Adaptive Line Transect Sampling

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SUMMARY. Adaptive line transect sampling offers the potential of improved population density estimation efficiency over conventional line transect sampling when populations are spatially clustered. In adaptive sampling, survey effort is increased when areas of high animal density are located, thereby increasing the number of observations. Its disadvantage is that the survey effort required is not known in advance. We develop an adaptive line transect methodology that, by varying the degree of adaptation, allows total effort to be fixed at the design stage. Relative to conventional line transect surveys, it also provides better survey coverage in the event of disruption in survey effort, e.g., due to poor weather. In analysis, sightings from the adaptive sections are downweighted in proportion to the increase in effort. We evaluate the methodology by simulation and report on surveys of harbor porpoise in the Gulf of Maine, in which the approach was compared with conventional line transect sampling.

KEY WORDS: Adaptive sampling; Harbor porpoise; Line transect sampling; Wildlife abundance estimation.

1. Introduction

Line transect sampling is widely used in wildlife population assessment, e.g., to estimate abundance of marine mammal populations. Many wildlife populations occur in loose spatial clusters or aggregations, and if the number of aggregations is small, the sample size may be inadequate for reliable estimation and precision may be poor. In addition, marine line transect surveys are typically expensive, involving the hire of ships or aircraft as well as the salary and living costs of observers and crew. Generally, the survey platforms are available for a fixed time, but marine surveys are easily disrupted by external factors, such as the weather, and as a result there can be poor or uneven coverage of the survey area. Adaptive line transect sampling has been proposed by Pollard and Buckland (1997) both as a potential mechanism to improve precision of line transect density estimates for clustered populations and also to help improve survey coverage.

Thompson (1992) and Thompson and Seber (1996) have proposed a number of mechanisms for adaptive sampling, where neighboring units are added to the sample whenever the value of the variable of interest satisfies some criterion. Typically, these approaches are design unbiased (Thompson, 1992, p. 17), but the designs are not easily adapted to line transect sampling. In particular, in shipboard surveys, the designs can waste expensive ship time in moving from one transect line to another, detracting from any potential benefits in estimator precision. More problematic for design-unbiased methods, the amount of effort cannot be reliably predicted in advance, so that ship time may expire long before the study area has been fully surveyed if more animals than expected are encountered

or available time is not fully utilized if fewer animals than expected are found.

In adaptive line transect sampling, sampling intensity is increased when the number of observations within a sampling unit exceeds some limit (the trigger function). We advocate an approach in which the increase in sampling intensity is a function of the degree to which the vessel is ahead of or behind schedule. The increase in sampling intensity is measured by the effort factor; if, e.g., effort is doubled when the trigger is activated, the effort factor is two. The effort factor is then used to weight sightings to account for bias. The approach conditions on the effort factors, which are data dependent, and thus the method is not design unbiased. We use simulations to explore the properties of the methodology.

Harbor porpoise (*Phocoena phocoena*) are common in inshore waters through much of the world. They are small cetaceans that generally occur singly or in very small groups. They are vulnerable to entrapment and drowning in fisheries nets and are therefore subject to detailed study in several regions. One such region is the Gulf of Maine, where shipboard line transect surveys are routinely carried out to monitor population levels and trends. Such surveys are expensive, so it is important to use ship time efficiently. A series of experimental surveys was set up to explore the feasibility of adaptive line transect sampling (Palka and Pollard, 1999), and we illustrate the methodology through the analysis of these surveys.

2. Methods

The amount of adaptation is measured by the effort factor. The effort factor is defined to be the ratio of the effort used
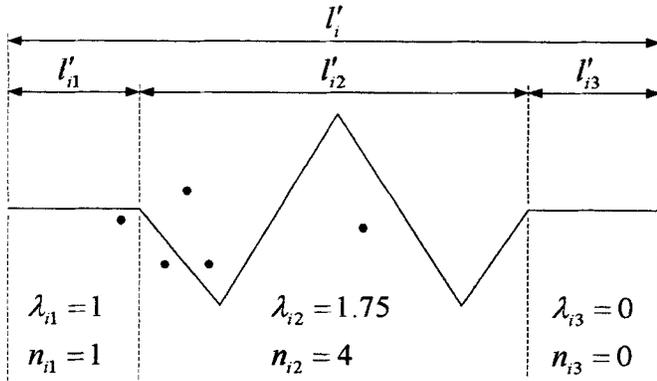
Figure 1. Example notation, with constant effort factor over an adaptive section. The zigzag line signifies the actual effort, while the total nominal effort would be a straight line, l_i' for the section shown.

following an adaptive track relative to the effort that would be used following the corresponding straight-line (nominal) track. Using conventional line transect estimators, systematically increasing the effort in areas of higher animal density would lead to abundance overestimation. The adaptive line transect approach downweights the data from the adaptive sections to compensate for the increased effort. The weighting used is inversely proportional to the effort factor so that each section of transect is weighted in proportion to the length of straight-line (nominal) effort through that section.

Many tracking designs for increasing the effort are possible (e.g. zigzag, hounds tooth, sinusoidal). For this article, we concentrate on the zigzag pattern (Figure 1) because it has a number of advantages. In particular, the trackline does not cross itself, there are no gaps in the trackline so that no search effort is lost in traveling from one transect to the next, and the track is easily followed (important for shipboard surveys). In addition, the increase in effort is directly related to the length and angle of the zigzags and thus can be fixed at any value ≥ 1 by changing either or both of these factors.

2.1 Notation

Each transect is divided into a number of subtransects or legs, where the start and finish of each leg occurs at a change in effort. Throughout this article, group or school size is used to refer to the number of animals in a single detected group, while cluster refers to a spatial cluster of animal groups (where a group may comprise just one animal).

Define the total line length (total effort) as L, the length (and thus effort) of a single transect or transect leg as l, and the effort factor as λ. Let the number of animal groups detected be n and the encounter rate (number of groups detected per unit length of transect) be e, so that $e = n/l$. The group size (number of animals in the group) is given by s, the animal density (animals per unit area) by D, and the value of the probability density function of perpendicular distances from observations to the line evaluated at zero distance by $f(0)$.

Subscript i is used to refer to the transect, $i = 1, \ldots, k$, and subscript j refers to the leg within the transect, $j = 1, \ldots, m_i$. One leg is deemed to end and the next to start whenever

adaptive effort is triggered or whenever normal effort is resumed. Thus, l_{ij} is the actual distance traveled, or effort, for the jth leg of the ith transect. Subscript X refers to the observation within a leg, $X = 1, \ldots, n_{ij}$. Thus, s_{ijX} refers to the Xth observation of the jth leg of the ith transect (see Figure 1).

Nominal values refer to the values expected if a conventional straight-line transect is followed. Nominal effort is signified with a dash, such as L', the total nominal effort, whereas the corresponding actual effort is L. The expected sample size if only the nominal effort had been used is represented by, e.g., $\mathrm{E}(n \mid L')$. The same approach is also used for both the expected encounter rate and expected group size if only the nominal effort had been used, giving, e.g., $\mathrm{E}(e_i \mid l_i')$ and $\mathrm{E}(s_i \mid l_i')$.

2.2 Assumptions

In deriving the estimating equations, the following standard line transect assumptions are made:

(i) Probability of detection on the line, $g(0)$, is one.
(ii) There is no size bias (the probability of detection is independent of the group size).
(iii) There is no responsive movement of animals in advance of detection and any nonresponsive movement is slow relative to the speed of the observers.

These assumptions can be weakened or removed using similar strategies as for conventional line transect sampling. In addition, the following assumptions are made specifically for adaptive line transect sampling:

(iv) The expected encounter rate for an adaptive track is the same as the expected encounter rate for the corresponding nominal track.
(v) The expected group size for an observation on an adaptive track is the same as the expected group size for an observation when following the corresponding nominal track.
(vi) Conditional on the location of the actual (as distinct from the nominal) track line, each observation is an independent event; i.e., the probability of an observation is only a function of its perpendicular distance from the actual line (although the position of the line itself may depend on past observations).

Approaches to dealing with heterogeneity in the detection function estimate, and thus weakening assumption vi, are explored at the end of the Methods section.

2.3 Effort Factor Calculation

The effort factor, λ, is the ratio of the actual effort to the nominal effort. Thus, the effort factor for the jth leg of the ith transect is

$$\lambda_{ij} = \frac{l_{ij}}{l_{ij}'}. \tag{1}$$

Suppose additional effort is triggered so that we need to calculate the effort factor as a function of the remaining effort available. Let $L_E(t)$ (measured in units of time or distance) be the total excess effort remaining at time t. This quantity is calculated as total effort available at the start of the survey less the actual effort used up to time t less the nominal effort required to complete the survey (without any further adaptive

effort). Let ξ be the expected number of times the effort will increase above the nominal level for the remainder of the survey. Then the increase in effort following an observation is given by the excess effort available divided by the expected number of times the effort will increase plus one (for the current increase). So the increase in effort for a leg is given by $l_{ij} - l'_{ij} = L_E(t)/(1 + \xi)$. Thus, from equation (1), we get $\lambda_{ij} = 1 + L_E(t)/\{l'_{ij}(1 + \xi)\}$.

If each effort increase is applied for the same fixed distance along the nominal trackline, then ξ can be calculated from an estimate of the trigger rate (the expected number of times the survey will meet the trigger condition per unit effort). Let l'_Z be the nominal effort over which the effort increase occurs, $L'_R(t)$ be the nominal effort remaining at time t, and γ be an estimate of the trigger rate (γ can be obtained from previous survey data or be a best guess provided by the user). If the trigger condition is a single observation, then γ is just the encounter rate. Then $\xi = \gamma\{L'_R(t) - \xi l'_Z\}$, so $\xi = \gamma L'_R(t)/(1 + \gamma l'_Z)$.

2.4 *Estimating Equations*

Conceptually, we estimate animal density separately for each transect line using formulas from conventional line transect sampling. To avoid bias arising from concentrating more effort in areas of high density, weighted means of encounter rate and group size are found, weighting by the reciprocal of the effort factor. To simplify the methodology, we assume that $f(0)$ is independent of animal density and use a single pooled estimate of $f(0)$.

2.4.1 *Density estimate.* The density for conventional line transect sampling, assuming detection on the line is certain, is given by (Buckland et al., 1993, p. 56) $D = E(n)f(0) E(s)/2L'$. Assuming $f(0)$ is constant across transects, in the absence of adaptive effort, the density corresponding to the ith transect is $D_i = E(n_i)f(0)E(s_i)/(2l'_i)$. Replacing the parameters by their estimators, we have

$$\hat{D}_i = \frac{\hat{E}(n_i \mid l'_i)\hat{f}(0)\hat{E}(s_i \mid l'_i)}{2l'_i}, \tag{2}$$

where $\hat{E}(n_i \mid l'_i)$ and $\hat{E}(s_i \mid l'_i)$ are, respectively, estimates of the sample size and group size if the nominal track line had been followed. For conventional surveys, where the effort factor is one, these estimators are simply n_i and, assuming no size bias, $\bar{s}_i$, respectively, where $\bar{s}_i$ is the mean size of groups detected on the transect. Derivation of the estimators is explained in the sections that follow.

Thus, the overall density estimate is (Buckland et al., 1993, p. 92)

$$\hat{D} = \frac{1}{L'}\sum_{i=1}^{k} l'_i\hat{D}_i. \tag{3}$$

The estimate of $f(0)$ is based on pooled data across all transects; thus, an estimate of the variance of the density estimate, $\hat{V}(\hat{D})$, can be separated into two components, $\hat{V}\{\hat{D}/\hat{f}(0)\}$ and $\hat{V}\{\hat{f}(0)\}$, which we assume are independent. Using the delta method (Seber, 1982, p. 5–7), an estimate of the variance of the density estimate is

$$\hat{V}(\hat{D}) = \hat{D}^2 \left[\frac{\hat{V}(\hat{H})}{\hat{H}^2} + \frac{\hat{V}\{\hat{f}(0)\}}{\{\hat{f}(0)\}^2}\right], \tag{4}$$

where $\hat{H} = \hat{D}/\hat{f}(0)$ and $\hat{V}(\hat{H}) = [1/L'(k-1)]\Sigma_{i=1}^{k}\{l_i(\hat{H}_i - \hat{H})^2\}$, with $\hat{H}_i = \hat{D}_i/\hat{f}(0)$.

2.4.2 *Effort.* By definition, the nominal effort for the jth leg of the ith transect is $l'_{ij} = l_{ij}/\lambda_{ij}$, with the nominal transect effort and nominal total survey effort given by $l'_i = \Sigma_{j=1}^{m_i} l'_{ij}$ and $L' = \Sigma_{i=1}^{k} l'_i$.

2.4.3 *Sample size.* An estimate of the sample size if only the nominal effort had been used for the jth leg of the ith transect is given by $\hat{E}(n_{ij} \mid l'_{ij}) = n_{ij}/\lambda_{ij}$, with the corresponding transect and survey estimates of

$$\hat{E}(n_i \mid l'_i) = \sum_{j=1}^{m_i} \hat{E}(n_{ij} \mid l'_{ij}) \tag{5}$$

and

$$\hat{E}(n \mid L') = \sum_{j=1}^{k} \hat{E}(n_i \mid l'_i). \tag{6}$$

An estimate of the variance of estimated expected sample size if only the nominal effort had been used is given by

$$\hat{V}\{\hat{E}(n \mid L')\} = \frac{L'}{k-1}\sum_{i=1}^{k}\left[l'_i\{\hat{E}(n_i \mid l'_i) - \hat{E}(n \mid L')\}^2\right]. \tag{7}$$

2.4.4 *Encounter rate.* The encounter rate for the jth leg of the ith transect is given by $e_{ij} = n_{ij}/l_{ij}$. So from assumption iv, an estimate of the expected encounter rate if only the nominal effort had been used for the jth leg of the ith transect is given by $\hat{E}(e_{ij} \mid l') = n_{ij}/l_{ij} = \hat{E}(n_{ij} \mid l'_{ij})/l'_{ij}$. Using weighted averages, an estimate of the expected encounter rate if only the nominal effort was used for the ith transect is

$$\hat{E}(e_i \mid l'_i) = \frac{\sum_{j=1}^{m_i}\{l'_{ij}\hat{E}(e_{ij} \mid l'_{ij})\}}{\sum_{j=1}^{m_i} l'_{ij}} = \frac{\sum_{j=1}^{m_i}\{E(n_{ij} \mid l'_{ij})\}}{\sum_{j=1}^{m_i} l'_{ij}}$$

$$= \frac{\hat{E}(n_i \mid l'_i)}{l'_i}, \tag{8}$$

and an estimate of the survey encounter rate if only the nominal effort was used is

$$\hat{E}(e \mid L') = \frac{\sum_{i=1}^{k}\{l'_i\hat{E}(e_i \mid l'_i)\}}{\sum_{i=1}^{k} l'_i} = \frac{\sum_{i=1}^{k}\{\hat{E}(n_i \mid l'_i)\}}{\sum_{i=1}^{k} l'_i}$$

$$= \frac{\hat{E}(n \mid L')}{L'}. \tag{9}$$

Thus, an estimate of the variance of the expected survey encounter rate if only the nominal effort had been used is

$$\hat{V}\{\hat{E}(e \mid L')\} = \hat{V}\left\{\frac{\hat{E}(n \mid L')}{L'}\right\} = \frac{\hat{V}\{\hat{E}(n \mid L')\}}{(L')^2}. \tag{10}$$

2.4.5 *Group size.* In the absence of size bias, an estimate of the expected group size for the jth leg of the ith transect is

given by the observed mean group size for the leg. So from assumption v, an estimate of the expected group size if only the nominal effort had been used is $\hat{E}(s_{ij} \mid l'_{ij}) = \hat{E}(s_{ij}) = \Sigma_{X=1}^{n_{ij}} s_{ij}X / n_{ij}$. Using weighted averages, an estimate of the expected group size for the ith transect if only the nominal effort had been used is given by

$$\hat{E}(s_i \mid l'_i) = \frac{\sum_{j=1}^{m_i} \left\{ \hat{E}(n_{ij} \mid l'_{ij}) \hat{E}(s_{ij} \mid l'_{ij}) \right\}}{\sum_{j=1}^{m_i} \hat{E}(n_{ij} \mid l'_{ij})}$$

$$= \frac{\sum_{j=1}^{m_i} \left\{ \hat{E}(n_{ij} \mid l'_{ij}) \hat{E}(s_{ij} \mid l'_{ij}) \right\}}{\hat{E}(n_i \mid l'_i)}. \qquad (11)$$

Similarly, an estimate of the expected group size if only the nominal effort had been used is

$$\hat{E}(s \mid L') = \frac{\sum_{i=1}^{k} \left\{ \hat{E}(n_i \mid l'_i) \hat{E}(s_i \mid l'_i) \right\}}{\sum_{i=1}^{k} \hat{E}(n_i \mid l'_i)}$$

$$= \frac{\sum_{i=1}^{k} \left\{ \hat{E}(n_i \mid l'_i) \hat{E}(s_i \mid l'_i) \right\}}{\hat{E}(n \mid L')}. \qquad (12)$$

An estimate of the variance of the expected group size if only the nominal effort had been used is

$$\hat{V} \left\{ \hat{E}(s \mid L') \right\} = \frac{1}{\hat{E}(n \mid L')(k-1)}$$

$$\times \sum_{i=1}^{k} \left[\hat{E}(n_i \mid l'_i) \left\{ \hat{E}(s_i \mid l'_i) - \hat{E}(s \mid L') \right\}^2 \right]. \qquad (13)$$

2.4.6 $f(0)$. It is assumed there is no correlation between density and $f(0)$ and so observation data are pooled across all transects to produce a single estimate of $f(0)$ using conventional techniques (cf., Buckland et al., 1993).

2.4.7 *Modeling heterogeneity in $f(0)$.* The above methods do not allow for heterogeneity between groups in the probability of detection due to group size, weather conditions, etc. In practice, adaptive effort is more likely to be triggered in good sighting conditions, and so the probability of detection on the adaptive leg may be enhanced. Because such observations will be overrepresented in the sample, the $f(0)$ estimate (which is the reciprocal of the estimated effective strip half-width) will be negatively biased.

We can seek to model the heterogeneity; however, if we have not measured the relevant covariates or if probability of detection of further animals changes following an observation (because observers become more alert or they continue to watch detected animals), this approach may not be wholly effective. Another approach is to downweight the influence of

observations made during adaptive legs on the likelihood. Adopting the principle that a single observation at distance y from the line when the effort factor is one should have the same contribution to the likelihood as λ observations at distance y when the effort factor is λ, we obtain the modified likelihood $L(\underline{\theta}) = \Pi_{i=1}^{n} \{ f(y_i) \}^{1/\lambda_i}$, where y_i is the perpendicular distance from the line of the ith observation, $i = 1, \dots, n$; λ_i is the effort factor corresponding to the ith observation; and $\underline{\theta}$ represents the parameters of $f(y_i)$.

We now maximize this modified likelihood function with respect to the parameters of $f(\cdot)$. For example, consider the half-normal model with ungrouped data and no truncation. So $\underline{\theta}$ is the scalar σ^2 and $f(y) = e^{-y^2/2\sigma^2}$, $y \geq 0$. Then a weighted estimate of $f(0)$ is given by

$$\hat{f}_w(0) = \sqrt{2/\pi \hat{\sigma}_w^2}, \qquad (14)$$

where

$$\hat{\sigma}_w^2 = \frac{\sum_{i=1}^{n} y_i^2 / \lambda_i}{\sum_{i=1}^{n} 1/\lambda_i} = \frac{\sum_{i=1}^{n} y_i^2 / \lambda_i}{\hat{E}(n \mid L')},$$

and the variance estimate is given by

$$\hat{V} \left\{ \hat{f}_w(0) \right\} = \frac{\left\{ \hat{f}_w(0) \right\}^2}{2\hat{E}(n \mid L')}. \qquad (15)$$

3. Simulation

To investigate the efficiency of the adaptive approach, a computer program was developed to simulate clustered populations and then simulate conventional and adaptive line transect surveys on these populations. For these simulations, it was assumed that animals occurred singly, i.e., group size was always one. Estimation of the detection function was performed using the distance sampling analysis software DISTANCE 2.2 (Laake et al., 1994) using the following models: half-normal key + cosine adjustments, half-normal + hermite polynomial, hazard-rate + cosine, hazard-rate + simple polynomial, and uniform + cosine.

3.1 *Population Models*

Three base types of population were simulated using the computer program: a population exhibiting complete spatial randomness (CSR), a clustered population, and a highly clustered population. Each population had an expected size of 600 and was created within a square area (population frame) of 100×100 units. The clustered and highly clustered populations were simulated using a Poisson cluster process (Diggle, 1983). The number of parent clusters was simulated using a Poisson(40) distribution for the clustered population and a Poisson(15) distribution for the highly clustered population. The number of animals within each parent cluster was then simulated using a Poisson(15) distribution for the clustered population and a Poisson(40) distribution for the highly clustered population. For each parent cluster, the location of the center of the cluster was simulated using a uniform(0, 100) distribution for the vertical coordinate and another uniform(0, 100) for the horizontal coordinate. Finally, the position of each animal within each parent cluster was
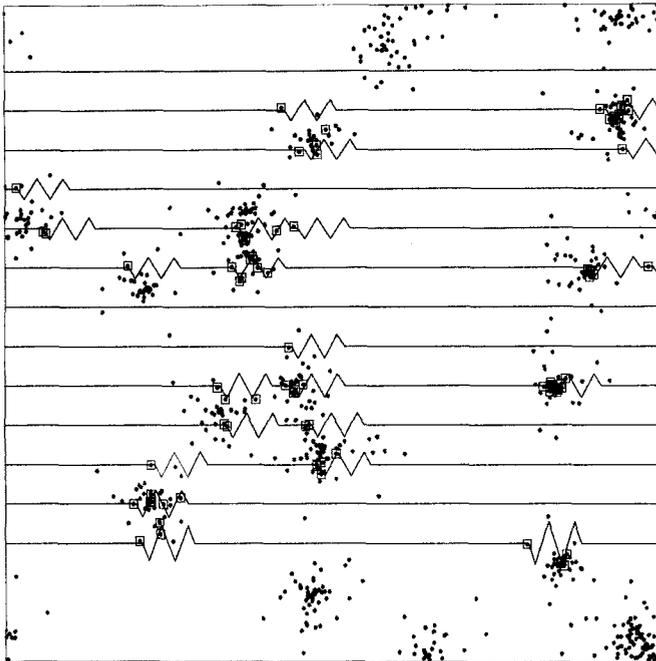
Figure 2. Example simulation of an adaptive line transect survey for a highly clustered population. Animals are represented by dots and each observed animal is bounded by a square. In this case, the population size is 724 and the number of observations is 80.

calculated relative to the parent cluster center. The radial distance to each animal was simulated from a normal(0, 4) distribution and the radial angle using a uniform(0, 2π). If, following this, the animal lay outside the population frame, the distance to the animal was wrapped around to the opposite edge, horizontally or vertically as necessary, until the animal was within the population frame. An example adaptive simulation of a highly clustered population is shown in Figure 2.

3.2 *Survey Simulation*

Each simulated population was sampled first using a conventional line transect survey and then using an adaptive line transect survey. The transects were systematically spaced with a random start for the first transect and a buffer zone was defined in which transects could not be located to reduce edge effects. For each survey, the total effort was set at 1500 units and, for the adaptive surveys, the nominal effort was set at 1300 units. The detection function was simulated using a half-normal detection function with parameter $\sigma = 0.3$, with perpendicular distances truncated at 2 units (effectively no truncation).

The trigger to start adapting was a single observation in the previous 0.66 length of transect, after which zigzagging occurred for 12 steps (3 complete zigzag cycles), spanning approximately 6 units of nominal line, with the angle of the zigzags adjusted appropriately for the effort factor. If there was an observation during the last step of an adaptive section, the adapting continued for another 12 steps. Each transect started in straight-line mode irrespective of whether

Table 1
Efficiencies of adaptive simulation estimates, where efficiency is measured as mean variance of conventional estimator from 1000 *simulations divided by mean variance of corresponding adaptive estimator*

Population	Estimator adaptive efficiency		
	$\hat{V}\{\hat{E}(e \mid L')\}$	$\hat{V}\{\hat{f}(0)\}$	$\hat{V}(\hat{D})$
CSR	0.959	1.032	0.990
Clustered	0.993	1.265	1.050
Highly clustered	1.035	1.349	1.059

the survey was still adapting at the end of the previous transect.

Additional simulations were performed using the highly clustered populations to investigate the effects of heterogeneity in the detection function. First, to simulate an increase in observer awareness, following an observation, the detection function for the adaptive surveys was changed. For the conventional surveys and the straight-line sections of the adaptive surveys, a half-normal detection function with $\sigma = 0.3$ was used as before. However, to simulate an increase in observer awareness, σ was increased to 0.4 on the adaptive (zigzag) sections of the adaptive survey. Second, to simulate heterogeneity introduced by changes in weather, simulation of the highly clustered population was again rerun, this time using a half-normal detection function with $\sigma = 0.15$ for the first 400 units of survey effort, reverting to $\sigma = 0.3$ for the remainder of the survey. This type of heterogeneity was applied to both the adaptive and the conventional surveys because they are equally likely to encounter bad weather. For these simulations, the detection function was estimated, assuming the half-normal model, using equations (14) and (15).

3.3 *Simulation Results*

For each population type, 1000 populations were generated, with both a conventional and an adaptive survey run on each population. Two additional runs of 1000 highly clustered populations were generated to test heterogeneity in the detection function due to increased observer awareness and changes in weather conditions. The comparative efficiencies of estimators were calculated by dividing the mean estimator variance from 1000 conventional survey simulations by the mean estimator variance of the corresponding 1000 adaptive survey simulations. The efficiencies for the expected nominal encounter rate, $f(0)$, and density estimators for the three population types are given in Table 1.

For the clustered populations, adaptive sampling indicated improved density estimate precision, with an efficiency of 1.050 for the clustered and 1.059 for the highly clustered populations. As expected, adaptive sampling was less efficient, at 0.990, than conventional sampling for the CSR population type. This is because all animals are randomly located, so increasing the search effort following an observation does not increase the probability of detecting another animal. Thus, with a CSR population, the expected total number of sightings for an adaptive survey is the same as the expected total for a conventional survey. However, the sightings in the

Table 2

Estimated 95% confidence intervals for mean percent relative bias over all 1000 simulations. For each estimator, the top confidence interval is for the adaptive survey simulations and the lower one is for the conventional survey simulations.

Population	Estimator		
	$\hat{\mathrm{E}}(e \mid L')$	$\hat{f}(0)$	$\hat{D}$
CSR	$[-0.91\%, 0.52\%]$	$[-1.45\%, 0.83\%]$	$[-1.96\%, 0.07\%]$
	$[-0.56\%, 0.86\%]$	$[-1.41\%, 0.16\%]$	$[-1.54\%, 0.56\%]$
Clustered	$[-1.46\%, 0.32\%]$	$[-1.84\%, -0.35\%]$	$[-2.86\%, -0.58\%]$
	$[-1.32\%, 0.38\%]$	$[-1.34\%, 0.25\%]$	$[-2.15\%, 0.15\%]$
Highly clustered	$[-2.00\%, 0.19\%]$	$[-0.67\%, 0.74\%]$	$[-2.16\%, 0.44\%]$
	$[-0.50\%, 1.55\%]$	$[-2.01\%, -0.32\%]$	$[-1.90\%, 0.78\%]$

adaptive survey are then weighted to account for any adaptive bias and so there is a decrease in efficiency.

Ninety-five percent confidence intervals, assuming a normal distribution, for the mean percent relative bias of the encounter rate, $f(0)$, and density estimators are given in Table 2. Overall, there appears to be no or minimal bias. There is a small negative bias in the $f(0)$ estimate for the clustered adaptive and the conventional highly clustered surveys. This is probably because Akaike's Information Criterion (AIC), which was used to select between the contending models, tended (70% of the time) to select the Fourier series model rather than the (true) half-normal model. There was also a small negative bias for the density estimate of the adaptive clustered survey, presumably largely due to the negative bias in the $f(0)$ estimate.

The mean root mean square errors (RMSE) for the encounter rate, $f(0)$, and density estimators are given in Table 3. The adaptive sampling encounter rate estimators do not perform well. However, the improvement in the $f(0)$ estimate outweighs this, leading to an overall improvement in the precision of density estimates.

Table 4 shows the coverage of a log-normal 95% confidence interval for the encounter rate, $f(0)$, and density estimators. Values are presented as the percentage of occasions the true value is below or above the estimated confidence interval. Coverage for the $f(0)$ estimates was poor, with the true value being larger than the upper confidence limit for 13–16% of the time. Much of this can be explained by the tendency for AIC

to select the Fourier series model rather than the half-normal. In general, the confidence interval coverage was very similar for the two approaches.

The simulations of heterogeneity in $f(0)$ were analyzed using the estimating equations (24) and (26) for the detection function. These gave improved adaptive density variance estimator efficiencies of 1.068 for the simulation of increased observer awareness and 1.036 for the simulation of bad weather. However, in the case of the bad weather simulation, there was an improvement in the encounter rate efficiency and a decrease in the $f(0)$ efficiency. This was borne out in the mean RMSEs for the density variance estimators. In the increased observer awareness simulation, the mean adaptive RMSE (0.0115) improved on the mean conventional estimator RMSE (0.0119), while for the bad weather simulation, the mean adaptive RMSE (0.129) was larger than the mean conventional RMSE (0.0120). There was a small negative bias in the adaptive density estimate for the increased observer awareness simulation, while the conventional survey indicated a small positive bias. Ninety-five percent confidence intervals for the mean percent relative bias were $[-3.347, -1.009]$ and $[0.358, 2.786]$, respectively. The corresponding bad weather simulation confidence intervals were $[-8.623, -6.157]$ and $[-6.276, -3.899]$ for the adaptive and conventional surveys; thus, both density estimates demonstrated a negative bias.

Table 3

Mean root mean square errors for 1000 simulations. For each estimator, the top value is the mean for the adaptive simulations and the bottom value is the mean for the conventional simulations.

Population	Mean RMSE		
	$\hat{\mathrm{E}}(e \mid L')$	$\hat{f}(0)$	$\hat{D}$
CSR	0.00520	0.330	0.0098
	0.00519	0.336	0.0101
Clustered	0.00648	0.321	0.0111
	0.00618	0.341	0.0112
Highly clustered	0.00804	0.304	0.0127
	0.00752	0.362	0.0131

Table 4

Percentage of occasions the true value is below, above a 95% confidence interval for the estimator for 1000 simulations. For each estimator, the top values are for the adaptive simulations and the bottom values for the conventional simulations.

Population	Estimator		
	$\hat{\mathrm{E}}(e \mid L')$	$\hat{f}(0)$	$\hat{D}$
CSR	3.0%, 3.2%	2.9%, 13.2%	2.8%, 5.7%
	3.0%, 2.7%	4.1%, 13.2%	3.4%, 4.9%
Clustered	1.2%, 1.7%	5.3%, 16.2%	1.1%, 3.5%
	0.4%, 1.2%	3.8%, 12.9%	0.8%, 2.3%
Highly clustered	0.4%, 1.1%	6.3%, 13.1%	0.6%, 2.1%
	0.3%, 0.6%	5.0%, 14.0%	0.4%, 2.5%

4. Harbor Porpoise Example

4.1 Overview

To assess the viability of adaptive line transect sampling, a series of experimental surveys of harbor porpoise was performed in August 1996 by the Northeast Fisheries Science Center (NEFSC), Woods Hole, Massachusetts, U.S.A. Comparative conventional and adaptive surveys were made using the methods of this article. To simplify the approach for this first trial, the effort factor was fixed and both survey types followed the same nominal transects. This meant that the adaptive surveys used a greater total effort than the effort used for the conventional surveys. The surveying was conducted in areas of expected high porpoise densities to provide a better comparison between the two sampling strategies.

To identify a suitable fixed effort factor, a series of simulations was run. Population parameters were adjusted, by eye, to match expected abundance estimates and sighting patterns using data from previous surveys of the area (Smith, Palka, and Bisack, 1993; Palka, 1995, 1996). Experimentation with different adaptive patterns and effort factors identified a single zigzag with a fixed effort factor of two to be the most efficient of the adaptive mechanisms assessed.

4.2 Survey Procedures

A team of five observers collected sighting data, with three observers working at a time, one observer concentrating to the left, one ahead, and one to the right. Observers were trained to pay particular attention to the area on the outside of each turn, where there is a greater area to cover than on the inside. This is highlighted by the shaded triangles in Figure 3, in which the survey strip is conceptually shown as a series of parallelograms; ideally, the survey design should keep these triangles small relative to the survey strip to reduce the turning effect.

Observation was with the naked eye, while binoculars were used to confirm school (group) size and species if necessary. Because harbor porpoise are small and difficult to see, surveys were generally conducted only in Beaufort sea state 3 or less, although some of the adaptive surveys included effort above Beaufort 3. For the adaptive surveys, the trigger to increase the effort (zigzag) was based on the number of animals seen within the previous 15 minutes. The trigger value was held constant within a single survey but was set at two animals for some surveys and four for others.

4.3 Harbor Porpoise Survey Results

Surveying was carried out between August 6 and August 28, 1996, in the Gulf of Maine/Bay of Fundy region. During this time, a total of seven comparative conventional/adaptive survey pairs were conducted across four locations in the area.

The data from the seven comparative surveys were pooled to create one conventional survey and one adaptive survey. Because harbor porpoise can be difficult to sight in even low Beaufort, the data were divided into two strata for analysis, Beaufort 0–1 and Beaufort 2–3. To aid the comparison of the methods, all survey legs and associated sightings carried out above Beaufort 3 were dropped. This led to the adaptive survey having a smaller nominal effort than the conventional survey, although both surveys had originally used the same nominal transects. For the conventional survey, 29% of the
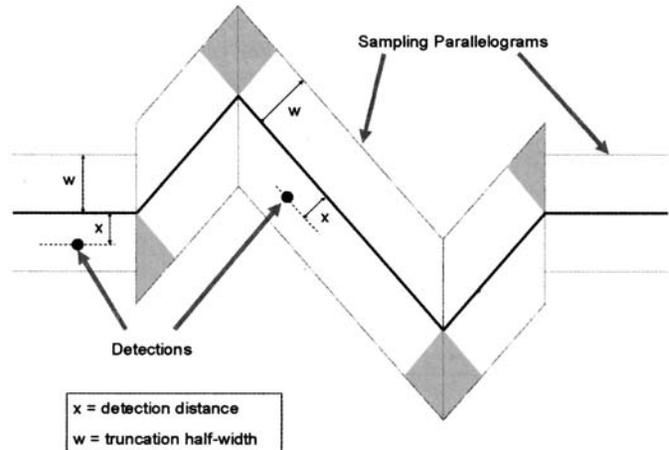

Figure 3. Conceptually, the survey strip can be considered as a series of parallelograms. Ideally, the shaded triangles will be small relative to the size of the strip and observers should be made aware of the need to pay particular attention to the areas on the outside of each turn.

effort was at Beaufort 0 or 1 and 71% at Beaufort 2 or 3, while for the adaptive survey, the figures were 42 and 58%, respectively. Total effort for the conventional survey was 233.9 nautical miles (Nm) with 313 sightings before truncation, and total effort for the adaptive survey was 281.7 nautical miles (nominal effort 183.1 nautical miles) with 551 sightings before truncation. Sightings were truncated at 700 m, giving 303 conventional sightings and 523 adaptive sightings (312.2 nominal sightings). There was evidence of school size bias, and so for the school size estimates only (equations (12) and (13)), the truncation distance was reduced to 400 m, giving 252 conventional and 409 adaptive sightings.

The sightings were analyzed with DISTANCE 2.2 (Laake et al., 1994) to produce adaptive and conventional survey $f(0)$ estimates. Model selection was with AIC from the Fourier, half-normal with Hermite adjustments, and hazard-rate models, with the hazard rate selected in each case. The encounter rate, school size, school density, and harbor porpoise densities for the conventional and adaptive strata were then estimated using equations (2)–(13). Finally, parameters were estimated by averaging the stratum estimates weighted by the proportion of effort in each stratum. The variance and CV of all parameters were estimated by bootstrapping 500 times, resampling transects, with the restriction that the total effort should be within 5% of the base sample. Normally, it would not be valid to bootstrap transects using this adaptive approach; however, as the effort factor was fixed for the survey, it was appropriate in this case.

For the adaptive surveys, the total effort was approximately 1.2 times greater than the total effort for the conventional survey. To account for this, the conventional density estimate CVs were adjusted using the approximation (Buckland et al., 1993, p. 304) $L_e = L_c \{CV(\hat{D}_c)\}^2 / \{CV(\hat{D}_e)\}^2$, where L_c and D_c are the effort and density estimate for the conventional survey and L_e and D_e relate to a conventional survey with the total effort extended. Thus, the equation becomes $CV(\hat{D}_e) = (L_C/L_e)^{1/2} CV(\hat{D}_c)$.

Table 5

Summary of analysis estimates for harbor porpoise surveys. CVs are shown in brackets. The adaptive improvement is measured as the conventional estimate CV divided by the associated adaptive estimate CV.

Survey	$\hat{E}(e \mid L')$ (Schools per Nm)	$\hat{E}(s \mid L')$	$\hat{f}(0)$ $(m^{-1} \times 10^{-3})$	$\hat{D}$ (Porpoises per Nm²)	$\hat{D}s$ (Schools per Nm²)
Conventional	1.30	2.21	4.45	11.24	5.05
	(12.2)	(8.9)	(14.9)	(21.5)	(19.7)
Adaptive	1.71	2.43	2.83	11.07	4.71
	(10.2)	(9.1)	(14.1)	(19.8)	(17.4)
Adaptive improvement	1.20	0.97	1.06	1.08	1.14

A summary of the estimates for the pooled surveys is provided in Table 5. Two density estimates are provided, one corresponding to individual porpoises $(\hat{D})$ and one to porpoise schools $(\hat{D}s)$. For the simulation exercise, efficiency was measured by the ratio of the conventional and adaptive variances; however, this assumes the means are equal, which may not be true because this was a field experiment. Thus, the results were compared by dividing the coefficient of variation (CV) of the conventional estimate by the CV of the adaptive estimate.

A randomization version of Levene's test (Manly, 1997) was used to test if the adaptive and conventional variances were equal, and a randomization version of a one-way ANOVA was then used to test if the means varied between the two survey types. In both cases, the computer package RT (Manly, 1996) was employed to perform the tests. All parameters except the encounter rate had a significant difference in the variances, and all parameters except the school densities showed a significant difference in the point estimates.

5. Discussion

Overall, the simulation results indicate that conditioning on the effort factors only introduces small bias and that adaptive sampling offers potential for improving density estimator precision for clustered populations. They also indicate a correlation between the degree of clustering and the adaptive efficiency. Adaptive line transect sampling will offer no benefit for a population that is not spatially clustered and will in fact be detrimental to efficiency. However, most natural populations will display some clustering, and for populations with high clustering, a benefit is certainly apparent. An indication of clustering is provided by the relative variance (cf., Cressie, 1993, p. 590), with the three simulated population types having mean values of 1 for the CSR, 12 for the clustered, and 31 for the highly clustered.

The efficiency is also dependent on appropriately selecting the trigger and stopping function, effort factor calculation, adaptive pattern, and amount of excess effort available. Thus, further work is necessary to estimate the degree of clustering for which adaptive sampling is beneficial and how to tune the adaptive settings to maximize efficiency. Ideally, simulation will be used to identify suitable parameters prior to any survey. However, as a rule of thumb, the zigzag pattern with two or three complete cycles performs well and a suitable trigger value could be obtained either from a short pilot survey or by examining previous survey data.

The simulations were sensitive to changes in the adaptive pattern. In particular, if the adaptive track was too large so

that it frequently stepped outside an animal cluster, this introduced (small) bias into the encounter rate estimate. This is due to violation of assumption iv, that the expected encounter rate for the adaptive track is the same as the expected encounter rate of the corresponding nominal track. In reality, extra effort is more likely to be triggered when passing near the center of a cluster, so that adaptive legs may tend to have a slightly lower expected encounter rate than the corresponding nominal legs. It should also be noted that the higher the effort factor the more acute the turn on the zigzags, which may introduce both navigation issues and heterogeneity through problems such as double counting.

The ad hoc approach to handling heterogeneity in $f(0)$ performed reasonably well. For the bad weather simulation, the mean adaptive density estimator RMSE was larger than the mean conventional RMSE, although this can partly be explained by the reduced increase in adaptive observations compared with the other surveys. Poor sighting conditions were simulated for 400 units, meaning that the adaptive survey seldom triggered during this time. Thus, the majority of the adaptive triggering occurred during the remaining 900 units of nominal effort, causing larger adaptive zigzags, which for much of the time would then step outside clusters.

Ideally, the simulations would have estimated group size instead of modeling observations as single animals. However, the survey experienced group size bias and so, to provide a useful comparison, the simulations would have also needed to model the bias.

Investigation is also necessary into how to handle a survey involving multiple species. Users could select to trigger on one species only, but then the weights will result in inefficient estimation of density of other species unless their areas of high density correspond to those for the trigger species. If the primary species and the secondary species are not spatially correlated by habitat, feeding, or other factors, it may be acceptable to treat the secondary species' sightings as conventional sightings and analyze appropriately. The effort factor calculation does not adjust for changes in expected encounter rate as the survey progresses, so if there was a density gradient in the survey area, there is the potential for the adaptive algorithm to be inefficient. This may adversely affect precision, but bias should be unaffected. To minimize this effect, nominal tracklines should run roughly perpendicular to known density contours. If the gradient was extreme and there were few tracklines such that there was an excess of additional effort remaining at the end of the survey, there is the potential for the adaptive track to step outside clusters and so induce a small amount of bias.

Because the effort factor is a function of whether the survey is ahead of or behind schedule, the method can accommodate some loss of effort due to poor conditions. Effort simply resumes when conditions improve, and the effort factor in adaptive legs is reduced accordingly. One, so far unexplored, area of adaptive line transect sampling is the use of effort factors less than one. Survey coverage may be incomplete in some regions, and it may be possible to treat these incomplete areas as sections with an effort factor less than one so that the missing data do not bias abundance estimation.

Applying the methods to porpoise surveys was relatively straightforward, although for this survey, it was simplified by the use of a fixed effort factor. The encounter rate was also considerably improved, which may be partly due to a higher proportion of the conventional survey, relative to the adaptive survey, being carried out in Beaufort 2 or 3, when sighting would be more difficult.

In summary, the methods proved both practical and beneficial to apply to the harbor porpoise survey, with an 8% improvement in the porpoise density estimate CV over the conventional survey. The survey was fortunate because there was sufficient information available to allow appropriate adaptive parameters to be identified prior to commencing. The experiment did not, however, exploit the method's potential to enable a survey to complete to a fixed time and cost. It is expected that this may well prove the most significant benefit, as it allows additional effort assigned to a survey to, e.g., account for bad weather, to be efficiently allocated throughout the survey.

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RÉSUMÉ

L'échantillonnage adaptatif par transect offre par rapport à l'échantillonnage classique par transect, la possibilité d'améliorer l'efficacité de l'estimation des densités de populations, dès lors que ces dernières sont réparties en tâches. Dans ce type d'échantillonnage, l'effort de collecte est amplifié pour les zones de fortes densités en augmentant le nombre d'observations. Son inconvénient vient du fait que l'effort de collecte n'est alors plus connu à l'avance. Nous développons pour ce type échantillonnage, une méthodologie qui en variant le degré d'adaptation, permet de fixer l'effort total de collecte au niveau du plan d'échantillonnage. Par rapport à l'échantillonnage classique par transect, la méthodologie proposée fournit une meilleure prise en compte des aléas rencontrés lors de la campagne d'échantillonnage comme, par exemple, une mauvaise météo. Dans l'analyse, les observations issues des sections adaptatives sont contre-balancées par l'augmentation de l'effort. Nous évaluons la méthodologie par simulation et sur des données issues d'inventaires de marsouins du Golfe du Maine, en comparant l'approche proposée à l'approche conventionnelle.

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