Comparison of subjective and statistical methods of dive classification using data from a time-depth recorder attached to a gray whale (*Eschrichtius robustus*)

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ABSTRACT

This paper presents dive data obtained from the deployment of a suction-cup attached time-depth recorder (TDR) on a gray whale off the west coast of Vancouver Island, Canada. Data are presented in the form of dive profiles. This represents the first time that dive data have been collected from a gray whale. The data were used to compare subjective classification of dive types to statistical methods of classification, and to test the ability of the statistical methods to classify dives. Each dive was analysed using maximum depth, dive duration and bottom time variables for both subjective and statistical methods to make direct comparison of results. Subjective classification suggests that the tagged animal performed five distinct dive types. Two of these dive types, termed Interventilation and Feeding, were assigned a purpose. Two statistical techniques were then used to classify dives: *k*-means cluster analysis and discriminant function analysis. Cluster analysis and subjective classification showed poor agreement due to the statistical technique's inability to account for dive geometry. Discriminant function analysis proved more successful, although this technique also demonstrated some weakness in testing for dive geometry. It was concluded that while statistical analysis of dive data is useful to classify dive types in a general manner, subtle differences, which may be indicative of behavioural differences, still depend on subjective analysis for identification. Detailed analyses of the third, or depth, dimension of the marine mammal environment will be important for the development of effective management strategies, especially as whalewatching grows in popularity.

KEYWORDS: GRAY WHALE; DIVING; NORTH AMERICA; NORTHERN HEMISPHERE; PACIFIC OCEAN; RADIO-TAGGING

INTRODUCTION

Wildlife managers are currently faced with issues beyond the bounds of their historical practice. Non-consumptive wildlife use (e.g. wildlife viewing and photography) is a rapidly growing sector. Wildlife management is becoming more complicated due to both a large 'user' population and increasing economic impact (Duffus and Dearden, 1990; 1993). Detailed understanding of species' life history, ecology and behaviour (e.g. foraging, reproduction and spatial behaviour) will now, more than ever, dictate a programme's success in mitigating human impact on the focal species. Within the spectrum of wildlife watching activities, whale and dolphin watching has grown extremely rapidly (Hoyt, 1995; 2000). Management concerns have now arisen in many locations and for several species (IFAW Tethys and Europe Conservation, 1995; IFAW, 1998). The issue is also being examined by the International Whaling Commission (e.g. IWC, 1997a) and its Scientific Committee (e.g. IWC, 1997b; 1999; 2000).

Records of underwater behaviour are now available through the use of time-depth recorders (TDRs). This paper reports on the use of a TDR attached to a gray whale (*Eschrichtius robustus*). Individual dives ($n = 651$) were analysed using data collected from Clayoquot Sound, on the west coast of Vancouver Island, Canada. Gray whales aggregate and forage in Clayoquot Sound between May and September and a whalewatching industry has developed in the villages of Tofino and Ucluelet based on whales (approximately 100) that move between Barkley, Clayoquot and Nootka Sounds during these months (Duffus, 1996). While information from a single individual does not provide a foundation upon which to generalise behaviour, it does provide the first record of the underwater behaviour of a gray whale. More importantly, these data provide an opportunity to compare and analyse dive classification methods in a dataset for which feeding dives (the main behaviour of gray whales in Clayoquot Sound during the summer) are identifiable due to their foraging habits.

In the past, analyses of dive data collected by TDRs initially focused on maximum depth and duration of dives (e.g. Le Boeuf *et al.*, 1988; 1989; DeLong and Stewart, 1991). Subsequently, researchers expanded their analyses to include shape (depth *versus* time) to classify dive types (e.g. Le Boeuf *et al.*, 1992; 1993; Martin *et al.*, 1993; 1994; Baird, 1995). This type of analysis typically relies on subjective examination of individual dive records to differentiate shape.

Analysis of dive data beyond summary description is still in its infancy. The use of multivariate statistical techniques has been introduced to deal with large datasets and to reduce bias in subjective analysis (Hindell *et al.*, 1991; Schreer and Testa, 1995; 1996; Burns *et al.*, 1997). However, subtle differences in shape, discernible in subjective analysis, may not be recognised statistically (Schreer and Testa, 1996). The desire to derive more than description, however, will continue to stimulate advances in this area.

METHODS

The tag

The tag used was based on the original design of Goodyear (1981; 1989). The attachment mechanism follows the design of Goodyear, modified by Baird (1995). A VHF transmitter (*Telonics* Dart 4, Mesa, AZ) and time-depth recorder (Mk5 TDR, Wildlife Computers, Redmond, WA) were incorporated into the tag body. The depth sensor (precision +/- 1m) on the TDR was set to record once per second for this study. Data collected during deployment was stored and downloaded following recovery of the tag.

The attachment mechanism consisted of a 7.8cm, soft rubber suction cup, fastened to the tag body by flexible plastic tubing. The detachment mechanism was a stainless steel tube running through the stalk of the suction cup opening into the inside of the suction area. A stainless steel spring maintained a stainless steel washer in constant contact with a magnesium cap screwed onto the top of the tube. The detachment mechanism relied on electrolysis to erode the cap, releasing the device. Once free, the tag was located using a VHF receiver and 3-element Yagi antenna.

The TDR tag was attached to a gray whale foraging with a group of 12 animals at Rafael Point, Flores Island, on 6 August 1994. A SCUBA diver reconnaissance and plankton tows, undertaken from a support vessel during the tagging period, revealed that the animal was feeding on planktonic crab larvae (*Pachycheles* spp. and *Petrolisthes* spp.) swarming 0-3m above the ocean bottom at an average depth of 18m. The tag remained attached for 8 hours, 21 minutes, collecting 29,842 depth points, representing 651 dives.

Data were downloaded from the TDR in a hexadecimal format for analysis with DIVE ANALYSIS (Wildlife Computers, Redmond, WA) and a decimal-formatted listing of each single-depth reading for statistical analysis. DIVE ANALYSIS produced individual, two-dimensional dive profiles, displayed in order of occurrence. DIVE ANALYSIS also generated the following user-selected variables for each dive: dive duration, maximum depth, bottom time, descent time, average descent rate, ascent time and average ascent rate.

Classification techniques

Dives were classified subjectively based on shape, dive duration, maximum depth and bottom time variables generated for each dive. Fig. 1 illustrates the decision tree employed in the subjective classification process. Dives were sorted into classes through *k*-means cluster analysis based on *k a priori* user-designated clusters (Everitt, 1980). This method allows direct comparison with the subjective classification.

The first *k*-means clusters were generated using the same variables as the subjective classification (dive duration, maximum depth and bottom time). To compare the results of the two methods, dives classified subjectively were grouped according to the clusters generated statistically.

A second cluster analysis was performed using converted variables. Maximum depths were converted to z-scores to reduce the effect of the large range of the variable relative to the other two variables. Relative bottom time was calculated by dividing bottom time by maximum depth to differentiate between dives to similar depths with varying bottom times (e.g. v-shaped dives *versus* square-shaped dives). The dive duration variable was not altered. Results using the dive duration, maximum depth z-score and relative bottom time variables were then compared with the subjective classification.

Discriminant Function Analysis (DFA) predicts group membership by creating a linear regression function based on the test variables. This function is the least squares predictor of group membership, whereby observations are split into two groups by the discriminant function (Sokal and Rohlf, 1981). In cases where observations belong to more than two groups, multiple discriminant functions are created. The number of functions created is either equal to the number of variables or one less than the number of groups, whichever is lower. The first discriminant function maximises the between-groups to within-groups sum of squares, the second function derived is the second best explainer of variance, and so on (Norusis, 1994). For the data in this study, three discriminant functions were derived, equalling the number of variables.

By converting the subjectively determined dive classes into numerals (e.g. Feeding = 5) and inserting them as a variable (along with dive duration, maximum depth and bottom time) into the analysis, the accuracy of the subjective classifications is tested by comparing the analysis results to the subjective classification (*sensu* Schreer and Testa, 1996). The resulting comparison calculates an error rate of the subjectively determined classifications.

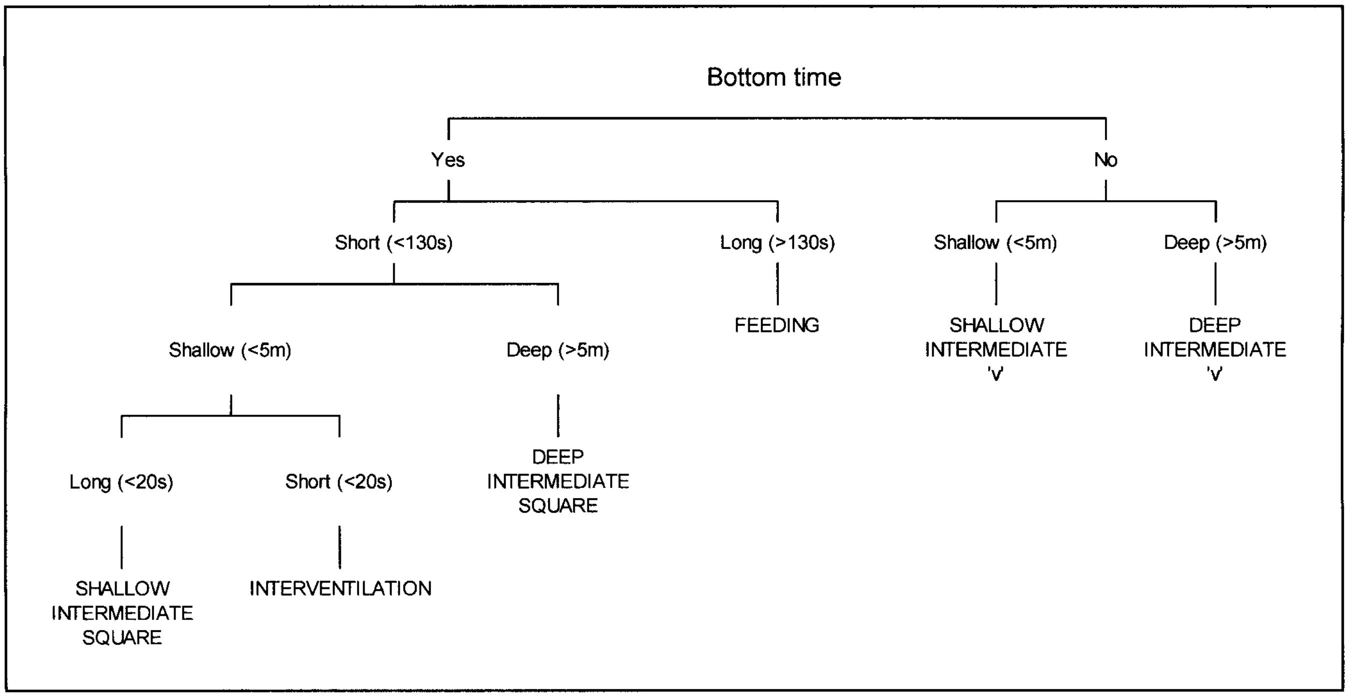

Fig. 1. Decision tree for subjective classification of dive types.

RESULTS

Subjective analysis classes were labelled: (1) Interventilation; (2) Shallow Intermediate Square; (3) Deep Intermediate 'v'; (4) Deep Intermediate Square; and (5) Feeding (Fig. 2). Function was ascribed to the Interventilation and Feeding dive types. Interventilation refers to short, shallow dives performed during oxygen recharge and Feeding refers to long, deep dives to the prey patch. There is no basis presently upon which to ascribe function to the other three dive types.

K-means cluster analysis is based on five groups, replicating the number of groups categorised in the subjective method in order to compare the two classification methods. The summary statistics as well as the location of proportions of members in other categories classified by each technique respectively illustrates the level of agreement in the two techniques (Table 1).

Clustering of geometrically distinct dives within the same groups and the large range of the maximum depth variable was addressed in a second cluster analysis. Two new variables were used for this analysis: maximum depth converted to a z-score and relative bottom time calculated by dividing bottom time by maximum depth. The second cluster analysis classification was again based on five clusters. The new clusters again agree poorly with the subjective classification (Table 2).

DFA was used to test the validity of the subjective classifications by predicting group membership (Table 3). There was better agreement between the discriminant functions and the subjective classifications than with the *k*-means cluster analyses and subjective classification. The only subjective category that DFA determined to be misclassified was the Shallow Intermediate Square dive type, which had only 21.6% agreement. The overall error rate, given by the number of dives identified as misclassified divided by the total number of dives, was 8.6%.

DISCUSSION

In the subjective examination of the data, the TDR provided evidence of five different types of dive. Function was ascribed to two of these. The short, shallow, Interventilation dives were part of the cycle of oxygen recharge that the whales perform between pursuit dives to obtain prey. The Feeding dives appeared readily discernible by their length, depth and shape, and showed the animal pursuing supra-benthic swarms, confirmed by underwater observation. The three intermediate dives, while classified through the subjective process as separate dive types, were too scarce in this dataset to attempt any explanation. Nothing in the dive sequence or geographic location provided clues as to their function.

Dives classified by both subjective and statistical methods explore the application of multivariate statistical techniques to dive data. The small dataset ($n = 651$) allowed inspection of every dive to compare subjective and statistical analysis of gray whale diving data for the first time. By using the same variables for both the subjective and initial *k*-means cluster analysis (maximum depth, dive duration, bottom time) a direct route for comparison between the two methods is possible. The subjective method focuses primarily on geometry as well as the maximum depth, dive duration and bottom time, with the ultimate goal of assigning purpose to each dive. However, assigning purpose, with *a priori* ideas (e.g. feeding, oxygen recharge), may create bias. Statistical analysis applies rigid criteria to data to provide comparison.

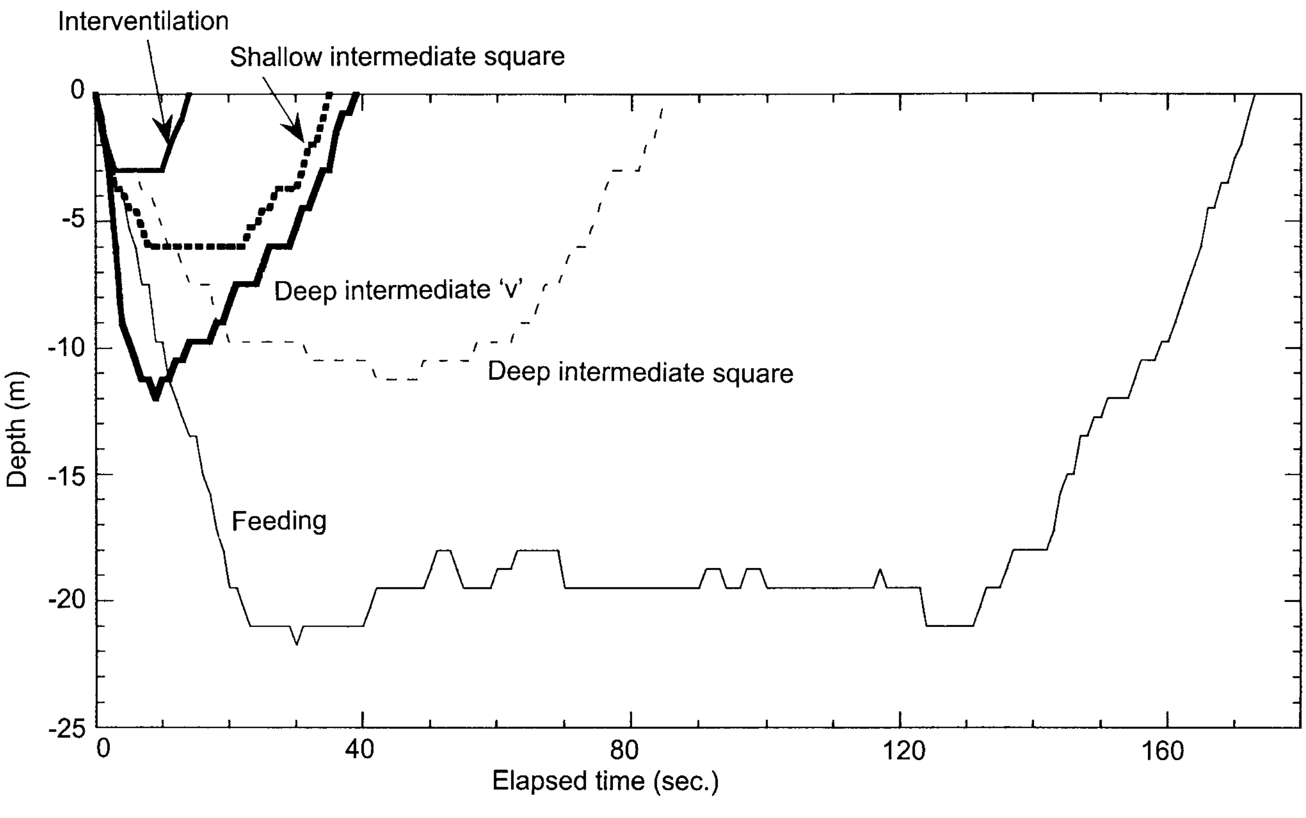

Fig. 2. Subjectively classified dive profile examples.

Table 1
Comparison of cluster analysis to subjective classification.
Key: Depth = Mean Maximum Depth; Dive = Mean Dive Duration; Bottom = Mean Bottom Time. Under 'Cluster analysis' and 'Subjective' I = Interventilation; SIS = Shallow Intermediate Square; DIV = Deep Intermediate 'V'; DIS = Deep Intermediate Square; F = Feeding. Under 'Subjective' Cluster 1 = 1; Cluster 2 = 2; Cluster 3 = 3; Cluster 4 = 4; Cluster 5 = 5.

	Cluster analysis	Subjective
	Cluster 1 (*n*=515)	**I (*n*=466)**
Depth (m)	2.2	2.2
Dive (s)	13.3	12.6
Bottom (s)	7.3	0.12
Classification:	90.5% in I; 9.5% in SIS	100% in 1
	Cluster 2 (*n*=40)	**SIS (*n*=51)**
Depth (m)	6.8	3.5
Dive (s)	56.3	28.2
Bottom (s)	31.4	9.8
Classification:	5.0% in SIS; 32.5% in DIV; 62.5% in DIV	96.1% in 1; 3.9% in 2
	Cluster 3 (*n*=17)	**DIV (*n*=18)**
Depth (m)	12.0	9.0
Dive (s)	110.3	44.4
Bottom (s)	53.3	11.0
Classification:	17.6% in DIV; 47.1% in DIS; 35.3% in F	72.2% in 2; 16.7% in 3; 11.1% in 4
	Cluster 4 (*n*=42)	**DIS (*n*=33)**
Depth (m)	16.8	8.0
Dive (s)	178.8	79.8
Bottom (s)	125.4	46.2
Classification:	4.8% in DIV; 95.2% in F	75.8% in 2; 24.2% in 3
	Cluster 5 (*n*=37)	**F (*n*=83)**
Depth (m)	18.8	17.5
Dive (s)	208.2	190.8
Bottom (s)	150.6	130.4
	100% in F	48.2% in 4; 44.6% in 5; 7.7% in 3

Table 2
Comparison of second cluster analysis using transformed variables to subjective classification. Under 'Cluster analysis' and 'Subjective' I = Interventilation; SIS = Shallow Intermediate Square; DIV = Deep Intermediate 'V'; DIS = Deep Intermediate Square; F = Feeding. Under 'Subjective' Cluster 1 = 1; Cluster 2 = 2; Cluster 3 = 3; Cluster 4 = 4; Cluster 5 = 5.

Cluster analysis	Subjective
Cluster 1 (*n*=504)	**I (*n*=466)**
92.3% in I; 7.7% in SIS	99.7% in 1; 0.03% in 2
Cluster 2 (*n*=54)	**SIS (*n*=51)**
1.9% in I; 22.2% in SIS; 27.8% in DIV; 48.1% in DIS	76.5% in 1; 23.5% in 2
Cluster 3 (*n*=20)	**DIV (*n*=18)**
15% in DIV; 35% in DIS; 50% in F	83.3% in 2; 16.7% in 3
Cluster 4 (*n*=37)	**DIS (*n*=33)**
100% in F	78.8% in 2; 21.2% in 3
Cluster 5 (*n*=36)	**F (*n*=83)**
100% in F	44.6% in 4; 43.4% in 5; 12.0% in 3

Table 3
Predicted group membership determined by discriminant function. Under 'Subjective' I = Interventilation; SIS = Shallow Intermediate Square; DIV = Deep Intermediate 'V'; DIS = Deep Intermediate Square; F = Feeding.

	% DFA predicted group membership (*n*)				
Subjective group	1	2	3	4	5
I (*n*=466)	99.6	0.4	0	0	0
SIS (*n*=51)	78.4	21.6	0	0	0
DIV (*n*=18)	0	0	66.7	22.2	11.1
DIS (*n*=33)	0	0	9.1	87.9	3.0
F (*n*=83)	0	0	1.2	3.6	95.2

While it is possible that dive types may be continuous, and not amenable to separation by artificial boundaries in some circumstances, in this case the advice of Shreer and Testa (1995) was followed, i.e. that cluster analysis is the most efficient multivariate procedure for analysing dive data solely by statistical techniques.

The difficulty in the statistical analysis lies in its insensitivity to shape. The initial cluster analysis (Table 1) has no variable that deals with depth and geometry simultaneously. The Deep Intermediate dives, both 'v' and square, are scattered into three central clusters with depth centres of 6.8m, 12m and 16.8m. The subjective analysis separates the two Deep Intermediate classes not by depth, with 9.0m and 8.0m means, but by bottom time, 10.8s and 46.2s, respectively, which clearly differentiates between the distinct dive shapes.

The division of Feeding dives between three clusters is due to the range of the maximum depth variable for Feeding dives (8.33m), resulting in longer dive time and bottom time centres for the deeper dive clusters. The range may be explained by two aspects of the environment: (1) although the prey was observed by SCUBA divers to be supra-benthic during the tagging session, prey swarms may have been several meters thick in some areas; and (2) the rocky substrate results in variable depths throughout the Rafael Point feeding site. Identifiable geometric characteristics of feeding dives (long, deep dives with long, flat bottom times) and knowledge of environmental conditions, included in subjective analysis, could not be considered in cluster analysis.

Depth may also be the main criterion for clustering 96.1% of Shallow Intermediate Square dives in the same cluster as Interventilation dives. However, the subjective analysis revealed the Shallow Intermediate Square dive to be more than twice the duration of the Interventilation dive.

The second cluster analysis attempts to moderate the large range of the depth variable and address the relationship of bottom time to depth. However, dive geometry shape remains undistinguished. The percentages of Deep Intermediate 'v' and Deep Intermediate Square dives grouped together in Cluster 2 (83.3% and 78.8% respectively) is even higher with the new variables.

The insensitivity to shape in both *k*-means cluster analyses reinforces the importance of subjective analysis. The ability to subjectively analyse and allocate dives to particular groups appears essential for analysis of dive behaviour to assign purpose to dives. This level of understanding is needed for effective management. However, databases containing thousands of dive records may prohibit the possibility of individual subjective analysis. Random selection of < 1,000 dives from a database for subjective analysis may be useful, although the chance of missing a rare, yet potentially important, diving behaviour is a possibility. Although Burns *et al.* (1997) describe a method for transforming dive data that cluster analysis can classify into general groups, their method was not used at this stage of the analysis for three reasons: (1) Burns *et al.* were analysing Weddell seal dive data which had much longer average dive durations ($\bar{x} = 8.83 \pm 1.49$min) compared to the large percentage of short dives ($\bar{x} = 0.67 \pm 1.03$ min for all dives) in our own dataset - their method would not have given us a fine enough scale to work with; (2) Burns *et al.* had to subsequently divide groups by depth, whereas for our data, with an identifiable food source depth, depth had to be a primary factor in classification; and (3) as our primary goal was to compare subjective with statistical classification the same variables were needed for both methods. However, the method described by Burns *et al.* is useful for the analysis of lengthy dives and is not ruled out for use in the future, especially with larger datasets.

The inability to account for shape encountered in this study poses a problem, as shape must be taken into account in assigning purpose. In the case of some skim-feeding baleen whales (or benthic feeding gray whales), in which a long, flat bottom time indicates a feeding behaviour, this problem is not as severe. In other situations, however, this may not be the case.

DFA can be used as a statistical test of the grouping algorithms created by other methods (Schreer and Testa, 1995). In this study, it was used to test the subjective classifications. As in the cluster analysis, DFA determined Interventilation and Shallow Intermediate Square dives to be similar. DFA determined that 78.4% of Shallow Intermediate Square dives belonged in the same group as Interventilation dives (Table 3).

This result leaves a small group of 13 dives (including two from the Interventilation dive class) as the DFA analogue of the Shallow Intermediate Square dive class. Although both cluster analysis and DFA revealed that these two dive types were similar statistically, it remains difficult to conclude whether these two dive types should be considered as one. The mean dive durations of the two dive types, when classed subjectively, were 12.6 and 28.2 seconds, respectively, suggesting a difference. This difference could have an energetic component. With only one animal's dive behaviours recorded and only 51 dives in the Shallow Intermediate Square dive class, there are insufficient data for a more robust interpretation.

With respect to the other subjectively determined dive types, DFA results agree more than cluster analysis. The Feeding dive type was determined by DFA to be 95.2% correct. DFA also appeared more adept at analysing shape. Deep Intermediate 'v' and Deep Intermediate Square dive types were determined by DFA to be classified 66.7% and 87.9% correctly, and still represented the highest variability across different classes.

The overall error rate (number of misclassified dives divided by total number of dives) for the DFA analysis was 8.6%. This percentage may be artificially low due to the high percentage of agreement between the subjective and DFA classifications for the Interventilation dives, which constituted 71.5% of the sample. Schreer and Testa (1996) reported a mean error rate of 48%, calculated from a number of individual DFA analyses using different datasets for their Weddell seal study, a much higher rate than this study. Schreer and Testa, however, employed a much larger dataset and subjectively identified nine dive types, several classes of which are only subtly different. It is also possible that the gray whale tagged in this study performed dives that were drastically different (based on the maximum depth, dive duration and bottom time variables used) and thus easily identified subjectively.

CONCLUSION

This study presents the first application of a TDR tag on a gray whale. While the single application does not provide an appropriate dataset upon which to base generalised behavioural hypotheses, it does provide an opportunity to examine the applicability of statistical methods to classify dives from a continuous dive record.

Continued work with subjective and multivariate analysis techniques for dive data will prove important for the conservation and management of marine mammals, especially in light of the growing whalewatching industry throughout the world. Surface behaviour data has yet to yield much significant change in the presence of vessel traffic. Neither technique on its own is completely satisfactory in dealing with the differences in dive morphology. Exploratory application of multivariate analyses methods, such as those by Schreer and Testa (1995; 1996), Burns *et al.* (1997), and those emerging from this study, reveal the statistical techniques' ability, at least in part, to identify characteristic dive types. However, subjective analysis, examining overall shape of each dive, remains an important element of analysis. The effectiveness of the statistical techniques employed in this study to test for shape, within similar dive depths and durations, was not sufficient; however, a solely subjective analysis may introduce bias. A combination of sub-sampled subjective runs and large scale statistical testing may prove the most effective route for large datasets, coupled with sound biological knowledge of the animal and its behaviours.

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