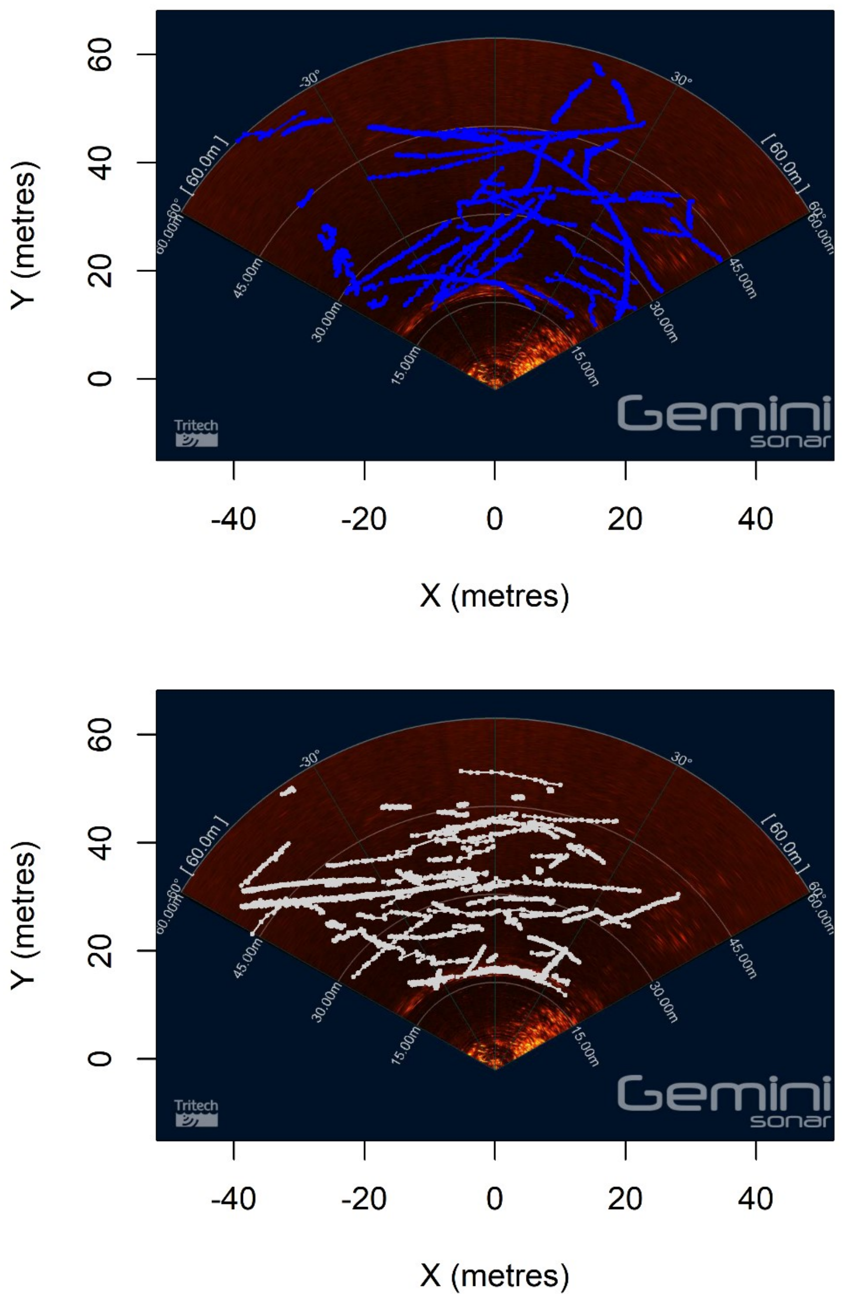


Figure 5: The XY tracks of a series of targets detected during the deployment of the multibeam sonar on the HiCUP in a tidally energetic channel. Each panel shows the XY locations of targets that were automatically detected and tracked using the Tritech SeaTec target tracking software. The upper panel shows the tracks of targets that were confirmed as seals through visual observations of animals made from the boat, and the lower panel shows other targets that were identified as turbulence or items of debris.

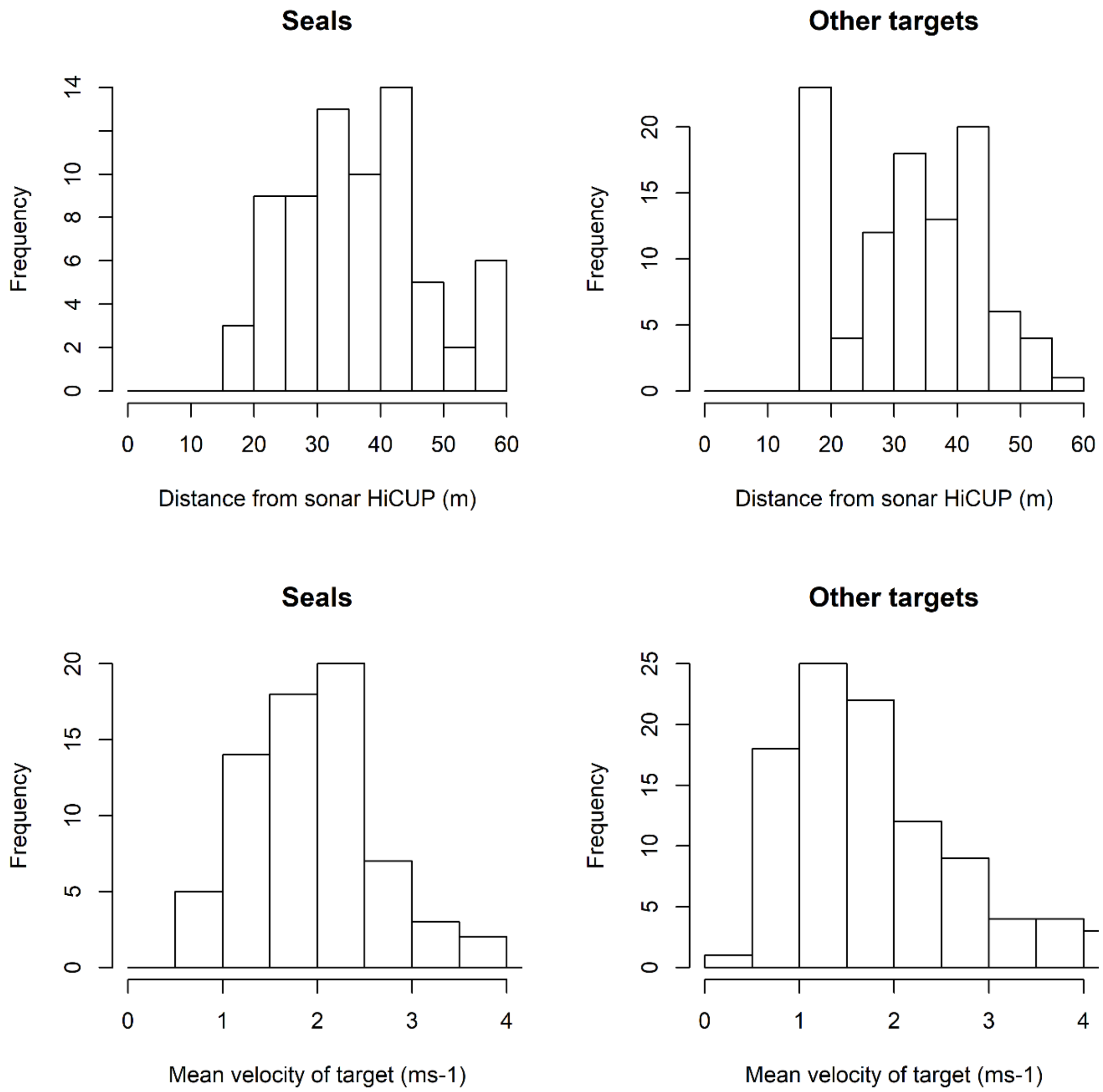


Figure 6: Distributions of (A) the mean distances (m) of confirmed seals and non-seal targets from the sonar HiCUP, and (B) the mean velocities (ms-1) of confirmed seals and non-seal targets.

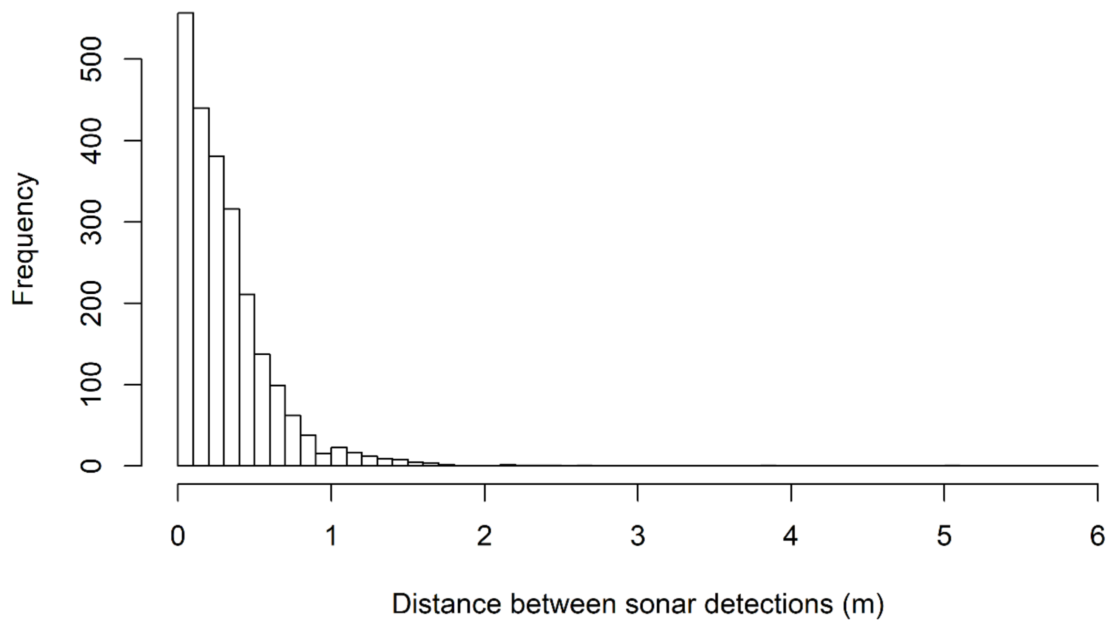


Figure 7: Distribution of the distances (metres) between consecutive sonar detections of seals.