Network-Based Kernel Density Estimation for Home Range Analysis

J.A. Downs, M.W. Horner

Department of Geography, The Florida State University, 323 Bellamy Building, Tallahassee, FL 32306 USA
Telephone: 1+ 740 603 3729
Fax: 1+ 850 644 5913
Email: jad05m@fsu.edu, mhorner@fsu.edu

1. Introduction

Home range estimation is the most common form of spatial analysis used by ecologists. The home range refers to the area occupied by an animal during its normal activities of food gathering, mating, and caring for young (Burt 1973). Home range estimation involves quantifying an individual animal's utilization distribution (UD), the relative frequency distribution of its location over time. Kernel density estimation (KDE), which produces a smoothed, continuous intensity surface of an animal's UD based on sample point locations (Silverman 1986, Worton 1989) is the home range estimator most widely accepted and applied by ecologists (Kernohan, Gitzen and Millspaugh 2001). KDE is the preferred home range estimator, because it: (1) it does not assume sample points lie on the home range boundary, as in most hull-based methods, (2) it generates isopleths of relative intensity, which allows core areas to be delineated, and (3) confidence intervals can be generated for the estimates (Kern et al. 2003).

However, use of KDE for home range estimation has recently been criticized, because it overestimates home ranges for animals with UDs that are linear (Blundell, Maier and Debevec 2001) or that contain large amounts of empty space within their interior (Hemson et al. 2005). KDE also has been shown to produce inaccurate home range estimates for fish species (Topping, Lowe and Caselle 2005) and herptofauna (Row and Blouin-Demers 2006). The reason most often cited for the poor performance of KDE in these studies is the use of least-squares cross validation to select the bandwidth, or smoothing parameter. Recent research has explored alternative methods of bandwidth selection (Gitzen, Millspaugh, and Kernohan 2006).

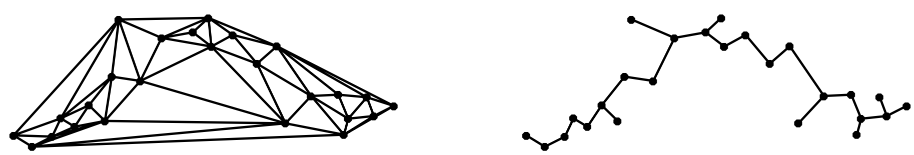
Downs and Horner (2007) suggested that an examination of one of KDE's basic assumptions provides a better explanation of its poor performance as a home range estimator than the methods used in selecting bandwidths. KDE assumes that the process generating the pattern occurs in Euclidean space (Miller and Wentz 2003). If a set of points is generated by a network-related process, then using KDE to characterize the point pattern will yield misleading results. Because animal movements actually occur in network space as a series of trajectories, Euclidean-based KDE may be inappropriate for home range analysis. Downs and Horner (2007) described a method for adapting KDE as a function of networks: network-based kernel density estimation (NKDE). In this paper, we extend NKDE for home range analysis and describe alternative methods for representing animal locational data as networks of movement trajectories.

2. Methodology

Downs and Horner (2007) described NKDE as a method for adapting KDE to characterize the intensity of point patterns generated in network space. NKDE is identical to Euclidean-based KDE, except that the distance-weighting kernel measures distances as a function of a network. First, each grid point where the intensity is to be evaluated is connected to the nearest node in the network. Then, distances from each grid point to each event point are calculated as shortest paths along the network. Finally, a bandwidth is specified, and a distance-weighting kernel is applied to compute density estimates at each grid point. The result is a continuous surface of the relative intensity of the point pattern.

In home range estimation, generally the only data available are point locations sampled from an animal's movement trajectory over time; the exact network of travel paths used by the animal is unknown. To apply NKDE to animal locational data, a network must either be specified in advance (e.g. a stream network for fish species) or generated from the points themselves. Delaunay triangulation (DT) and minimum spanning trees (MST) are two options for constructing networks from point locations that can be used for home range estimation.

In DT, points are linked together to form triangles, such that the minimum angle in the triangulation is maximized (Figure 1a). The MST is a subset of the DT, where the MST is the shortest path that connects all points in the graph (Figure 1b). Both DT and MST are plausible networks for home range estimation by NKDE, because they approximate paths used by the animals. Paths between neighbouring points are represented by straight lines, while paths between more distant points are represented as pathways that connect intermediate points. This effectively alters the shortest-path structure of the locational data, where animal movements between non-neighbouring sample points are assumed to have occurred via sample points located between them.



a. b.

Figure 1. Delaunay triangulation (a) and minimum spanning tree (b) for a set of points.

For illustration, we computed NKDE home range estimates for the linear point pattern shown in Figure 1. We applied NKDE using both the DT and MST networks. We used a Gaussian kernel for the estimates. We specified a single, arbitrary bandwidth for illustrative purposes, because a procedure for selecting optimal bandwidths has not yet been developed for NKDE. The density estimates were computed using TransCAD GIS and mapped using ArcGIS 9.1.

3. Results and Conclusions

Results of the DT- and MST-based NKDE home range estimates are shown in Figure 3. The 50% and 75% intensity contours are shown for comparison. Both network representations produced density estimates that preserved the linear shape of the point pattern, suggesting that they are appropriate for home range estimation. The intensity contours differed between the two approaches, with the MST producing a slightly smaller area that fit more closely to the sample points. This suggests that a MST network representation may be more appropriate for estimating home ranges of animals with UDs that are distinctly linear with well-defined boundaries. Future research on home range estimation by NKDE will determine which network representations are best suited for different types of animal UDs. Additionally, NKDE results will be compared to those computed using Euclidean-based KDE, and different bandwidth selection techniques will be explored.

a. b.

Figure 2. Results of network-based kernel density estimation applied to a set of 25 points using Delaunay triangulation (a) and minimum spanning tree (b) network representations.

4. References

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