Fisheries Research 181 (2016) 63–76

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

Investigating acoustic diversity of fish aggregations in coral reef ecosystems from multifrequency fishery sonar surveys

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ARTICLE INFO

Article history:
Received 25 November 2015
Received in revised form 28 March 2016
Accepted 31 March 2016
Available online 13 April 2016

Keywords:
Fisheries acoustics
Remote classification
Coral reef fishes
Multifrequency

ABSTRACT

Remote species classification using fisheries acoustic techniques in coral reef ecosystems remains one of the greatest hurdles in developing informative metrics and indicators required for ecosystem management. We reviewed long-term marine ecosystem acoustic surveys that have been carried out in the US Caribbean covering various coral reef habitat types and evaluated metrics that may be helpful in classifying multifrequency acoustic signatures of fish aggregations to taxonomic groups. We found that the energetic properties across frequencies, in particular the mean and the maximum volume backscattering coefficient, provided the majority of the discriminating power in separating schools and aggregations into distinct groups. To a lesser extent, school shape and geometry helped isolate a distinctive group of reef fishes based on shoaling behaviour. Schools and aggregations were clustered into five distinct groups. The use of underwater video surveys from a Remote Operating Vehicle (ROV) conducted in the proximity of the acoustic observations allowed us to associate the clusters with broad categories of species groups such as large predators, including fishery important species to small forage fishes. The remote classification methods described here are an important step toward improving marine ecosystem acoustics for the study and management of coral reef fish communities.

1. Introduction

Increased use of ecosystem approaches to support ocean planning and management of ecosystem resources requires rapid and synoptic collection and synthesis of geospatial data. Remote sensing approaches such as satellite, airborne or ship-based optical and acoustic sensors have proven useful in collecting high resolution seafloor imagery over very large spatial extents (Costa et al., 2009; Pittman and Brown, 2011). The power of these datasets is further improved when seafloor habitat types can be interpreted to geological form (e.g., rock, sediment) and biological cover (e.g., coral, vegetation). In coral reef ecosystems, distribution of reef fish has been closely associated with geomorphology, biological cover, and reef topographic complexity (Gratwicke and Speight, 2005; Komyakova et al., 2013; Kuffner et al., 2006; Luckhurst and Luckhurst, 1978; Roberts and Ormond, 1987; Walker et al., 2009). Because these complex habitats preclude the use of trawls and many other extractive fishing methods, the primary method to assess fish distributions in tropical reefs is through visual or optical surveys. However, limitations in coverage of these methods, especially in deeper waters, constrains our understanding of the distribution of fish over habitats across a range of spatial resolutions and extents. Further limitations in visual techniques arise when attempting to enumerate or characterize behaviours of large aggregations or schools of fish.

Fishery sonar surveys have been used for several decades as an assessment tool for temperate fish populations, but have not been used extensively in coral reef systems. The primary challenge in reef systems is the high diversity and the inability to identify species using sonar (echosounders) alone. A recent paper by Costa et al. (2014) found that maps of taxa-independent fish densities derived from fishery echosounder surveys conform to predictions based on seafloor habitat complexity (e.g., rugosity, depth, and slope; Pittman and Brown, 2011). Higher densities are found over seafloors of higher rugosity, slope and depth (where shallow depths are usually correlated with high-relief and high rugosity reefs).

To be the most useful to fisheries and ecosystem management goals, assessments of fish and other living marine resources in coral reefs would ideally provide density and biomass for each species over broad spatial extent and at fine spatial resolution. Currently,

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http://dx.doi.org/10.1016/j.fishres.2016.03.027
0165-7836/

acoustic surveys of reef fishes have been able to separate fish densities according to broad size classes focusing on individual fish resolvable by the echosounder (Costa et al., 2014). This approach is not always applicable considering that many species aggregate into dense schools resulting in the overlapping of the individual fish echoes. For this reason, there is the need to improve the acoustic methodology and further develop approaches for data analysis. Multi-frequency fishery echosounders, as used in recent acoustic surveys for reef fishes, have shown some progress in recent years in discerning size and age classes, species or functional groups of mixed aggregations of fishes, and fish from marine invertebrates (Fablet et al., 2012; Fernandes, 2009; Horne 2000; Kloser et al., 2002; Korneliussen and Ona, 2003; Korneliussen et al., 2009). The approach relies on two acoustic properties of fishes and fish schools. First, fish species may have swim bladders (or not) with morphologies that differentially reflect sound across frequency bands. Second, species may form groups or schools that have unique shapes or internal densities that can be differentiated using acoustic backscatter.

For this paper, we evaluate existing metrics that describe the shape and acoustic backscatter (energetic) properties of Caribbean reef-fish aggregations and schools in order to investigate the fish acoustic diversity and identify meaningful patterns that could help to classify the acoustic signatures. We use an unsupervised statistical clustering approach and discuss the repeatability of the method for describing the acoustic variability in the coral reef areas. Finally, we use underwater video surveys of fish aggregations and schools from remotely operated vehicle (ROV) to guide our interpretation of the multi-frequency acoustic clustering approach.

2. Materials and methods

2.1. Study area

The research was conducted in the US Virgin Islands and Puerto Rico in spring 2011, 2013 and 2014. The surveys were part of a U.S. National Oceanic and Atmospheric Administration (NOAA) program to map the benthic habitats using multibeam echosounders and simultaneously map the distribution of fish using scientific splitbeam echosounders (Kracker et al., 2011). The fish acoustic surveys covered areas identified as “hotspots” for the presence of high abundance of commercially important species such as groupers and snappers (Fig. 1).

2.2. Splitbeam echosounder surveys

Acoustic sampling was conducted on board the NOAA Ship *Nancy Foster* during daytime (08:00–18:00) using a SIMRAD EK 60 splitbeam echosounder operating at 3 frequencies (38, 120, 200 kHz). Pulse length was set to 128 μs for the 120 kHz and 200 kHz and 256 μs on the 38 kHz. During some parts of the survey, a multibeam sonar (Reson 7125 operating at 400 kHz) was used to simultaneously map the seafloor. Pulse interval was defined automatically based on the range or depth and triggered by the pulse interval of the multibeam sonar. All the frequencies were calibrated following the standard sphere method using a tungsten carbide sphere (Foote et al., 1987). The survey design was generally based on parallel transects. The inter-transect distance, transect length and direction varied among sampling sites and were chosen according to the characteristics of the reef. The vessel speed was approximately 6.5 knots.

2.3. Data analysis

The acoustic data were processed using the software Echoview (ver. 6.0; Echoview Software Pty Ltd.). The data processing workflow consisted of three parts: first, data were corrected based on the transducer geometry and for vessel pitch and roll in order to get the correct beam directivity. In order to ensure a good degree of beam overlap across the frequencies, the data were compensated for the distance between the transducers along the longitudinal axes of the ship. In particular, the data were shifted by a number of pings that were equivalent to the distance between the transducers. Since the pulse length used at 38 kHz was different from the other two frequencies resulting in different vertical resolutions, the data at 120 and 200 kHz were integrated along the vertical axis to match the lower vertical resolution in the 38 kHz data (~4 cm). Noise from ship systems and unwanted backscatter from bubbles and other sources were removed from the data in order to get a “clean” echogram. In the second part, the data at each frequency were averaged generating a synthetic echogram and an image filtering procedure was used to stabilize the data following the method fully described in Korneliussen et al. (2009). Finally, automatic school detection was applied on the averaged and filtered data using the SHAPES algorithm in Echoview (Barange, 1994). The detection parameters used were: minimum total school length of 2 m, a minimum school height of 1 m, a minimum candidate length of 2 m, a minimum candidate height of 1m, a vertical linking distance of 1 m, a maximum horizontal gap distance of 5 m, and a minimum volume backscattering coefficient (Sv) of −60 dB. This set of parameters was selected based on the characteristics of the aggregations in the data in order to minimize the false detection of the schools. The schools were also visually scrutinized and edited when the algorithm failed to identify the correct structure of the aggregations. A series of metrics describing the characteristics of the schools were exported at each frequency using a Sv threshold of −60 dB. In particular, geometric, energetic and bathymetric parameters, which have been used previously for acoustic target classification (Haralabous and Georgakarakos, 1996; Korneliussen et al., 2009; Reid, 2000), were taken into account. These variables provide detailed information of the acoustic characteristics and behaviour of fish schools. The geometric features describe the morphology of the schools. The calculation of the geometric variables is based on image analysis techniques given that the echogram can be seen as a raster image where the pixels correspond to the data points. The geometric properties of each datapoint depend on frequency, pulse interval, pulse length and vessel speed (Reid, 2000). The energetic features provide information on both target characteristics (e.g., size, presence of swimbladder) and school behaviour (e.g., packing density, presence of patches inside the schools). The bathymetric variables give us an indication of habitat selection that can be species-specific. We included the majority of variables previously used in acoustic target classification so as not to omit any information that may be important for the classification, especially considering the high diversity of the system. The school descriptors with their relative meanings and references are listed in Table 1. The resulting schools library consisted of 2268 schools.

2.4. Clustering

An unsupervised clustering approach was used for the classification of aggregations. This approach does not require “a priori” information about the school category and the species class label will be inferred on the basis of the school descriptors considered. The basic assumption using this method is that the detected classes of aggregations correspond to biologically meaningful structures that can be related, for instance, to morphological similarity between species, similar aggregation behaviour etc. In particular the Robust Sparse K-Means (RSKM) was applied (Kondo et al., 2012). This method is the combination of the trimmed k-means (Gordaliza, 1991a,b) and the sparse k-means (Witten and