A Test for Independence of Movements as Shown by Live Trapping

Abstract: Although statistical models of home range assume that successive observations are independent, no method is currently available for testing the independence assumption when data are collected by live trapping. Using a measure of bivariate autocorrelation proposed by Schoener (1981), we develop a technique for testing the null hypothesis of independence with movements shown by live trapping. A hypothetical example is provided to illustrate the use of the test. In contrast to data collected using radiotelemetry or direct observation, trap captures generally are separated by appreciable time intervals; thus spatial patterning of movements is the most likely cause of autocorrelation in trapping studies. If a lack of independence is demonstrated by the test, we suggest that nonstatistical home range measures be used rather than statistical ones.

Introduction

Many home range models permit estimates of home range size as probability contours (e.g., Hayne, 1949; Jennrich and Turner, 1969; Koeppel et al., 1975, 1977; Van Winkle, 1975; Anderson, 1982; Don and Rennolls, 1983). These contours are derived either by assuming (Jennrich and Turner, 1969; Koeppel et al., 1975, 1977) or estimating (Anderson, 1982) the distribution of use of space by an organism. A common feature of all such statistical estimates is that they rely on the assumption that locational observations are independent. Independence occurs when the i_th record of an animal’s position in no way influences its location during subsequent observations. Dependence, then, can be caused by spatial patterning of home range use or by collecting observations using too short a sampling interval (Swihart and Slade, 1985a).

Schoener (1981) recently developed a bivariate measure of autocorrelation for use in detecting departures from the independence assumption. The measure, r^2/σ^2, is the ratio of the mean squared distance between successive observations (r^2) and the mean squared distance from the center of activity (σ^2). Swihart and Slade (1985a) derived the sampling distribution of r^2/σ^2 for continuous distributions, thereby permitting significance tests of the null hypothesis of independence between successive observations when data were collected using techniques such as radiotelemetry or direct observation. Mark-recapture studies of animal movements differ qualitatively from telemetric and observational studies because they yield discrete rather than continuous distributions. That is, although an animal may move freely throughout its home range, movement data collected via live trapping provide the investigator with only a discrete number of locations (trap sites) at which the animal was observed.

Because radiotelemetry and direct observation are expensive or difficult to use for many small, secretive species of vertebrates, live trapping remains an important method for obtaining movement data (Metzgar, 1979; Mares et al., 1980; Slade and Swihart, 1983; Lacki et al., 1984). In this paper we develop a test of the null hypothesis of independence for data collected via live trapping.

Methods

Monte Carlo simulation techniques were used to derive critical values for r^2/σ^2. Samples of independent random variables (X, Y) representing the Cartesian coordinates of the traps in an animal's home range were drawn from multinomial distributions with parameters n_x, Θ_1, Θ_2, ..., Θ_n, (for X) and n_y, Ω_1, Ω_2, ..., Ω_n, (for Y), where n_x and n_y are the number of rows and columns of traps in the home range and Θ_i and Ω_i represent probabilities of capture in row i and column j, respectively. Thus, the probability of capture at trapping station (i, j) is the product of Θ_i and Ω_j. For each simulation we computed the number of traps in the animal’s home range (k = n_x × n_y) and the eccentricity (ε) of the trap-revealed home range. Eccentricity is a measure of the length of a home range relative to its width; as ε increases, home ranges become more elongate. We used the parametric values of the variances of X and Y when calculating ε; i.e., ε = (σ_x^2/σ_y^2), where σ_x^2 > σ_y^2. When parametric values are unknown (i.e., under field conditions), eccentricity can be estimated as ε = (λ_1/λ_2)^½, where λ_1, and λ_2 represent eigenvalues of the variance-covariance matrix of X and Y and λ_1 > λ_2.

Next, Schoener’s ratio was calculated 1000 times, thereby empirically constructing the r^2/σ^2 distribution (i.e., the sample probability density function) corresponding to a given combination of k and ε. Select percentiles (median and upper and lower first, fifth, 10th and 25th) of the distribution were saved, and the process was repeated 10 times to permit means and standard errors of the percentile values to be estimated. The standard deviation (σ), skewness and
kurtosis of the \( \ell^2/r^2 \) distribution were also computed. This procedure was repeated for 16 different multinomial distributions, and a unique \( \ell^2/r^2 \) distribution was generated for each. Distributions of \( \ell^2/r^2 \) were derived for \( k \) ranging from 4-20 and \( r \) ranging from 1.0-5.7. For each combination of \( k \) and \( r \), a separate simulation was conducted for \( n \), the number of captures, where \( n = 4, 5, ..., 16, 24, 32, 40, 100. \)

**Results and Discussion**

Testing for independence.—Approximate confidence intervals (±2 se) were calculated for percentile values from simulated \( \ell^2/r^2 \) distributions and compared with values expected from a normal distribution (see Swihart and Slade, 1985a). These comparisons and inspection of coefficients of skewness and kurtosis indicated that Schoener’s ratio did not differ significantly from a normal distribution with a mean of two. This was true for all combinations of \( r \) and \( k \) when \( n \) was greater than 11; moreover, a normal approximation was achieved in 18 of 97 simulations conducted at sample sizes of \( \leq 10 \). No pattern was evident between the underlying distributions and subsequent normality of \( \ell^2/r^2 \) at these small sample sizes.

Because \( \ell^2/r^2 \) was distributed normally with mean two and variance \( s^2 \), the ability to predict \( s \) permits calculation of critical values of \( \ell^2/r^2 \) using a standard normal table (cf., Sokal and Rohlf, 1981). Following Swihart and Slade (1985a), we used multiple regression to obtain an equation for predicting \( s \). Only simulations resulting in normally distributed values of \( \ell^2/r^2 \) were used in the analysis. An excellent fit (\( R^2 = 0.999, P < 0.001 \)) was provided by the regression equation:

\[
\ln s = -0.122 - 0.364(\ln n) - 0.0154(\ln n)^2 + 0.189(r) - 0.0190(r^2),
\]

and no discernible pattern appeared in the standardized residuals. Addition of \( k \) provided no measurable improvement in the fit of the model as judged by its influence on \( R^2 \), the residuals and the residual mean square. Although \( n \) in the regression equation ranged from 5-100 captures, use of the equation probably should be restricted to data sets with a minimum of 15-20 captures for two reasons. First, statistical estimates of home range are unreliable when used in conjunction with small sample sizes (Koeppel et al., 1975). Second, the correspondence between the parametric value of \( r \) used in the simulations and \( r \) may become weaker at smaller sample sizes because of increases in the variance of \( r \) at smaller \( n \) (Swihart and Slade, 1986). For reasonable \( n \), though, we doubt that the power of the test is affected by using \( r \) (see Swihart and Slade, 1986).

A one-tailed test of independence is appropriate in most instances because the alternative hypothesis of interest is that of positive autocorrelation between successive observations rather than negative autocorrelation (overdispersion). Although some types of movements may produce negative autocorrelation (e.g., territorial defense in *Vieugna vieugna*, G. E. Svendsen, pers. comm.), we believe positive autocorrelation to be a more common problem. Thus, the alternative hypothesis is that observations are positively correlated (i.e., \( H_a: \ell^2/r^2 < 2 \)). In general, critical values of a normally distributed random variable with mean \( \mu \) and variance \( \sigma^2 \) can be calculated as \( \mu - \sigma \), where \( \sigma \) is determined by the \( \alpha \) level of the test (Sokal and Rohlf, 1981). In our case, \( \mu = 2 \) and \( \sigma \) can be estimated using the above regression equation. The test, then, is to reject \( H_a \) when \( \ell^2/r^2 \) calculated from the data is less than the critical value of \( \ell^2/r^2 \). This scheme can be modified easily to accommodate a two-tailed test or alternative hypotheses dealing with negative autocorrelation.

An example.—To illustrate the use of the test, we present 25 sequential capture locations \((X, Y)\) for each of two patterns of movement on a grid with adjacent traps spaced equal distances from one another. Pattern \( A \) shows counterclockwise movement about a home range, and observations are relatively invariant: \((3,3), (2,3), (2,2), (1,2), (1,2), (1,1), (2,1), (3,1), (3,2), (3,2), (4,2), (4,3), (4,3), (3,3), (2,2), (2,1), (2,2), (3,1), (4,2), (4,3), (3,2), (3,2), (2,3), (2,2)). In contrast, pattern \( B \) is erratic and unpredictable, and the distance between successive captures is large relative to pattern \( A \): \((2,2), (1,2), (4,1), (1,1), (5,2), (2,2), (6,1), (7,2), (7,1), (3,2), (3,2), (1,1), (4,1), (1,2), (6,1), (5,2), (6,2), (2,1), (6,1), (7,2), (2,1), (4,1), (7,2), (5,2), (4,1)).

To calculate Schoener’s ratio, we used the expressions:

\[
\ell^2 = \frac{1}{m} \sum_{i=1}^{m} (X_{i+1} - X_i)^2 + \frac{1}{m} \sum_{i=1}^{m} (Y_{i+1} - Y_i)^2
\]
and

\[ r^2 = \frac{1}{m} \sum_{i=1}^{n} (X_i - \bar{X})^2 + \frac{1}{m} \sum_{i=1}^{n} (Y_i - \bar{Y})^2 \]

where \( m = n - 1 \) (cf., Swihart and Slade, 1985a). Using the locational data for pattern \( A \), \( \ell^2/r^2 \) was calculated as 0.69. To calculate \( s \), we used \( n = 25 \) and \( \hat{r} = 1.53 \) in the regression equation, obtaining an \( s \) of 0.299. At an \( \alpha \) level of 0.25, \( \epsilon = 0.675 \) and the critical value of \( \ell^2/r^2 \) was \( 2 - (0.299 \times 0.675) = 1.80 \). We chose \( \alpha = 0.25 \) because power analysis indicated that this value resulted in the most satisfactory combination of Type I and Type II errors for the continuous analog of the test presented here (Swihart and Slade, 1986). Because 0.69 < 1.80 we concluded that successive observations in \( A \) were not independent.

In an analogous fashion, we calculated \( \ell^2/r^2 \) for \( B \) as 1.88. Using \( n = 25 \) and \( \hat{r} = 4.19 \), \( s \) was calculated from the regression equation as 0.370. The critical value was \( 2 - (0.370 \times 0.675) = 1.75 \), which is less than the observed \( \ell^2/r^2 \). Thus, successive observations for animal \( B \) were not significantly positively autocorrelated.

Movement patterns \( A \) and \( B \) differed in both mean squared distance from the center of activity (\( r^2 = 1.4 \) and 4.8 for \( A \) and \( B \), respectively), and mean squared distance between successive captures (\( \ell^2 = 1.0 \) and 9.0, respectively). The disproportionately large difference in \( \ell^2 \) accounted for the increase in the \( \ell^2/r^2 \) ratio. Patterns such as \( A \) are typical of autocorrelated observations (Swihart and Slade, 1985b); for a given home range size, as distance between successive captures (and hence \( \ell^2 \)) decreases, the level of autocorrelation increases.

Sources and treatment of autocorrelated data. — The differences in degree of autocorrelation for \( A \) vs \( B \) could be caused by differences in both the time interval between successive captures and the spatial patterning of captures. With radiotelemetry and direct observation, an individual’s location can be recorded every few minutes; under these conditions, autocorrelation is temporally induced. For many small rodents (30-200 g), 4 hr is long enough to enable individuals to traverse their home ranges (Swihart, 1985). Because the time interval between successive captures is substantially longer than 4 hr in most trapping studies, spatial patterning of home range use (such as that exhibited in \( A \)) is probably the most common reason for lack of independence of movements disclosed by live trapping in small animals.

If a fixed time interval separates successive observations in an autocorrelated data set, the dependency can be removed by using observations separated by several intervals, thus permitting the use of statistical home range estimates (Swihart and Slade, 1985a). Unfortunately, movements depicted by trapping records rarely, if ever, meet this criterion. Swihart and Slade (1985b) showed that autocorrelated data resulted in serious underestimation of home range size when statistical models of home range were used. Although nonstatistical measures of home range also yielded underestimates when used in conjunction with autocorrelated data, this bias was partly offset by the fact that the accuracy of these estimates increased as sample size increased (Swihart and Slade, 1985b). We suggest that statistical models of home range not be used with autocorrelated trapping data. Numerous nonstatistical estimates exist (e.g., minimum convex polygon, Jennrich and Turner, 1969; boundary strip measures, Stickel, 1954), and robust estimators of these measures may enhance their utility by reducing their sensitivity to outlying observations (cf., Schoener, 1981; Koeppl and Hofmann, 1985; Koeppl et al., 1985). The lack of underlying statistical models precludes simple inferential comparison of individual home ranges, but mean values of home ranges can be compared for categories of organisms (e.g., males vs. females or adults vs. subadults). In addition, measures of the variation of individual home ranges could be estimated using jackknifing (Efron and Gong, 1983).

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