

DEVELOPING AN OPEN-SOURCE ANALYSIS PIPELINE FOR A GLIDER-BASED
ACOUSTIC ZOOPLANKTON FISH PROFILER (AZFP)

By

AILEY SHEEHAN

A thesis submitted to the

School of Graduate Studies

Rutgers, The State University of New Jersey

In partial fulfillment of the requirements

For the degree of

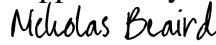
Master of Science

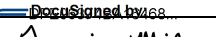
Graduate Program in Oceanography

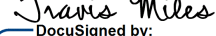
Written under the direction of

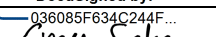
Nicholas Beaird

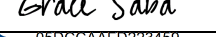
And approved by


DocuSigned by:
Nicholas Beaird


DocuSigned by:
Travis Miles


DocuSigned by:
Grace Saba


DocuSigned by:
Grace Saba


DocuSigned by:
Grace Saba

New Brunswick, New Jersey

October, 2021

ABSTRACT OF THE THESIS

DEVELOPING AN OPEN-SOURCE ANALYSIS PIPELINE FOR A GLIDER-BASED ACOUSTIC ZOOPLANKTON FISH PROFILER (AZFP)

by AILEY SHEEHAN

Thesis Director:

Grace Saba and Nicholas Beard

Multi-frequency acoustic sensors such as the Acoustic Zooplankton Fish Profiler (AZFP) simultaneously observe marine species of various sizes and trophic levels. As such, they are now routinely being used to augment or replace traditional vessel-based sampling. When acoustic sensors are integrated into underwater autonomous vehicles such as gliders, they can record data at a wider depth range and over longer time periods than vessel-based sampling. The AZFP requires specialized processing and software packages that can be expensive to purchase or subscribe to. Additionally, software packages are typically designed for vessel hull-mounted acoustic sensors, and therefore are limited in application to vertically profiling platforms including gliders. This study utilized modern, free open-source software, originally developed for vessel-based acoustic sampling (Echotype), and developed a pipeline to extend Echotype for processing novel glider-based AZFP acoustic data. Echotype is a free acoustic processing package that, with alterations, can be used as an alternative to other packages such as Echoview, the proprietary software that is frequently used for processing these types of datasets. Using a case study focused on Antarctic krill, we then compared processed data outputs of Echotype and Echoview. The adapted Echotype processing method was able to reproduce the results that Echoview accomplished in calculating and plotting acoustic backscatter strength recorded by a glider-

mounted AZFP. However, this correlation became weaker with more complexity integrated into the data processing stream, particularly in the comparison of data outputs after applying seafloor masking and krill swarm detection. Therefore, future efforts to address these more complex analysis features would further improve Echotype application to glider-based acoustic data.

Acknowledgments

I thank Rutgers University Center for Ocean Observing Leadership (RU COOL) glider technicians David Aragon, Nicole Waite, and Chip Haldeman for glider preparation, deployment planning, and piloting glider missions. I also thank Rutgers software technician Lori Garzio for data management, Quality Assurance/Quality Control, and processing support.

Table of Contents

Abstract.....	ii
Acknowledgments.....	iv
List of Figures	vi
Introduction	1
Methods.....	4
Results.....	11
Discussion	13
Summary	16
Bibliography	17

List of Figures

Figure 1. Front end view of Slocum Glider with Integrated AZFP.....	3
Figure 2. Map image of glider path.....	4
Figure 3. Processed data segment showing krill backscatter strength.....	6
Figure 4. Processed data from an alternate segment showing krill backscatter strength..	6
Figure 5. Processed data from an alternate segment demonstrating seafloor removal	7
Figure 6. Direct comparison of backscatter strength [Sv(dB)] processed in Echopype and Echoview	12
Figure 7. Backscatter strength mean [Sv (dB)] plotted over latitude versus longitude using echopype processed data binned into 5m x 5m bins..	14

Introduction

Active acoustic sensors that can estimate biomass of pelagic organisms over large portions of the water column are now routinely being used to augment or replace traditional vessel-based sampling (Reiss et al. 2021). Acoustic sensors are a non-invasive tool that examine many ecological questions in marine ecosystems by utilizing the most practical feature of the ocean, the way in which sound propagates through water (Benoit-Bird & Lawson 2016). The Acoustic Zooplankton Fish Profiler (AZFP), is an autonomous, low-power echosounder with significant internal storage and the capability to include up to four frequency channels. It possesses the capabilities to study the abundance, distribution, and behavior of various sizes of both fish and zooplankton throughout the water column by measuring acoustic backscatter returns with ultrasonic frequencies (Chave et al. 2018). Different acoustic properties result in different target strength responses, and different organisms can be identified from different types of scatter. Higher frequencies are optimal for detecting smaller organisms such as krill. Importantly, low power consumption makes the AZFP well-adapted for long-term operations.

The AZFP is a versatile instrument that was originally designed to be attached to a stationary structure such as a mooring, but in recent years has been adapted to be mounted on autonomous underwater vehicles (AUVs) such as an ocean glider (Figure 1) (Chave et al. 2018, Guihen et al. 2014). The compact size and low power consumption of modern echosounders allow them to be easily mounted on gliders (Chave et al. 2018, Reiss et al. 2021), providing a far more cost-effective approach compared to vessel-based sampling which has limited persistence. Furthermore, gliders fitted with acoustic

packages can observe large pelagic ecosystems while producing high-resolution data at greater depths compared to a ship-borne echosounder or surface mooring (Chave et al. 2018). This allows the AZFP to expand the range at which it observes its target species. Furthermore, the benefit of multiple science sensors operating on a single glider enables observation of the physical, biological, and chemical properties of the water column in concert with horizontal and vertical distribution patterns of fishes and smaller organisms such as Antarctic krill (*Euphausia superba*), the focus of this case study.

The importance of monitoring krill abundance with an AZFP is reflected in the role they play in pelagic ecosystems as a key species in the Antarctic food web (Benoit-Bird & Lawson 2016). Krill are the target for predominant fisheries in the Southern Ocean and are a significant food source for multiple predators (Reiss et al. 2021, Watters et al. 2020). Fluctuations in krill populations impact all higher trophic levels. Changes in fishing intensity can have negative consequences on the performance of krill-dependent predators such as penguins and pinnipeds (Watters et al. 2020, Warren et al. 2009). Because krill are continuously at the mercy of ocean currents and they undergo swarming behavior, their horizontal and vertical distributions in the water column are extremely patchy. This inherent variability makes it difficult to determine their abundance and biomass using traditional net- or trawl-based sampling techniques (Benoit-Bird & Lawson 2016). Therefore, krill biomass estimates over the past several decades have also been made using data collected from ship-borne echosounders which contributes to the management of krill fisheries (Reiss et al. 2021). Using glider-mounted echosounders like the AZFP in place of ship-based acoustic surveys would extend the territory that is measured and monitor krill populations at a lower cost (Chave et al. 2018).

Multi-frequency sensors like the AZFP typically require specialized processing and software packages that can be expensive to purchase or subscribe to. In this study we use open-source Python tools to develop a processing pipeline for a glider-mounted AZFP. This project utilizes modern, free open-source software, Echotype (<https://echotype.readthedocs.io/en/latest/index.html>), originally developed for vessel-based acoustic sampling, that we adapt to process novel glider-based acoustics data. Echotype is a free acoustic processing package that, with alterations, can be used as an alternative to Echoview (<https://www.echoview.com/>), the proprietary software that is frequently used for processing these types of datasets. Echotype is an excellent resource for creating an interoperable data format that manages the accelerating rate at which instrumentation for observing pelagic ecosystems is being produced.



Figure 1. Front end of a Slocum glider with integrated multi-frequency AZFP echosounder (38, 125, and 200 kHz transducers). The AZFP transducers are oriented 22.5 degrees from glider axis to omit pings directly downward.

In this work we integrated data collected by the glider, specifically acoustic data recorded by the AZFP, to estimate Antarctic krill distributions using Echotype and compared the output to that produced using the traditional processing package Echoview.

The Echopype output was also used to examine spatial and temporal krill swarm distribution in the Palmer Deep Canyon, Antarctica.

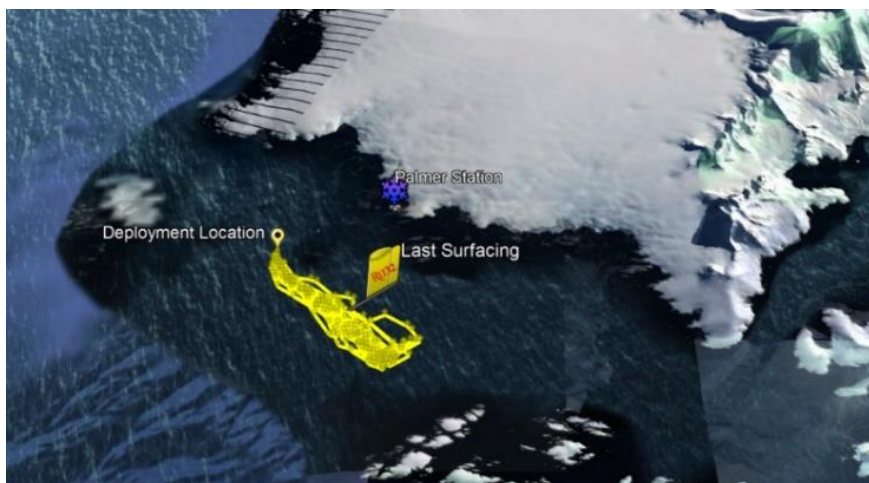


Figure 2. Google Earth image of the deployment path for Teledyne-Webb Slocum G2 glider (RU32) mission in Palmer Station, Antarctica from January 2nd to January 20th, 2019. The recovery location is labeled as 'Last Surfacing'.

Methods

This case study used a dataset from a Teledyne-Webb Slocum G2 glider (designated RU32) that was deployed from January 2nd to January 20th, 2019 out of Palmer Station in Antarctica (Figure 2). The glider traveled a total of 271.2 km over the course of the mission, crossing Palmer Canyon repeatedly, following the path shown in yellow in Figure 2. The Slocum glider profiles the water column in a sawtooth pattern and covers roughly 3 m horizontally for every 1 m traveled vertically. It is capable of reaching a depth of 1000 m and begins its ascent within 50 m of the seafloor (Chave et al. 2018); however, this distance can be altered depending on the purpose of the dive. The glider was equipped with a multi-frequency Acoustic Zooplankton Fish Profiler as well as additional sensors measuring depth, pitch, roll, latitude, longitude, temperature, salinity, optical backscatter, chlorophyll biomass, and dissolved oxygen. The modified AZFP fits into a standard port on the

Teledyne Webb Research Slocum glider, and the transducer housings were oriented 22.5 degrees from the glider axis on the bottom of the hull so that they send out acoustic pings directly downward, perpendicular to a level sea surface given the nominal pitch of the glider on a dive (Figure 1). The AZFP can carry up to four frequency channels; however, on this krill-focused deployment it utilized three at 38, 125, and 200 kHz sampling at a rate of 1 Hz. This work focused primarily on 125 kHz which is the ideal frequency for examining Antarctic krill (Reiss et al. 2021). The 1 Hz sampling rate corresponds to approximately 0.38 m horizontal resolution for a standard glider flight speed of 0.38 m s^{-1} in the horizontal direction. The AZFP data is composed of 1999 range bins distributed over 70 meters, giving a vertical resolution of 3.5 cm.

Processing the acoustic data was done in an openly accessible Python Jupyterlab notebook (<https://github.com/a-sheehan/Echopype-Processing-Pipeline-for-AZFP-and-Glider-Data>). Echopype version 0.4.1 was used in this analysis. Echopype is able to convert raw AZFP files indicated by the extension '.01A' into standard netcdf files, a format that is widely used in oceanographic research and is supported by a range of Python packages, notably xarray. This requires a calibration file (.XML) for the sensor in addition to the .01A data file. The Echopype file conversion process assumes that temperature data is recorded by the AZFP. In the modified glider configuration, temperature was not recorded which resulted in an error when Echopype tried to convert the AZFP output. We therefore manually constructed a temperature calibration coefficient in the .XML file to be able to use the functionality of Echopype for reading raw data. Once Echopype converted and read in the data, several Echopype processing functions could be applied. Additionally, surface noise was eliminated by removing the

first 2 m of range bins during the cleaning process for the AZFP data. A signal to noise ratio mask was applied during the Echopype processing to remove other regions of ‘bad data’.

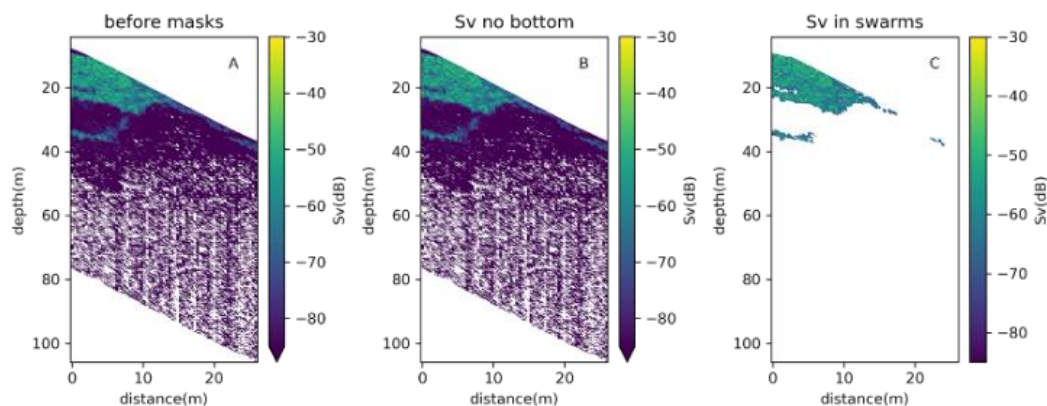


Figure 3. Processed data segment showing krill backscatter strength [Sv (dB)] plotted over a horizontal distance of 25m versus a depth of 100m. Panel A shows the fully processed AZFP data prior to Echopy processing. Panel B shows the same data after removing the seafloor using the Echopy seafloor mask. Panel C shows the processed data after going through both a seafloor mask and swarm mask created in Echopy, leaving only data that represents a krill swarm.

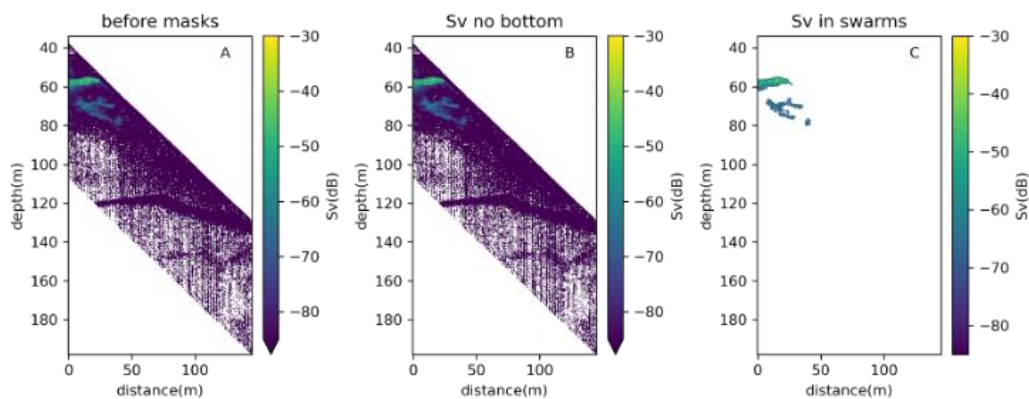


Figure 4. Processed data segment showing krill backscatter strength [Sv (dB)] plotted over a horizontal distance of 40m versus a depth of 200m. Panel A shows the fully processed AZFP data prior to Echopy processing. Panel B shows the same data after removing the seafloor using the Echopy seafloor mask. Panel C shows the processed data after going through both a seafloor mask and swarm mask created in Echopy, leaving only data that represents a krill swarm.

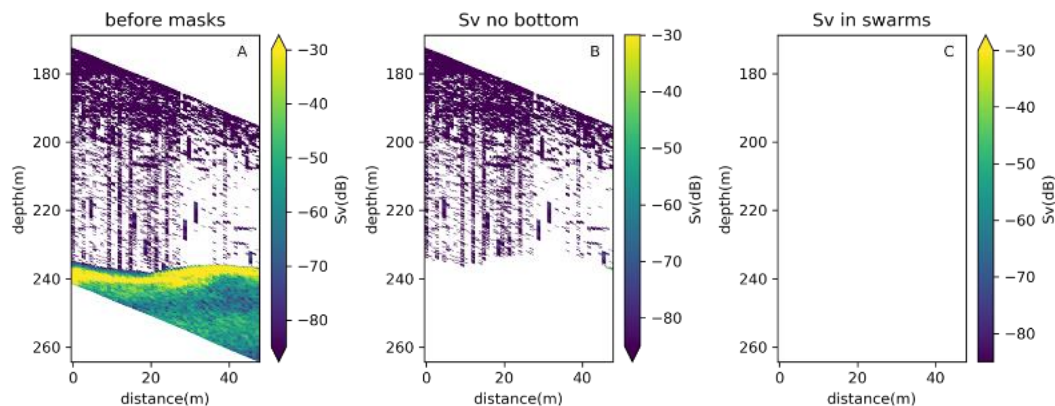


Figure 5. Processed data segment showing krill backscatter strength [Sv (dB)] plotted over a horizontal distance of 160m versus a depth of 265m. Panel A shows the fully processed AZFP data prior to Echopy processing. Panel B shows the same data after removing the seafloor using the Echopy seafloor mask. Panel C shows the processed data after going through both a seafloor mask and swarm mask created in Echopy, leaving only data that represents a krill swarm. This segment of glider data does not contain a krill swarm and therefore Panel C is blank.

The AZFP data was recorded in an independent data stream and at a different sampling rate from the other glider data. Processing acoustic data with Echopy requires some data which was not recorded by the AZFP. Temperature and salinity are needed to calculate the speed of sound which is used to calibrate the backscatter and ranges, and depth, latitude, longitude, pitch, and roll allow Echopy to properly orient the acoustic data in the water column. These variables were collected by other sensors on the glider, therefore the AZFP and other glider sensors needed to be merged to fully evaluate krill biomass. The glider data were accessed using ERDDAPY (<https://ioos.github.io/erddapy/v0.9.0/>) and converted to an xarray dataset format. Initial cleaning and data wrangling steps were required to organize the glider data into a form ready to be merged with the AZFP. These include identifying real-time or delayed mode datasets, removing any duplicated timesteps, and QA/QCing glider data variables. After reading, calibrating and conducting noise reduction QC steps with Echopy, interpolation of the glider dataset and the AZFP dataset can take place. To interpolate glider dataset onto AZFP pings, the glider data was subsetted

onto the AZFP file time range, then interpolated onto the AZFP ping times. A merged xarray dataset was created containing the ancillary glider observations of depth, latitude/longitude (dead reckoned), pitch, roll, temperature, salinity, chlorophyll, and estimated bottom depth, along with the AZFP data (backscattering strength for each frequency, range bin). This merged dataset allowed for geolocation of the acoustic data in depth, latitude, longitude, and time.

Common analysis variables such as the Mean Volume Backscatter Strength (MVBS) need to be calculated after merging the glider and AZFP data as Echopype assumes the AZFP is at a constant depth throughout the file. To calculate MVBS from the glider, the changing depth and width of the acoustic bins must be taken into account. Our pipeline contains an additional step to recalculate these quantities from the profiling platform once the glider motion has been incorporated into the dataset. The newly cleaned dataset can also be used to calculate target strength (TS) and volume backscattering strength (S_v) which are measured in decibels.

Due to the flight pattern of the glider, the AZFP may not be oriented directly downward during several flight phases, namely: during an upcast, during a transition period near the sea floor, or at the sea surface. To isolate usable, vertically oriented, acoustic data, times with a pitch value less than -30° or greater than -15° were masked out. This removed data from climbs and times when the AZFP is not oriented correctly throughout a dive.

After merging the two datasets, a second open-source Python package, Echopy (v1.0.0) (<https://github.com/open-ocean-sounding/echopy>), was used to identify krill swarms and detect and remove the seafloor (termed ‘seafloor masking’). Echoview includes similar algorithms that accomplish these tasks. From Echopy we used the

“Ariza” algorithm to detect seabed features by looping over each frequency and removing any backscatter above a threshold of -40 dB (<https://github.com/open-ocean-sounding/echopy>). This produced a mask that removed any backscatter data identified as seafloor (Panel B Figures 3-5). The algorithm performed the search ranging from 10 m below the sea surface to a maximum depth of 1000 m, while the range offset was set to zero meters. Erosion cycles are a standard parameter included in the Echopy package and were set to one and evaluated on a horizontal and vertical plain of 1 x 3 grid points. Another standard parameter are the number of dilation cycles which were set to three and evaluated on a horizontal and vertical plain of 3 x 7 grid points. With the exception of the dilation cycles, these parameters were set to the default values used in the Ariza algorithm and were customizable.

Once the seafloor mask was added to the dataset, similar measures were taken to create a swarm mask, removing any remaining backscatter that did not represent a krill swarm, also known as a shoal. For shoal detection we used the ‘echoview’ algorithm within Echopy with a maximum threshold value of -70 dB, eliminating anything less than this value. This algorithm approximates the swarm or shoal detection done by the proprietary Echoview software. The minimum size Echopy used to distinguish any possible candidates that may represent a solitary krill shoal was 17.5 cm x 190cm bins prior to searching for adjacent shoals. The algorithm then identifies neighboring shoals at a maximum distance of 105 cm x 76 cm bins and links them together as a single swarm. Anything farther apart than these parameters was considered a separate shoal. After this calculation, Echopy then looks back and considers the minimum requirement that defines a shoal, 105 cm x 76 cm bins, and reclassifies shoals based on these parameters. The same number of dilation cycles was used

for creating the swarm mask which looked at a cluster of points identified as a swarm and searched for neighboring clusters that were close enough in proximity to compose one swarm. Following the addition of the swarm mask to the dataset, a final plot (Panel C Figures 3-5) of the isolated krill shoals with the seafloor and other irrelevant backscatter was produced.

The calibrated, processed, and merged AZFP-glider dataset was saved as an analysis-ready netCDF file. One netcdf file is created for each raw AZFP file from the deployment. Additionally, the same dataset was processed using Echoview (version 10) (<https://www.echoview.com/>). Pitch, roll, latitude, longitude, and depth data from the glider were calculated into .csv files compatible with Echoview software. Echoview uses the timestamps from each of these files to merge glider orientation information with the AZFP acoustic data, resulting in geo-referenced echograms. Glider downcasts were isolated by eliminating data with a pitch greater than -15° or less than -30° . Surface noise within the top 2 m and the ocean bottom (where applicable) were manually removed from the analysis. Calibration parameters and offsets were applied to the echogram, including speed of sound and absorption coefficients calculated from five-day averages of glider CTD data. Raw S_v data was then exported from Echoview for comparison to Echotype-processed S_v data.

To better visualize spatial and temporal distributions of krill swarms, the processed AZFP netcdf files were compiled into a gridded dataset, binned into 5 m x 5 m bins. Prior to binning, S_v represents the volume backscattering strength summed within one cubic meter. In an echogram (Panels A and B Figures 3-5), an individual point represents a S_v value. The original vertical resolution of the data has a thickness of 3.5 cm prior to binning.

The horizontal resolution lacks uniformity due to the varying speed of the glider throughout each dive, producing inconsistent distances between each ping. The binned data represent the Mean Volume Backscatter Strength (S_v_mean in Echoview). As in Echoview, the mean in each bin is calculated as the linear mean but then reported in the decibel domain. While binning the data into 5 m x 5 m cells decreases the resolution, it creates a uniform grid by which the data can be analyzed.

Results

Each netcdf file produced from the Echopy processing was used to produce a three-panel plot demonstrating the capabilities of the Echopy package. Figures 3-5 highlight the effectiveness of the bottom and swarm detection algorithms and closely resemble an echogram produced with the same data using the Echoview acoustic processing package. Because krill are typically found in patchy aggregations, or swarms (Benoit-Bird & Lawson 2016), uniform backscatter readings are not to be expected. Figures 3 and 4 show how the echoview algorithm from Echopy successfully removed data that did not represent a krill swarm. Panel C in Figure 3 clearly outlines a large krill swarm at the surface that extends roughly 20 m horizontally and 15 m vertically, with a smaller swarm approximately 10 m beneath it. Panel C in Figure 4 shows multiple smaller swarms that covers an area of about 45 m horizontally and 20 m vertically. Both figures plot the upper 100 m - 200 m of surface water. Figure 5 demonstrates the capabilities of the bottom detection algorithm in Echopy. There was no presence of a krill swarm from the glider segment used to plot Figure 5; however, the Ariza algorithm successfully detected the seafloor at a depth of 170 m - 260 m. While there was a clean removal of all data

representing the bottom in this case, the Ariza algorithm did not perfectly mask the bottom throughout the full glider dataset, and additional parameter testing is needed.

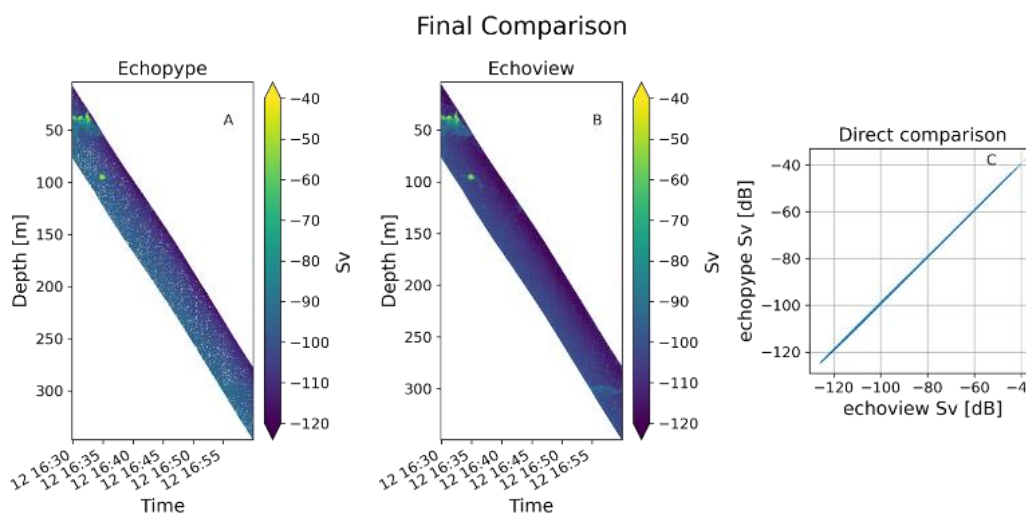


Figure 6. Direct comparison of backscatter strength [Sv(dB)] processed in Echopype and Echoview. Echopype (Panel A) and Echoview (Panel B) plot backscatter strength as depth versus time. Panel C shows the correlation between the Echoview and Echopype backscatter strength data outputs on a scatter plot. Data collected from a single glider segment at a depth range of 0-350m.

To test the open source processing pipeline developed in this work, we directly compared the same file processed with the Echoview software to that processed with Echopype. The steps to process the acoustic data using Echopype compared to Echoview are similar in that both involve orienting the acoustic data given the glider platform, creating a calibration file, isolating the downcasts, defining analysis region by removing bad data, and defining the krill swarms. Both processes used the same original raw data and, if effective, should produce identical results. In Figure 6, panels A and B show the processed original resolution data from each software package. The echograms are identical with exception of the white specks shown in Panel A which are the result of the noise removal process that was done in Echopype but not Echoview. Both plot backscatter strength with a krill swarm at a depth of 30 m - 60 m and a smaller swarm at around 90 m

depth. These swarms were recorded from 4:30-4:40 pm on January 12th. In a quantitative comparison of the two approaches (Figure 6C), the scatter of Echoview processed data against the Echopype output exhibited a slope of 1 ($r^2 = \text{xx}$) with very little scatter. This confirms that the Echopype package and the processing pipeline developed here can be an effective option for processing acoustic data collected from gliders.

From the 5m x 5m binned Echopype-produced dataset used in the present study, spatial distributions of Antarctic krill in Palmer Canyon were plotted (Figure 7). Here, the depth-averaged Sv over the upper 70m is plotted to focus on the region where the majority of krill distributions are found. Higher readings of backscatter at shallower depths at the head of the Canyon were consistently observed.

Discussion

The Echopype processing method was able to reproduce the results that Echoview accomplished in calculating and plotting acoustic backscatter strength recorded by a glider-mounted AZFP. The pipeline for analyzing acoustic data developed in Echopype is free and therefore more accessible and affordable for users compared to the similar approach used with Echoview. Additionally, Echopype is capable of efficiently scaling to the continuously growing volume of data collected from developing instrumentation used in ocean observing. Echopype can process large datasets produced by ocean observing instruments by applying the functionality of Xarray and converting data from various formats into netCDF files. Therefore, it can be used by a wide range of Python packages such as Echopy. Furthermore, users are also able to integrate additional climate related or oceanographic datasets into their work, expanding the scope of oceanographic research that can be analyzed with Echopype. Echopype's programming capabilities made it possible to

analyze the same data used in Echoview and produce nearly identical plots showing krill swarms represented in Sv, proving that Echopype can be used as a free opensource alternative to analyze acoustic backscatter.

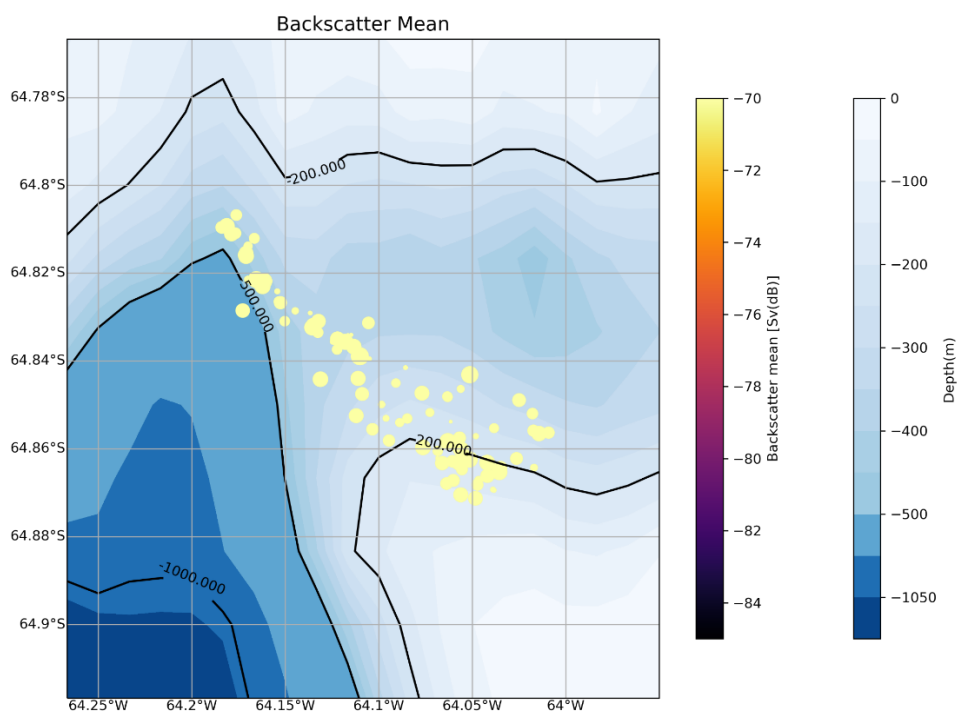


Figure 7. Backscatter strength mean [Sv (dB)] plotted over latitude versus longitude using echopype processed data binned into 5m x 5m bins. Bathymetry contour lines plotted at 200m, 500m, and 1000m. Bubbles depict the depth-averaged backscatter (Sv) over the upper 70m. This removes the risk of including signals given off by the seafloor.

Acoustic data produced through the Echopype pipeline can be applied to examine spatial distributions of marine organisms. For example, from the Echopype-produced dataset used in the present study, spatial distributions of Antarctic krill in Palmer Canyon were plotted (Figure 7). Krill tend to aggregate towards steep bathymetric slopes such as Palmer Canyon (Santora & Reiss 2011), and are typically found within the top few hundred meters of the water column (Alonzo et al. 2003). Circulation that occurs within

canyons can cause upwelling onto canyon shelves which favors productivity and acts as a mechanism to concentrate krill (Santora & Reiss 2011). In these environments krill play a vital role in ‘trophic-focusing’ as they support multiple top predators (Santora & Reiss 2011); therefore further examination into their spatial distribution should take place as their abundance impacts multiple trophic levels. The comparison shown in Panel C of Figure 6 examines one netCDF file or a segment of a single downcast. However, the agreement between the Echotype and Echoview processing pipelines would be the same regardless of which file is analyzed. Visually, the Echograms shown in Panels A and B in Figure 6 are identical with the exception of the blank spaces in Panel A caused by the noise removal process done in the Echotype dataset. The processing steps in Echoview did not include noise removal; therefore Panel B in Figure 6 appears more filled in.

While Echotype has proved to be an effective, viable option to perform acoustic analysis, further research must be done to address several challenges in the Echotype approach. Although outputs of the data processed by Echotype and Echoview were highly correlated, the degree of correlation between the two pipelines decreases once Echopy is incorporated and more complexity (e.g., seafloor masking and krill swarm detection) is integrated into the data processing stream. Figure 5 Panel A plots the data prior to sea floor masking or swarm detection taking place; therefore the echogram produced with Echotype includes all irrelevant backscatter. One setback when examining krill distributions is caused by inconsistencies with the sea floor mask in Echopy. The Ariza algorithm failed to completely remove around 43% of the files containing seafloor backscatter data. Consequently, the depth limit had to be restricted to the upper 70m when evaluating spatial distributions (Figure 7) to ensure that potential bottom readings the Ariza algorithm did not

detect were avoided. This could be attributed to strong backscatter readings given off by the seafloor and may be solved with further investigation into the optimal threshold range used to define the seafloor, or by developing a method to manually edit the remaining backscatter. Future steps in this process could include performing a comparison between the krill swarm detection and seafloor masking features in Echoview and Echotype.

Summary

Integrating glider recorded data with an AZFP dataset through a free open source platform in this study established a new approach to oceanographic research that looks at marine ecosystems on large spatial and temporal scales. In this work we extended the vessel-based Echotype acoustic analysis package for glider-based application. The results produced in this study demonstrate that Echotype is an effective open source alternative for analyzing acoustic data and allows one to avoid the cost of processing data with more expensive software packages such as Echoview. However, challenges related to increasing complexity of acoustic data analysis should be a focus of future efforts to improve the application of Echotype to glider-based acoustic processing.

Bibliography

Alonzo, S. H., Switzer, P. V., Mangel, M. (2003). Ecological Games in Space and Time: The Distribution and Abundance of Antarctic Krill and Penguins. *Family Research and Creative Activity*, 233, 1598-1607.

Benoit-Bird, K. J., & Lawson, G. L. (2016). Ecological Insights from Pelagic Habitats Acquired Using Active Acoustic Techniques. *Annual Reviews*, 8, 463-492.

Chave, R., Buermans, J., Lemon, D., Taylor, J. C., Lembke, C., Decollibus, C., et al. (2018). Adapting multi-frequency echo-sounders for operation on autonomous vehicles. *OCEANS 2018 MTS/IEEE Charleston*. IEEE, 1-6.

Echoview: <https://www.echoview.com/>

Echopy: <https://github.com/open-ocean-sounding/echopy>

Echotype: <https://echotype.readthedocs.io/en/latest/index.html>

Echotype pipeline developed in this study: <https://github.com/a-sheehan/Echotype-Processing-Pipeline-for-AZFP-and-Glider-Data>

ERDDAPY: <https://ioos.github.io/erddapy/v0.9.0/>

Guihen, D., Fielding, S., Murphy, E. J., Heywood, K. J., and Griffiths, G. (2014). An assessment of the use of ocean gliders to undertake acoustic measurements of zooplankton: the distribution and density of Antarctic krill (*Euphausia superba*) in the Weddell Sea. *Limnology and Ocean Methods*, 12, 373–389.

Reiss, C. S., Cossio, A. M., Walsh, J., Cutter, G. R., Watters, G. M., (2021). Glider-based estimates of meso-zooplankton biomass density: a fisheries case study on Antarctic krill (*Euphausia superba*) around the northern Antarctic Peninsula. *Frontiers in Marine Science*, 8, 256.

Santora, J. A., & Reiss, C. S. (2011). Geospatial variability of krill and top predators within an Antarctic submarine canyon system. *Marine Biology*, 158, 2527–2540, doi10.1007/s00227-011-1753-0.

Warren, J., Santora, J. A., Demer, D. A. (2009). Submersal distribution of Antarctic krill and its avian and pinniped predators before and after a near gale. *Marine Biology*, 156, 479-491.

Watters, G. M., Hinke, J. T., & Reiss, C. S.. (2020). Long-term observations from Antarctica demonstrate that mismatched scales of fisheries management and predator-prey interaction lead to erroneous conclusions about precaution” *Scientific Reports*, 10:2314, 1-9, <https://doi.org/10.1038/s41598-020-59223-9>.