A Semiautomated Approach to Estimating Fish Size, Abundance, and Behavior from Dual-Frequency Identification Sonar (DIDSON) Data

Article *in* North American Journal of Fisheries Management · June 2008

DOI: 10.1577/M07-116.1

Kevin Mershon Boswell
Florida International University

James Howard Cowan
Louisiana State University

North American Journal of Fisheries Management 28:799–807, 2008

DOI: 10.1577/M07-116.1

[Management Brief]

A Semiautomated Approach to Estimating Fish Size, Abundance, and Behavior from Dual-Frequency Identification Sonar (DIDSON) Data

KEVIN M. BOSWELL*
Department of Oceanography and Coastal Sciences, School of the Coast and Environment, Louisiana State University, Baton Rouge, Louisiana 70803, USA

MATTHEW P. WILSON
SonarData Pty., Ltd., General Post Office Box 1387, Hobart Tasmania 7001, Australia

JAMES H. COWAN, JR.
Department of Oceanography and Coastal Sciences, School of the Coast and Environment, Louisiana State University, Baton Rouge, Louisiana 70803, USA

Abstract.—We present a semiautomated analytical approach incorporating both image and acoustic processing techniques to apply to dual-frequency identification sonar (DIDSON) data. Our objectives were (1) to develop a standardized analysis pathway in order to reduce the effort associated with counting, measuring, and tracking fish targets; and (2) to empirically obtain estimates of basic target information (e.g., size, abundance, speed, and direction of travel). Analyses were conducted on DIDSON data collected at three different locations (the Kenai River, Alaska; Mobile River, Alabama; and Port Fourchon, Louisiana) with different equipment and deployment configurations. We developed an efficient postprocessing approach that can be applied to a variety of data sets, independent of user and deployment method. For two of the three data sets analyzed, the estimates of fish abundance derived from DIDSON analyses were not significantly different from the manual counts of DIDSON files. The analyses produced estimates of mean fish length, direction and speed of travel, and target surface area for all targets within each data set. A consistent analysis platform increases the acceptance and reliability of the DIDSON as a tool for fisheries surveys and further demonstrates the usefulness of DIDSON technology in fisheries applications.

Recent developments in sonar imaging have provided a means to obtain near-video-quality imaging of fish in dark or turbid waters (Moursund et al. 2003; Tiffan et al. 2004; Mueller et al. 2006). Originally developed for naval surveillance, the dual-frequency identification sonar (DIDSON; Sound Metrics Corp.) has been adopted by fishery scientists to obtain both size and abundance estimates of fish (Moursund et al. 2003; Holmes et al. 2006; Mueller et al. 2006; Burwen et al., 2007) and to image fish habitats (Tiffan et al. 2004). In addition, the behavior of fish relative to habitat and other stimuli can be observed regardless of ambient light levels and turbidity, providing an important advantage over traditional video census techniques (Willis et al. 2000; Stoner 2004). A unique feature of the DIDSON is the capacity to simultaneously image both substrate and other habitats and ensonified fish within the same transmitted pulse, yielding data that are more straightforward and interpretable than those obtained by other methods.

Although traditional acoustic techniques (e.g., single-beam and split-beam techniques) are often used in fishery assessments, the interpretation and classification of data are often challenging and require extensive experience and effort (Jech and Michaels 2006). These acoustic systems are more susceptible to boundary effects, turbulence, and background noise than is the DIDSON, particularly when attempting to enumerate or identify fish near scattering boundaries (Holmes et al. 2006; Boswell et al. 2007a). Furthermore, when accounting for noisy data, postprocessing of data obtained from an echo sounder can be very complicated and time consuming, often necessitating complex analyses (Simmonds and MacLennan 2005; Holmes et al. 2006; Boswell et al. 2007b).

Current capabilities for both handling and processing DIDSON data are limited and lack the functionality needed to adequately support the growing number of DIDSON users. To date, no methods have been devised that allow combined acoustic and image processing techniques to analyze and provide quantitative estimates of fish abundance, size and behavior. The integration of a defined pathway by which to postprocess and classify acoustic data from the DIDSON will both standardize and objectify the outcome, reducing the need to transfer expertise and biases in interpretation (Jech and Michaels 2006).

*Corresponding author: kboswe1@lsu.edu

Received June 21, 2007; accepted November 29, 2007
Published online May 8, 2008

Moreover, users operating from a defined framework will benefit from more efficient and timely analyses, thus increasing the overall effectiveness of postprocessing methods.

We offer comparative methods for analyzing DIDSON data. In this paper, we developed a semi-automated analysis pathway to obtain estimates of basic target information (e.g., length, abundance, and speed and direction of travel) of fish in DIDSON data. We discuss a defined framework that allows users to obtain general target information quickly while maintaining the ability to identify behavioral associations through target classification and visualization.

Methods

The DIDSON (see www.soundmetrics.com), developed at the University of Washington Applied Physics Laboratory, utilizes proprietary acoustic lenses to form, transmit, and receive beams. The lenses are adjustable in range from the transducer array and allow either manual or automated adjustment of the focal plane to enhance image focus. The DIDSON has the capacity to collect multibeam data at two frequencies, depending on the range and target resolution needed: high-frequency (1.8 MHz), where highest resolution in data is achieved at short ranges (<12 m), and low-frequency (1.1 MHz), where lower-resolution images are acquired at greater ranges (12–40 m). The high-frequency mode uses 96 beams (0.3° horizontal [H] × 14° vertical [V]) for a total field of view of 29° H × 14° V; the field of view of each beam in low-frequency mode is 0.4° H × 14° V. Data can be collected at frame rates of 4–21 frames/s, providing very high temporal resolution. Image resolution is effectively a function of distance from the DIDSON unit. An increase in range from the DIDSON unit will result in a decrease in resolution. Acoustic images allow users to classify data on the basis of target size (Holmes et al. 2006), behavior (Moursund et al. 2003), or species (Burwen et al., in press), given appropriate conditions.

Multibeam acoustic data were collected with a DIDSON (1.1–1.8 MHz) unit at three locations (Kenai River, Alaska [KR]; Port Fourchon, Louisiana [PF]; and a water control structure on the Mobile River, Alabama [MR]). Each deployment was conducted by a different user, resulting in variation in data collection methods and data quality. In the horizontal deployments (KR and PF), to collect side-aspect data the DIDSON unit was deployed below the surface of the water and angled downward approximately 5° from the horizontal to image the substrate and fish in the water column. In the vertical deployment (MR), the DIDSON unit was mounted to a pole with the lens aimed downward and perpendicular to the substrate.

In all instances, data were collected at 1.8 MHz (high-frequency mode) with a maximum range of 12 m from the imaging sonar. Frame rates varied from 4 to 7 frames/s. Data were collected continuously at 30-min intervals each hour for at least 4 h per site. At both PF and MR, a 420-kHz split-beam transducer operated by a BioSonics DE-X echo sounder was deployed alongside the DIDSON unit. Throughout the surveys, consistent interference between the DIDSON and BioSonics system was observed, though this produced no concerns about either data quality or integrity (E. Belcher, personal communication), and noise from echo sounder interference was removed during post-processing.

Acoustic data were imported, preprocessed, and analyzed in Echoview (version 4.1, SonarData Pty., Ltd.). The Echoview software creates two variables from each DIDSON file; the first variable is proportional to the received power (in dB) and the second is corrected for spreading and absorption losses, yielding an uncalibrated measure of S_v (mean volume backscatter [MVBS]; dB). Both variables are stored as a three-dimensional (3D) matrix of samples: samples were organized within each beam by their range from the transducer, and the beams were organized within each ping by their pointing angle within each beam plane; time was the third dimension. Our analyses include only the second variable, S_v frames (Figure 1).

We describe a process in Echoview that uses the virtual variable interface to sequence individual operations (mathematical and visual) into an analysis pathway. This functionality allows algorithms to be built and tested from smaller component operations. Though the following descriptions are specific to analyses conducted in Echoview, where the framework exists for postprocessing without the need for programming experience, operations can be implemented in other software (e.g., Matlab) to achieve similar results. The conceptual layout of the virtual variable interface is illustrated in Figure 1, where each object represents an operational step in the process. The data corresponding to each operational step can be visualized separately from the original data, enabling the tuning of individual steps within the analysis framework. The framework for two proposed standard DIDSON analysis pathways are presented as processes 1 and 2 in Figure 1.

The initial step in both processes removes static background objects from the data that would otherwise be erroneously detected as fish. A sample statistic subtract operator is implemented to generate a synthetic ping representing the background signal, and the synthetic ping is subsequently subtracted from each real ping. A user-specified ping subset is averaged to

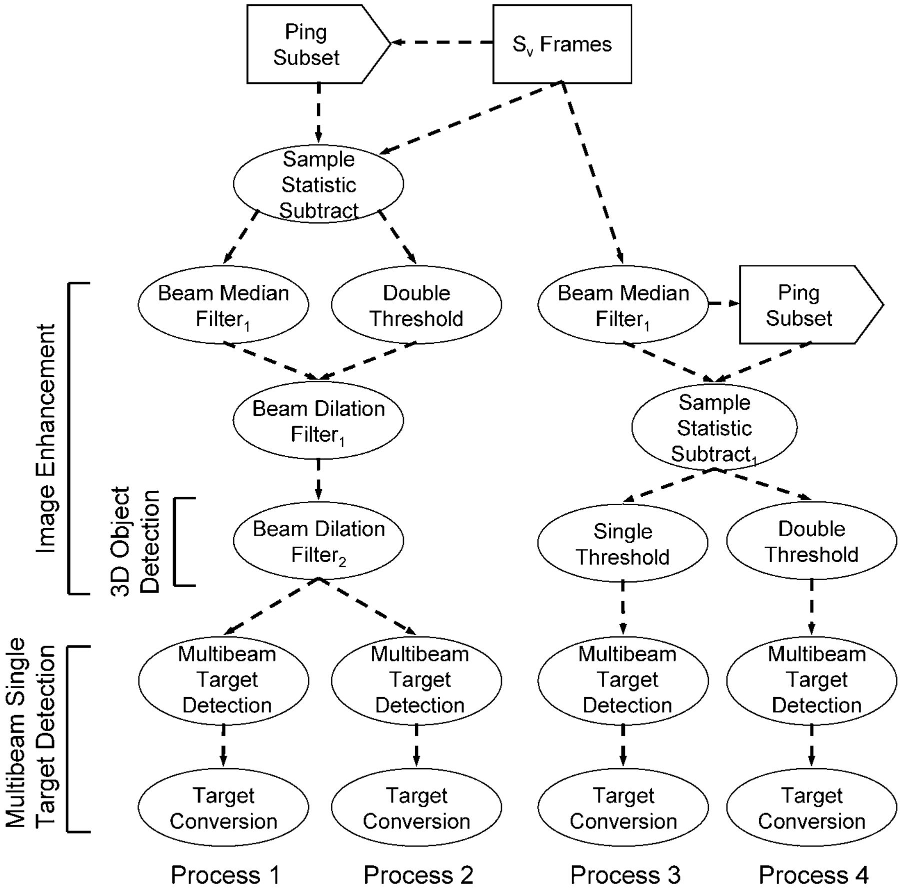

FIGURE 1.—Analysis pathways implemented in Echoview (version 4.1). Four parallel processes are presented that provide similar outcomes even though they are used to optimize analyses under various conditions. Processes 1 and 2 are proposed standard DIDSON analysis pathways that were applied to all three data sets (Kenai River, Mobile River, and Port Fourchon); processes 3 and 4 were experimentally applied to the Port Fourchon data set only. The S_v frames operator (acoustic volume backscattering strength) is the raw DIDSON data, and the subsequent operators are applied through the pathways. The bracketed regions (left side of diagram) denote the functions of the enclosed components within the pathways.

generate the synthetic background ping. Using a section of data where little or no change occurs is advantageous, allowing isolation of a subset of pings to generate the synthetic background ping. If the data have no such "quiet" section, then the entire ping set can be used. The subsequent averaging will smooth movement and yield a suitable background ping for use in the background subtraction. This operation is implemented immediately and, unlike in the DIDSON application (DIDSON version 4.5; Sound Metrics Corp.), is not dependent on an algorithm to filter the initial segments of a data file. The background subtraction has been employed in a stationary deployment (horizontal and vertical) and may not be useful for mobile horizontal deployments where large variation in bottom scattering may exist. However, given certain considerations (water depth, change in bottom contour or elevation, presence of vegetation), the background subtraction may offer utility in a vertical mobile deployment.

After subtracting the background, the standard analysis path splits into two processes (Figure 1) corresponding to alternative data enhancement methods, each consisting of a sequence of data manipulation operators. Process 1 is based purely on the enhancement of the signal with convolution and neighbor matrices. Process 2 makes use of the double threshold operator in Echoview, requiring the user to inform the analysis of the expected magnitude or size of the detected targets. The addition of process 2 was a result of the added functionality provided through the double threshold operator and simply allows the user more flexibility for selecting size ranges of targets. Processes 3 and 4 were generated in response to the failure of the standard technique to adequately analyze the PF data set.

Image Enhancement

Process 1.—After background subtraction, process 1 implements a 3×3 median filter to each sample in the data. This filter replaces each sample in the matrix with the median value from each data point and those of its eight direct neighbors. A 3×3 median filter is extremely effective in removing interference seen in individual beams that are well separated. The median value (the fifth coefficient in a 3×3 matrix) can therefore never be a contaminated sample, provided only one of the three beams are contaminated. After the median filter is used, two successive 3×3 dilation filters are applied to each sample in the data. A dilation filter is analogous to the median filter; however, the maximum value is selected to expand maxima within the data, effectively enhancing strong signals and closing thin holes or channels that may exist between adjacent maxima. A threshold (dB) is applied to the second beam dilation filter to facilitate object detection.

Process 2.—Process 2 utilizes a double-threshold operator as the first step following the subtraction of the background signal. Similar to a dilation filter, a double-threshold operation effectively expands maxima within the data but does so using two thresholds and an influence radius. The first threshold (dB) defines the maxima; the influence radius (cm) defines the spatial scope of the allowed expansion, and the second threshold (dB) applies a threshold to the signal within the expansion zone. The operator first selects all samples exceeding the first threshold and then identifies additional samples that fall within the influence radius of those samples. The second threshold is then applied to all identified samples. The double threshold requires knowledge of the minimum peak signal value (dB) expected for each individual fish detection, thereby determining the lower threshold. The expected size (cm) of each detected fish will determine the optimum size for the influence radius, and the expected signal value of the transition between background noise and genuine signal from a fish will determine the upper threshold. These settings can be visually tuned by analyzing individual fish observed in the data set or may be predetermined based on knowledge of the target species and their scattering properties. As in process 1, two successive dilation filters are applied to the result of the double-threshold operation to expand the isolated above-threshold signals (Figure 1). A threshold (dB) is applied to the second beam dilation filter to facilitate object detection.

Processes 3 and 4.—Two additional processes were implemented to determine the additional performance achieved by tuning the analysis pathway for optimum detection with a specific data set. The PF data were chosen as the only subject of the exercise because analyses showed that the standard processes worked least effectively for these data. Process 3 uses the following operators: ping subset, median filtering, and background subtraction (Figure 1) for image enhancement. A visually tuned threshold (dB) is applied to the remaining data. Instead of a single threshold as in process 3, process 4 uses a double threshold.

Target and Object Detection

For investigators to obtain estimates of the attributes of interest (size, surface area, speed, and direction), fish need to be detected as targets and objects and ultimately tracked through time. Attributes available through detection (target and object) include instantaneous estimates of size, surface area, and position. These instantaneous measurements can be used to inform tracking; tracking, in turn, provides more accurate estimates of those attributes by using multiple measurements. Track analysis provides measures of new attributes (mean fish length, mean fish surface area, mean speed and direction, and change in position), which are features of an individual track. Tracked fish can then be classified via analysis of features derived from their instantaneous detections, from their tracks, or both.

Two means of detecting and visualizing targets and objects from multibeam data are presented; one identifies 3D objects and the other identifies single targets. The multibeam target detection generates "single target" data, which is Echoview's data storage type for single-echo detections (SEDs), analogous to traditional single-target analyses (see Simmonds and MacLennan 2005). Single-target algorithms can be applied to the detected targets at the expense of shape information from each respective target. Alternatively, 3D object detection can both yield objects that can be visualized, tracked, and analyzed through time and provide an excellent mechanism by which to compare the detected objects with the original data. Fortunately, both techniques are integrated into the described pathways and are complementary to one another, preserving both single-target and shape information for quantitative analysis.

3D object detection.—The 3D object detection mechanism retains the outline of each group of adjacent samples within each ping as a two-dimensional shape. Detections are performed on the second beam dilation filter (Figure 1) in both of the standard processes and on the single threshold (process 3) and double threshold operator (process 4; Figure 1). The third dimension is added by extruding the two-dimensional shape in a perpendicular direction by a user-specified amount (cm). The resulting 3D surface is stored as a triangulated irregular network. The 3D objects can be analyzed for morphometric parameters (e.g., object surface area, speed and direction of travel, and energetic parameters such as mean scattering strength). The 3D object detections are examined by overlaying detected objects onto the original DIDSON data to validate proper detections.

Multibeam single-target detection (MST).—After detection of the 3D object, the MST detection operator calculates both the mean value of the set of samples that make up the object and its geometric center. Output from the MST detection operator consists of point targets with target strength (TS; the mean value of the samples that make up the object, though this is not a true measure of TS) values and a coordinate position (range and angle) within the beam plane. A subsequent target conversion operator transforms point targets into standard SEDs that can be displayed in an echogram, tracked, and analyzed.

Fish tracking.—Multiple ensonifications of the same fish are counted as separate detections, making target tracking necessary. Tracking provides useful estimates not only of abundance but also mean length and behavior of individual targets and morphometric information (Arrhenius et al. 2000; McQuinn and Winger 2003; Simmonds and MacLennan 2005). As a result, one can classify targets and partition information based on knowledge of ensonified fish. Correct filtering and tracking of detected objects (3D objects and MSTs) are obtained with tunable alpha–beta tracking algorithms. The coefficients for the alpha–beta algorithms are chosen on the basis of the visual performance of tracking and are a result of the combination of the quality of the data and quality control of the tracking results, much as in other current tracking applications. Given that abundance estimates are derived from proper tracking, users will need to manipulate and audit tracking results accordingly. These algorithms are applied to both the single targets and the 3D objects generated from the MR and KR data with processes 1 and 2. Objects detected from PF were tracked with processes 1, 3, and 4. Given that each data set was unique in character, the parameter values used to optimize tracking differed.

Manual Counts

Raw DIDSON data files were played back in the DIDSON software to obtain estimates of fish abundance. During this step, each data file was partitioned into five equal time intervals. Data were played back at 10 frames/s, the maximum number of fish appearing in a single frame being counted, as in the min/max method (Willis and Babcock 2000; Cappo et al. 2004; Mueller et al. 2006). Estimates of maximum fish abundance (fish per time interval) were compared with abundance estimates derived through the analysis pathways.

Data Analysis

Throughout each step, data were examined visually to ensure the proper operation of each variable within the standard processes, with particular attention to the 3D object and MST detection variables. Tracks were generated from 3D objects and from converted MSTs, both for each image enhancement process and for each survey station. Summary statistics were exported from Echoview (e.g., mean target size, speed, target direction, surface area, fish track association number), and comparisons were conducted between detection methods and among processes for each station with analysis of variance (ANOVA; SAS, version 9.1). The abundance estimates (fish per time interval) derived from the 3D object tracks, MST tracks, and manual counts were $\log_e(x + 1)$ transformed before analysis to satisfy the assumptions of homogeneity of variance. Post hoc tests were performed with Tukey's honestly significant difference test, and all tests were significant at $P < 0.05$.

Results and Discussion

Irrespective of the variation in deployment location and configuration, qualitative and quantitative review suggests that the standard techniques (processes 1 and 2) were generally well adapted for identifying and enumerating ensonified fish with predictable movement, as in KR and MR. At KR, several fish tracks corresponding to smaller fish were observed in process 1, although they were less separable in process 2, which thus resulted in lower mean abundance estimates (Figure 2). Manual abundance counts at KR (12.7 ± 3.3 fish [mean ± SE]) conducted on raw DIDSON data were not significantly different from those estimated by either detection method for either process (ANOVA; $F_{4,20} = 0.67$; $P = 0.618$). In contrast, at MR, both the mean number of 3D object tracks and MST tracks exceeded manual counts (12.1 ± 0.9 fish) by a factor of at least 1.9 in all cases (ANOVA; $F_{4,20} = 17.97$; $P < 0.001$), the result of multiple repeated counts of individuals. However, at MR, no significant differences existed between processes or detection methods ($P \geq 0.266$).

The PF data contained targets having variable speed and unpredictable trajectory, a result of fish converging into a school subsequent to interaction with a larger

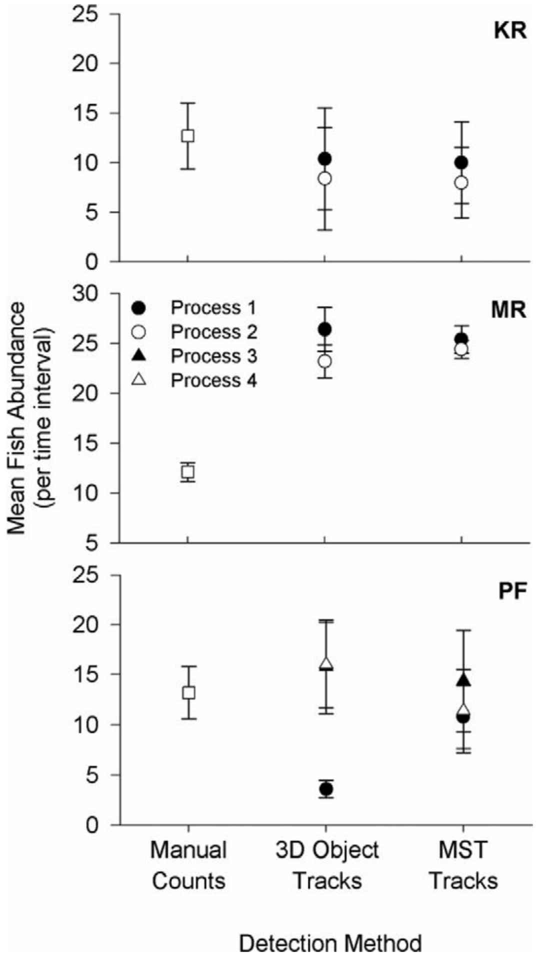

FIGURE 2.—Mean abundance of fish (number per interval) estimated through visual counts and DIDSON analysis pathways (processes 1–4) by tracking method (3D objects or multibeam single targets [MST]) at each station (KR = Kenai River, MR = Mobile River, and PF = Port Fourchon). Only processes 1, 3, and 4 were applied to the PF data. See Figure 1 for definitions of processes. The thin vertical lines represent standard errors.

single fish. The fish converged into a tight school, which made detection of individuals very challenging for the standard pathways (process 1 and 2). Examination of 3D object detections from process 1 indicated that clear and separate individuals were well detected; however, small groups of fish in close proximity were often detected as a single object. Abundance estimates within the main effects of process and detection method differed significantly (ANOVA; $F_{6,27} = 2.80$; $P = 0.032$); post hoc tests indicated that variation was attributed to the low abundance estimates of the 3D object tracks from process 1 ($P < 0.035$). The strength of the background signal from static objects and the low strength of the fish scattering relative to the background caused the complete failure of process 2. In that case, background subtraction moved all of the data below the upper threshold of the double-threshold operation, yielding empty data for the remainder of the process. This data set is unsuitable for the application of a "standard" pathway; appropriate fine-tuning and specialized data treatment, however, improved the results obtained. Processes 3 and 4 were successful in detecting fish at PF; the variation between these detection methods was small (Figure 2). For both processes the number of 3D object detections was greater than that of MST detections because of the range proximity filtering in the target conversion operator. Qualitatively, process 4 performed best, with the greatest overlap between fish observed in the underlying data and both 3D object and MST tracks. Visual comparison also led to the conclusion that all processes failed to detect some number of fish, most likely because of the small signal–noise ratio between the fish signal and the combination of background signal and noise.

The variability in the abundance estimates among stations was primarily attributed to differences between open and closed environments. Whereas the errors associated with the open systems (KR and PF) were large and driven by changes in fish abundance through time intervals, the error associated with the closed system (MR) was relatively small and approximated that of the manually derived counts. In closed systems, the probability of enumerating the same individual on multiple occasions is much greater than in open systems (Ricker 1975). In response, use of complementary approaches can account for double-counting and behavioral differences that data models do not (e.g., min/max method; Willis and Babcock 2000; Cappo et al. 2004; Mueller et al. 2006).

One must acknowledge that the number of detected objects is subject to various conditions (e.g., fish behavior and movement, dynamic aggregations and schooling, and position and time in the beam), which suggests that the objects detected be considered an index of relative abundance rather than an absolute count, particularly given the dependence on tracking parameters. Refinement of tracking algorithms to temporally and spatially linked detected objects (3D objects) and targets (MST) may compensate for current shortcomings in enumeration. Multibeam single-target tracks may be a more conservative approach to abundance estimation than 3D object tracks, given the target geometry requirements within the single-target detection algorithm. Furthermore, the tracking algorithms used to generate the MST tracks are more

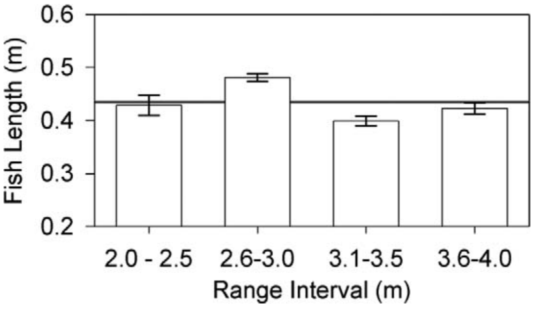

FIGURE 3.—Range-dependent length deviation of a single Chinook salmon at the Kenai River station estimated by process 3. The thin vertical lines represent standard errors. The horizontal line at 43.6 cm is the measured length of the salmon (Burwen, unpublished data).

stringent than those of the complementary 3D object tracking, the latter relying primarily on distance and time criteria. Regardless of the tracking procedures, we suggest user audits to validate the performance of the tracking algorithm.

Similar to the findings of Burwen et al. (2007), estimates of individual fish length were variable in time and range from the DIDSON unit. We specifically analyzed the large Chinook salmon *Oncorhynchus tshawytscha* in the KR data set for changes in estimated size with position and movement through the beam. The mean fish length (43.47 cm) was estimated through process 3 and compared with the actual fish size (43.5 cm; Burwen, unpublished). Fish lengths were compared with increasing range (Figure 3) in response to concerns described by Burwen et al. (in press) of potential biases with fish length estimates in DIDSON data. The estimated change in the range of the fish was 1.8 m towards the DIDSON unit, which was moving at approximately 0.2 m/s (Figure 4B). During fish passage, the estimated fish length ranged from 0.36 $\pm$ 0.01 to 0.49 $\pm$ 0.01 m (Figure 4B). Qualitative review suggests that biases in fish length are due to changes in fish orientation relative to the sonar, the largest deviations occurring with the fish azimuth ranging from 9° to 23°. Additionally, further bias may be attributed to limitations of the sonar to detect proximal and distal features of the fish, particularly when they are positioned in the periphery of the acoustic beam (Holmes et al. 2006). Clear interpretation of the bias in length estimates will require further evaluation with fish of known length at distance from the sonar (Burwen et al. 2006).

The processes detailed in this paper provide an efficient and reliable pathway for analyzing DIDSON data and will greatly reduce the current time required to postprocess DIDSON data. Within the Echoview

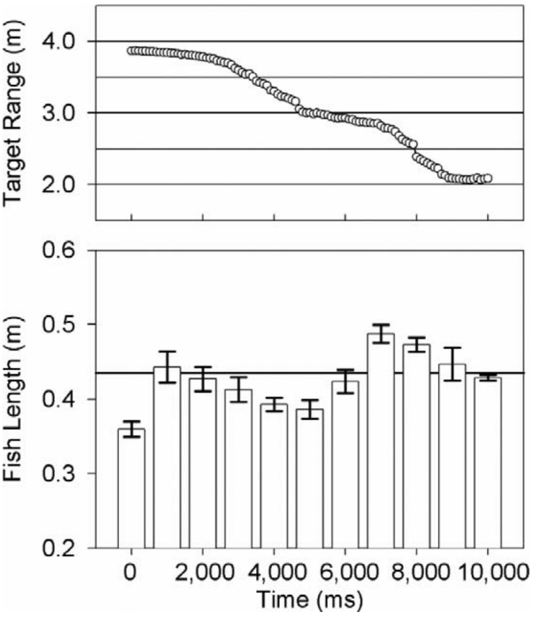

FIGURE 4.—Panel **(A)** shows the target range from the DIDSON unit for an individual salmon ensonified at the Kenai River station over time, panel **(B)** estimates of fish length corresponding to the track from (A). The reference line in (B) represents the measured length of the fish (43.6 cm; Burwen, unpublished data). The thin vertical lines represent standard errors.

framework provided, 1 h of DIDSON data (high frequency; 1.25–12 0.5-m window, 7 frames/s) can be analyzed and exported in approximately 1.5 h, depending on computer configuration, to include estimates of fish size, direction of travel, speed, and surface area, among many other variables. The user is required only to initiate the automated analysis process.

Conclusions

Enhancements in the ability to both handle and analyze DIDSON data will greatly assist researchers and biologists who currently use or plan to use DIDSON technology in field studies. The reduction in effort for analyses and robust platform will help to make the data more accessible and useful for quantitative fishery assessments, thereby furthering its use in fishery science. We have discussed the utility of using the DIDSON as a tool for collecting information on fish length and behavior in a variety of aquatic systems. The automated analyses described in this paper will help advance both the application of DIDSON and the ease with which the data are viewed and processed. As discussed in Holmes et al. (2006), the DIDSON has the potential to provide highly precise counts of fish, provided the protocol used for enumeration is adequate. A standard method will help objectify the approach to fish enumeration and probably will lead to reduction in systematic bias of quantitative estimates of fish length, abundance, and behavioral metrics to enhance the effectiveness of future surveys (Holmes et al. 2006; Jech and Michaels 2006).

The use of imaging sonar systems such as the DIDSON will enhance our ability to observe in situ behavior and abundance and will advance our understanding of various aspects of fisheries ecology (Moursund et al. 2003; Holmes et al. 2006; Burwen et al. 2007, in press). Moreover, conditions once considered to be limiting to visual techniques (e.g., diver surveys, camera arrays, and other optical techniques) do not negatively influence data quality or the ability to quantitatively and qualitatively assess fish abundance and behavior, although the challenge of species identification remains. However, with continued improvements in analysis techniques, we think it likely that resolution toward species identification will be achieved, particularly for systems low in species richness. As highlighted by Gerlotto et al. (1998), the combination of both multibeam sonar and fishery echo sounders have the potential to provide the most complete and quantitative assessment of fish. Furthermore, the foundation presented here will support additional analytical procedures and techniques for incorporating DIDSON technology into routine surveys.

The visual feedback tools, most importantly the qualitative 3D object and MST track overlays, were paramount for establishing the validity of object detections. Process 1 yielded results without the need for specific tuning, whereas process 2 required user-defined target information and proximity to optimize the double-threshold operator. Although the standard processes performed well in the presence of both large and small fish moving in a predictable manner (KR and MR), they were not suitable when applied to a data set with many closely spaced individuals having unpredictable trajectories (PF). Attempts to enhance detections for the PF data set were successful through processes 3 and 4, but extra effort was required to fit the data.

Acknowledgments

This work was supported by the Louisiana Department of Wildlife and Fisheries (Sport Fish Restoration Fund) and the School of the Coast and Environment at Louisiana State University. Debby Burwen (Alaska Department of Fish and Game) provided data collected for the Sport Fish Sonar Program. We thank David Nieland and David Wells for reviews of earlier drafts of this manuscript.

References

Arrhenius, F., B. J. A. M. Benneheij, L. G. Rudstam, and D. Biosclair. 2000. Can stationary bottom split-beam hydroacoustics be used to measure fish swimming speed in situ? Fisheries Research 45:21–30.

Boswell, K. M., M. W. Miller, and C. A. Wilson. 2007a. A lightweight transducer platform for use in stationary shallow-water horizontal-aspect acoustic surveys. Fisheries Research 85:291–294.

Boswell, K. M., M. P. Wilson, and C. A. Wilson. 2007b. Hydroacoustics as a tool for assessing fish biomass and size distribution associated with discrete habitats in a Louisiana estuary. Estuaries and Coasts 30:607–617.

Burwen, D. L., S. J. Fleischman, and J. D. Miller. 2007. Evaluation of a dual-frequency imaging sonar for detecting and estimating the size of migrating salmon. Alaska Department of Fish and Game, Fishery Data Series 00-43, Anchorage.

Burwen, D. L., P. A. Nealson, S. J. Fleischman, T. J. Mulligan, and J. K. Horne. 2007. The complexity of narrowband echo envelopes as a function of fish side-aspect angle. ICES Journal of Marine Science 64:1066–1073.

Cappo, M., P. Speare, and G. De'ath. 2004. Comparison of baited remote underwater video stations (BRUVS) and prawn (shrimp) trawls for assessments of fish biodiversity in inter-reefal areas of the Great Barrier Reef Marine Park. Journal of Experimental Marine Biology and Ecology 302:123–152.

Gerlotto, F., C. Hernandez, and E. Linares. 1998. Experiences with multibeam sonar in shallow tropical waters. Fisheries Research 35:143–147.

Holmes, J. A., G. M. W. Cronkite, H. J. Enzenhofer, and T. J. Mulligan. 2006. Accuracy and precision of fish count data from a "dual-frequency identification sonar" (DIDSON) imaging system. ICES Journal of Marine Science 63:543–555.

Jech, M. J., and W. L. Michaels. 2006. A multifrequency method to classify and evaluate fisheries acoustic data. Canadian Journal of Fisheries and Aquatic Sciences 63:2225–2235.

McQuinn, I. H., and P. D. Winger. 2003. Tilt angle and target strength: target tracking of Atlantic cod (*Gadus morhua*) during trawling. ICES Journal of Marine Science 60:575–583.

Moursund, R. A., T. J. Carlson, and R. D. Peters. 2003. A fisheries application of a dual-frequency identification sonar acoustic camera. ICES Journal of Marine Science 60:678–683.

Mueller, R. P., R. S. Brown, H. Hop, and L. Moulton. 2006. Video and acoustic camera techniques for studying fish under ice: a review and comparison. Reviews in Fish Biology and Fisheries 16:213–226.

Ricker, W. E. 1975. Computation and interpretation of biological statistics of fish populations. Fisheries Research Board of Canada Bulletin 191.

Simmonds, E. J., and D. N. MacLennan. 2005. Fisheries acoustics: theory and practice, 2nd edition. Blackwell Scientific Publications, Oxford, UK.

Stoner, A. W. 2004. Effects of environmental variables on fish feeding ecology: implications for the performance of baited fishing gear and stock assessment. Journal of Fish Biology 65:1445–1471.

Tiffan, K. F., D. W. Rondorf, and J. J. Skalicky. 2004. Imaging fall Chinook salmon redds in the Columbia River with a dual-frequency identification sonar. North American Journal of Fisheries Management 24:1421–1426.

Willis, T. J., and R. C. Babcock. 2000. A baited underwater video system for the determination of relative density of carnivorous reef fish. Marine and Freshwater Research 51:755–763.