

OpenJUMP HoRAE – A free GIS and toolbox for home range analysis

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Abstract Over the past twenty years a set of methods for home-range estimation and analysis of animal observation data have been developed. Whereas comparisons among the estimation methods and different estimation software are available, only the adahabitat analysis toolbox for R is under a free and open source software license and includes established and new home range estimation approaches, such as Kernel Density Estimation, Brownian Bridges and Local Convex Hulls. However, R and adehabitat are rather catering the needs of the scientific user and not the wildlife manager with respect to its general look & feel, and further, provide only a limited set of functions for the analysis of home ranges with environmental geodata, e.g. land-cover and elevation data. This article presents a free and open-source home range analysis toolbox that (i) focuses on the evaluation of GPS collar data, (ii) aims to be fairly straight forward to use by the wildlife manager, and (iii) integrates with a desktop GIS to allow data analysis beyond the creation of home ranges. Since the developed software is distributed under a free and open source license also research can benefit since implemented algorithms can be directly tested and improved.

Keywords home range analysis, kernel density estimation, movement analysis, GIS, open source software

Introduction

The determination of home ranges of animals, that is, the estimation of the geographical area that an animal utilizes in its normal activities of food gathering, mating, and caring for young (Burt 1934), is of importance for wildlife research but also from a wildlife management perspective. Whereas biologists may be interested in the analysis of the home range to evaluate behavioural aspects of an animal, wildlife managers may use information on home ranges to outline areas of protection. For instance, the analysis of home ranges of individual grizzly bears can help to establish measures of conservation for the threatened grizzly bear population in Alberta, Canada (Stenhouse and Munro 2000, Calgary Herald 2010).

Animal home ranges are usually derived based on observation data stemming from VHF telemetry, sightings, or GPS collars. With the help of mathematical models and/or statistical estimation methods such point-based data can then be transformed into (probabilistic) utilization density surfaces or ‘simple’ polygonal shapes that delineate geographically the home range. Several such estimation methods have been developed in the past decades ranging from geometric estimators, such as the minimum convex polygon technique (Burgman and Fox 2003), to more complex statistical methods, such as Kernel Density Estimation (Worton 1989, Powell 2000) and Brownian Bridges (Horne et al. 2007). These estimation methods have been implemented in different software packages, making them accessible not only to the researcher but also to the wildlife manager. For reviews on estimation methods we refer to Powell 2000, Kie et al. 2010 and Laver and Kelly (2008). The latter authors analyzed as well what software packages have been used in scientific articles, which have been published between the years 2004 and 2006.

Comparisons of home range estimation results have not only been undertaken with respect to the different estimation methods (c.f. Seaman and Powell 1996, Horne and Garton 2006, Huck et al. 2008, Downs and Horner 2008), but also with respect to differences – for the same estimation method – that emerge due to different implementations in software. Lawson and Rodgers (1997) as well as Mitchell (2006) note differences of the resulting home ranges, with respect to size and shape, among the software programs. In both articles it is also concluded that there is need for a comprehensive analysis program that (i) handles all phases of animal location data analysis (Lawson and Rodgers 1997), and (Mitchell 2006): (ii) integrates with a GIS, (iii) outputs utilization distributions as well as probability contours, (iv) produces results consistent with other software, and (v) provides a variety of automated methods for parameter estimation (e.g., for the kernel density approach). Mitchell (2006) further notes that certain programs are not very user friendly from today’s perspective. We like to add as a further criterion that the software should also provide newer estimation methods that have been recently developed, e.g. Brownian Bridges and Local Convex Hulls (Getz and Wilmers 2004), especially if such methods utilize the additional information that comes with GPS collar data. Having several estimation methods implemented in one software allows easier comparisons between the results of the different methods and enables to gain more information on an animal’s behaviour. Because as Harris et al. (1991) pointed out already two decades ago: “[...] *using more than one method of home-range analysis provides information on the pattern of space and time use [...]*”.

The only free software, of that we are aware of, which fulfils almost all of the criteria above is the adehabitat package for R by Calenge (2006). However, as adehabitat is based on the R language it may not be perceived as user friendly and is likely more appealing to the scientist than the wildlife manager. Besides its strength, such as (i) the inclusion of all well-known and newer home-range estimation methods, (ii) flexible methods for data manipulation and display, and (iii) a wide range of methods for statistic analysis, R and adehabitat provide

only limited functionality for spatial analysis methods as offered within a desktop GIS¹. Hence, our objective was to develop a new toolbox for Home Range Analysis and Estimation (HoRAE) for observation data from GPS collars, that is a) user friendly, b) includes most of the new estimation techniques, and c) integrates with a GIS - preferable a free and open source GIS so as to avoid proprietary (and costly) dependencies. In the following we will present the HoRAE toolbox. We describe first its functionality and later discuss points that are important for the use of the toolbox including data requirements, methods for parameter selection, and implementation limitations.

Software Functionality

The HoRAE toolbox was implemented as an extension for OpenJUMP GIS (Steiniger and Bocher 2009). The toolbox itself uses general processing functions from OpenJUMP and raster data processing functionality of the Sextante toolbox (Olaya 2008). We first list home range estimation functions which produce either a utilization density grid or polygons that delineated the home range. Then we describe a set of home range analysis functions that should allow to better explore and characterize the animal movement data and the derived home range/utilization density grids. We like to mention that the design of the toolbox with respect to its basic functionality was inspired by ABODE, a free toolbox for home range analysis in ArcGIS by Laver (2005).

Home Range Estimation Functions

The current version of the toolbox contains six different home range estimators (Table 1). With respect to the input data type we can classify those into point-based home range estimators and line- or track-based estimators. Especially the latter are useful for GPS collar data, as they can utilize additional information that comes with such type of data; for instance information on recording time and the possibility to calculate velocity vectors between subsequent GPS points.

The *point-based* estimators include (i) the basic version of the well-known Minimum Convex Polygon (MCP) approach that is extensively described and analysed by Burgman and Fox (2003) and Nilsen et al. (2008). We call it only the basic version as we did not implement outlier-removal techniques as described in Harris et al. (1991). (ii) The second approach implemented is the Local Convex Hull method by Getz and Wilmers (2004), which is essentially a localized version of the MCP approach with some post-processing, i.e. unioning of the hulls. Getz et al. (2007) present three different methods to define the neighbourhood of a point to construct the local hulls: (ii-a) a so-called adaptive LoCoH uses all those points around a center point for the local convex hull, those sum of distance is smaller than a distance a , (ii-b) a k -nearest neighbour approach using all k nearest points from the center point, and (ii-c) a radius-based LoCoH using all points within a circle of radius r from the center point to build the points local convex hull. (iii) As third method we implemented the well known point-based Kernel Density Estimation (KDE) approach that is thoroughly described in Silverman (1986) and Powell (2000), and recently re-evaluated in Kie et al. (2010).

The MCP method results in a polygon delineating the home range. The LoCoH approaches are able to calculate utilization density-like grids, so that different contours/home ranges for different probabilities of use can be derived (e.g. $p = 95\%$ is a value commonly used in the literature; Powell 2000). Also the KDE approach, as its name already suggests, is able to calculate density grids that can be transformed/re-scaled into probabilistic utilization surfaces.

¹ We like to note that the free Quantum GIS provides an interface to adehabiat, see http://www.qgis.org/wiki/HomeRange_plugin

To derive volume contours from the utilization density grids - or polygons that are formed by the contours - we also provide a contouring function within the toolbox. As suggested by others this function evaluates the volume (i.e. the density values) under the surface to derive a probability contour, and not the area of the grid cells.

Three *line-based* estimators are implemented that can use time information about the point recording for parameterization: (iv) A new developed line-buffer approach applies positive and negative buffer operations to movement tracks. Negative buffers are applied to remove portions of the home range stemming from exploratory walks by the animal, i.e. occasional sallies. The method can deliver a simple home range polygon, but is also able to create density grids based on buffer overlap counts. (v) A further home range estimator implemented is the Brownian Bridge (BB) estimator that has been proposed by Bullard (1991) and refined with respect to its parameterization by Horne et al. (2007). The Brownian Bridge estimator is based on a probability model that describes the possible location of a particle for the Brownian motion. For the home range estimation the GPS locations are considered as observed particle locations. To implement the function in our toolbox we ported the code that was distributed with the R *adehabitat* package (Calenge 2006). Result of the application of the BB method is a grid that contains probability values for each cell. (vi) Finally the last home range estimation method implemented is a scaled Line-based KDE approach that is described in Steiniger and Hunter (submitted). It essentially resembles a moving (bell-shaped) kernel along the segment that connects two movement locations. The size of the kernel is scaled with respect to its distance from the segment end points to obtain a bone-like shape for the probability of use (c.f. the error-band model in GIS; Caspary and Scheuring 1993). This bone-like shape should model the utilization density better than an equal probability of use along the track segment. Since the approach is based on the point KDE it will also return a utilization density grid as result.

Table 1. Implemented Home Range Estimators.

Estimation Method	Brief Description	Parameterization Options
Point-based		
(i) Minimum Convex Polygon (MCP)	Convex hull of points.	No parameter, but see Harris et al. (1991).
(ii) Local Convex Hull (LoCoH)	Union of local convex hulls of points.	Dependent on neighbourhood selection method, either distance a , circle radius r , or k neighbours.
(iii) Kernel Density Estimation (KDE)	A weighted kernel function is moved over a raster and point values summed.	Bandwidth/ window width h , Kernel function.
Line-based		
(iv) Line Buffer (LB)	Positive and negative buffering and union of the lines between two subsequent GPS points.	Buffer distance r
(v) Brownian Bridge (BB)	Uncertainty model for the location of a particle described by the Brownian motion model.	BB parameters σ_1 and σ_2 , with σ_1 assumed to be GPS accuracy.
(vi) Scaled Line-KDE (SLKDE)	A point-based kernel is moved along a rasterized line and scaled according to its distance from the end points.	Bandwidth/ window width h , Kernel function ¹ , Scaling function

¹) The choice of the kernel function for SLKDE is not implemented in the toolbox yet and the biweight kernel is used by default.

Home Range Analysis Functions

As described earlier the home range analysis functions should help to gain more insight into the movement data. Currently five different analysis functions are available:

Visualization - A visualization function that calculates and displays: a) the GPS movement track, b) bounding boxes for the daily travel – each box including only the points of one day (Fig. 1), c) the (median) average daily travel distance (MTD), and d) the reference bandwidth h_{ref} that can be used for the kernel density estimation methods (see Silverman 1986, Worton 1989).

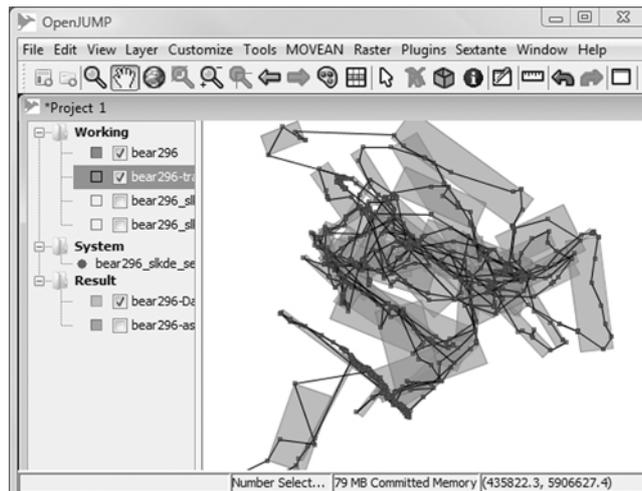


Figure 1. OpenJUMP GIS with home range analysis functions. Here the GPS tracks and bounding boxes of daily movement are shown.

Asymptotes - A function that allows to check if the area of the home range calculated shows an asymptotic behaviour if more (GPS) points are added to the dataset (Harris et al. 1991, Laver 2005). Adding points should be done sequential if the points have been recorded sequential as well (i.e. with GPS collars, see Fig. 2). If no recording information is available, then points should be added randomly (Harris et al. 1991). Asymptote analysis can be helpful in two cases: a) it shows if the number of sampling points (observations) is sufficient for the home range calculation or if more points are needed. I.e. more points are needed if no asymptotic behaviour occurs. b) An asymptote plot allows to study movement behaviour of one animal between seasons of the year. For instance with sample data of grizzly bears we could see that during the summer months one bear strongly extended its home range in comparison to spring and autumn. The toolbox allows asymptote analysis for sequential data with three home estimators: MCP, Line-Buffer and KDE. Asymptote analysis by adding random points has been implemented for MCP only. We chose to implement asymptote analysis for those three methods as they are not as computational costly when run several hundred times, compared to BB and Scaled-Line KDE (see next section).

Core area – The core area of a home range contains those parts of the home range that an animal uses more often than if the utilization would be uniformly random over the whole home range area (Powell 2000). Samuel and co-authors (1985, 1988) described a first approach for a quantitative analysis based on point data. However, we implemented two different methods for the determination of the probability p_{core} that defines the core area. Both methods are based on the evaluation of a graph that displays probability of use vs. area. The first version generates such a graph from evaluating the density/probability of use for each cell of the raster grid and is described in Seaman and Powell (1990). The second version is partly described in Harris et al. (1990) and is based on the calculation of contours for certain probability values, e.g. $p = 5...95\%$ in steps of 5%, and the area the contours enclose. The method for choosing the core probability was proposed in Seaman and Powell (1990), i.e. plotting the curve of area vs. probability of use and selecting the probability where this curve and the diagonal line from (area = 100%, probability = 0%) to (area = 0%, probability = 100%) are most distant from each other. We note that in our experiments both methods often gave different results, i.e. different probabilities that define the core area. However, when there are large differences, e.g. 10% or more, then we suggest using the value from the contour-based method as its computation is more comprehensible.

Skeletons – We implemented a function that calculates skeletons of the home range polygons (Haurert and Sester 2008). This should allow to visually compare if home ranges

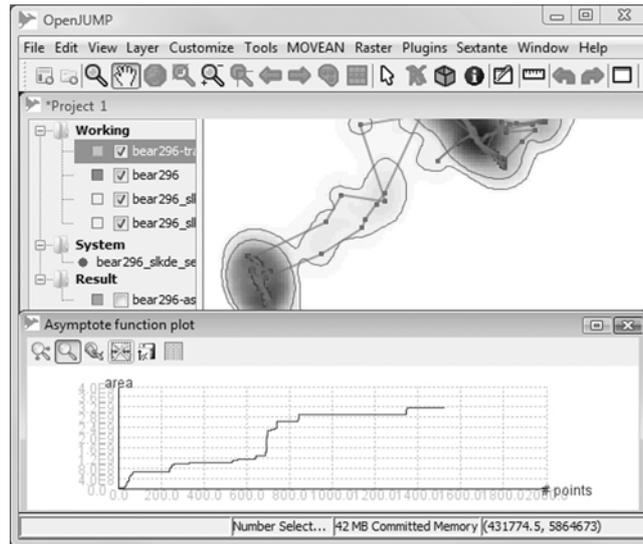


Figure 2. Screenshot showing GPS points, movement path, a line-KDE density raster, core and $p = 95\%$ contours, and asymptote plot.

calculated with different methods, different parameters, or for different seasons are similar or not, e.g. by comparing the branches of the skeletons. However, further work on similarity analysis of home ranges is still needed.

Home Range Classification – It may be useful to further analyse the derived home range polygon by classifying parts of it. For instance if the distance between the contour of the core area and the ($p = 95\%$) contour of the home range is known, then one can derive a classification of the home range into (i) core zones, (ii) home range edges, (iii) unconnected home range patches, and (iv) corridors that connect home range cores, as described in Steiniger (forthcoming) and Voigt et al. (2007).

Using the Software

The following subsections address several points that are important when home range estimation and analysis is performed with the toolbox, but contain also general comments on the application of the estimators. We first discuss conditions that should be known if using a particular home range estimator, then we will address input and parameterization of the estimators, and finally discuss problems that we encountered during the implementation.

Conditions on the Use of Home Range Estimation Methods

The six home range estimators implemented use different modeling techniques for the estimation, and subsequently assume certain conditions on the observation data. As the name of the MCP method already indicates, the method should only be applied to species data where it is known that their home range may be of convex shape. For instance grizzly bears don't have convex home ranges (Steiniger et al. 2010), whereas herpetofauna species may have (Row and Blouin-Demers 2006). Thus, the application of MCP for grizzly bears results in biased size and shape descriptions and may only be useful for initial visualization purposes - but not for detailed analysis. A further issue with MCP is that the boundaries will be formed by the outer observation points, i.e. there is no "buffer" around them that demarks possible animal occurrence as with other estimation methods, e.g. point-KDE, Brownian Bridge (BB), line-KDE, and Line-Buffer. This problem is also occurring for the LoCoH approach.

In comparison to MCP the other methods such as BB, point-KDE, Line-KDE, LoCoH and Line-Buffer are able to generate utilization density grids. Hence, in theory they can be used with multi-modal, non-uniform data that can represent non-convex and disjunct home ranges (Seaman et al. 1999). These five estimation methods should then be able to resemble the corresponding distributions. However, there are model assumptions for the BB and KDE methods: First, the BB approach is essentially an uncertainty model, i.e. does not model density of use. An effect of this is that the uncertainty value, which we aim to use as density value, is actually zero at a GPS location. However, in practical applications with ‘good’ observation point distribution the BB results are comparable to those of KDE methods since modelling focuses on the track segment and not the observation point (Steiniger and Hunter 2010). Second, the BB model assumes that the data stem from a random walk process that has a normal distribution (Horne et al. 2007). Third, the KDE approach may impose an assumption on the point distribution with respect to the selected kernel function. For instance, if the kernel is chosen to be of Gaussian form, then a Gaussian distribution of the points is assumed.

For the work with the toolbox it is also important to know that in comparison with other software the point data sets are not standardized and/or normalized with respect to their variance in x and y locations. Only zero-distance points are filtered, for example when the Least-Squares Cross-Validation method for the determination of the KDE bandwidth is used. Also, there is no option for the shifting of points if the input data are discretized, e.g. on a grid, as available in the ABODE toolbox by Laver (2005). Finally we note that we did run the estimation functions of the toolbox with GPS datasets containing up to 2000 points. But handling of more points should be possible when appropriate computer memory (RAM) is available.

Parameterization of Methods

Except the MCP method all home range estimators require the setting of one or multiple parameters as summarized in Table 1. An additional parameter that is not mentioned in Table 1, but needs to be set for all methods that produce a utilization density grid, is the cell size for the grid. Rasterization with different cell sizes will produce slightly different results. In the following we discuss for the estimation methods the available options for setting parameters:

LoCoH – Dependent on the neighbourhood selection method, i.e. adaptive, radius, or number of neighbours, a single parameter needs to be provided. The toolbox doesn’t contain any automated method that proposes parameter values. Hence, the parameter needs to be set manually and should be found iteratively based on qualitative (e.g. number of holes) or quantitative criteria (e.g.: values for area and shape index). For this purpose Getz et al. (2007) make suggestions for initial parameter values.

Point-KDE – The point-based KDE approach requires choosing the shape of the kernel function and providing a bandwidth/window width h that determines the smoothness of the generated density surface. Different kernel functions have been implemented in the toolbox, e.g. biweight, Gaussian, triangular functions etc. (see Silverman 1986). As noted by Silverman (1986, pgs. 43 and 86) changing the kernel function does not change the results as much as changing the bandwidth. The toolbox implements only a *fixed* bandwidth approach, since Seaman and Powell (1996) and Blundell et al. (2001) found that the adaptive bandwidth approach does not provide ‘better’ results. Besides using a fixed bandwidth the value h is used for both coordinate directions x and y in our implementation.

Several automated methods that help choosing the bandwidth h are provided in the toolbox: (i) the reference method delivers a value $h_{ref} = \sigma_{xy} \cdot n^{-1/6}$ (Silverman 1986) that assumes a normal distributed point cloud. (ii) The Least-Squares Cross Validation (LSCV) method returns a value h_{LSCV} that is derived with a step-wise minimization approach over

different bandwidths with respect to the least-squares error (Worton 1995, Sheather 2004). (iii) As a third method we implemented the ad-hoc method used in Berger and Gese (2007) and Jacques et al. (2009). h_{ad-hoc} is the last bandwidth value that keeps the home range continuous before the home range is split into two home range patches, i.e. the method is based on biological meaningful criterion. In our case we test at which value of h the $p = 99.5\%$ contour/region splits, and not for the $p = 95\%$ contour as in Berger and Gese (2007) and Jacques et al. (2009). Hence, if the continuous home range is wanted the 99.5% contour needs to be calculated from the resulting grid, since the 95% contour will contain the split already. The bandwidth may not only be derived from data-driven methods. Several authors (e.g. Powell 2000, Laver 2005) note that h may also be chosen based on expert knowledge, for instance the known location error, or the radius of perception of an animal.

Scaled Line-KDE (SLKDE) – The SLKDE function requires an orderable set of points, for instance by providing a recording ID. Since the SLKDE is based on the point-KDE approach the input parameters kernel function and bandwidth are needed as well. However, currently there is only one kernel function implemented (i.e. the biweight kernel), and the bandwidth h can be and should be set based on time information that comes with the GPS tracking data. As a third parameter the scaling function needs to be selected (Steiniger and Hunter, submitted).

With respect to choosing the bandwidth h we provide a function that calculates the median of the average daily travel distance (MTD) based on the track information. A requirement for the calculation of h_{mtd} is that the recording day for each GPS point is provided. Besides h_{mtd} the reference bandwidth h_{ref} can be used as well. However, in certain instances h_{mtd} may be (much) larger than h_{ref} . If that is the case, then we recommend to use h_{ref} to retain more detail for the home range outlines.

The scaling function defines how strong the bone-shape of the probability contours for one segment of the GPS track is. We performed testing with four point datasets obtained from grizzly bear GPS collars to compare two scaling functions; one with a scaling range of [0.5...1.0] and a second with [0.707...1.0] (Steiniger and Hunter, submitted). Those tests did not reveal major visual differences for $p = 95\%$ contours. But further testing with additional datasets and data from different species is needed before any conclusive statement can be made.

Line-Buffer – The line buffer approach requires only one parameter, the buffer size. Since it is a line-based estimation approach as well, like SLKDE, we recommend to use the median value of the average daily travel distance as buffer size. This approach also requires the provision of a GPS point attribute that allows to order the points with respect to its recording. We note that the negative buffer operation, which is used to remove sallies, uses the input buffer value and multiplies it with $m = 1.10$.

Brownian Bridge (BB) – To utilize the BB approach the given GPS points need to be orderable, e.g. by providing a recording ID, and the time of recording must be given in seconds for each point. The time information will be used to calculate the time differences (in seconds) between two subsequent observation locations. Aside from these location attributes the BB approach requires two input parameter, denominated as σ_1 and σ_2 . It has been suggested by Bullard (1991) and Horne et al. (2007) that the second value σ_2 is set according to the uncertainty of the observation point, e.g. $\sigma_2 = 30$ m for GPS collar data. Assuming that σ_2 is fixed for the whole data set Horne et al. (2007) propose a likelihood function and an optimization routine to estimate σ_1 . We implemented that likelihood function in the toolbox, using the code from the adehabitat package. But in opposite to Horne et al. (2007) the minimum of that function is not obtained via an optimization procedure, but by choosing the smallest value from function values calculated for a range of σ_1 .

For the BB approach as well as for line-KDE approach results can be different for the two options of track-segment rasterization (see also Steiniger and Hunter, submitted). For the first type of processing, the so-called: *rasterize-first* approach, all track segments are rasterized

together in a first step. Then the density calculations are performed for each grid cell of the raster. For the second type of processing, the so-called *segment-wise* approach, each segment is rasterized separately and the density calculation for each grid-cell performed - obtaining a small raster with the limits of the segment. Then the single-segment raster is “added” to a final (big) raster and the next track segment is processed. In Steiniger and Hunter (submitted) it is shown that the contour lines for the line-KDE look different. For instance, the centre of density for two subsequent track segments that meet in an acute angle is shifted. In the segment-wise approach the density center is above the connection point that is part of both segments. In the rasterize-first approach the center is shifted towards the middle between the track segments.

Discovered Problems with Algorithm Implementations

During the implementation and testing with grizzly bear collar data we discovered several problems that should be known by the software user. These issues include computational complexity/speed, numerical limitations, and problems with BB core area calculations.

Processing Speed – In particular the line-based estimators require many more calculations than the point-based methods. Subsequently computation times are much longer. For instance when we processed datasets that contained circa 1,500-2,000 GPS points the point-KDE and the MCP estimators required only a few seconds, whereas the line-KDE and the Brownian Bridge estimation run for 13 minutes and 21 minutes respectively (see Table 1 in Steiniger and Hunter, submitted). However, the Line-buffer approach is about as fast as the point-based estimators.

Failure of LSCV and Numerical Limitations – The LSCV approach failed for about 20 bear datasets that we tested (all with more than 500 GPS points), delivering too small values in comparison with h_{ref} . As a result the calculated home ranges consisted of small circles with one circle for each GPS point. The potential that LSCV results highly vary and may not be usable has been also noted by Sheather (2004), Hemson et al. (2005), Huck et al. (2008) and Kie et al. (2010). The problems may in particular be bound to datasets with more than 150 points and for clumped point distributions. Aside from the LSCV failures we noticed numerical problems when calculating the LSCV score $CV(h)$, as in Worton (1995), with our implementation using JAVA and a 32-Bit operating system. In particular the calculation of the expression e^x will result in wrong values for $CV(h)$ if $x > 709$ due to the 32-bit precision limits. This problem does not only occur for the calculation of the LSCV scores but also for the probability calculations of the Brownian Bridge approach, since using a normal distribution requires evaluation of e^x as well. Here the effect is in particular visible in the form of jumps in the graph of the likelihood function (Fig. 3). As a result the parameter σ_1 may be incorrectly obtained using the implemented minimum-value search and grid values may be incorrect too.

Failure of Core Area Calculation for Brownian Bridge Results – When we calculated p_{core} based on the (density) grid produced with the BB approach, then we sometimes obtained values that have been around or larger than $p = 95\%$. Both calculation methods, but in particular the cell-based method, returned such high p values. The reason for this behaviour may be the shape of the generated density distribution, i.e. if a profile perpendicular to a single track segment is generated, then long tails of small values are visible. This may also explain why Huck et al. (2008) found the calculated home-range for the $p = 90\%$ contours nonsensical, i.e. too big, and instead used the $p = 40\%$ contours. As a consequence care needs to be taken when knowledge gained from and methods developed for KDE are applied to BB results.

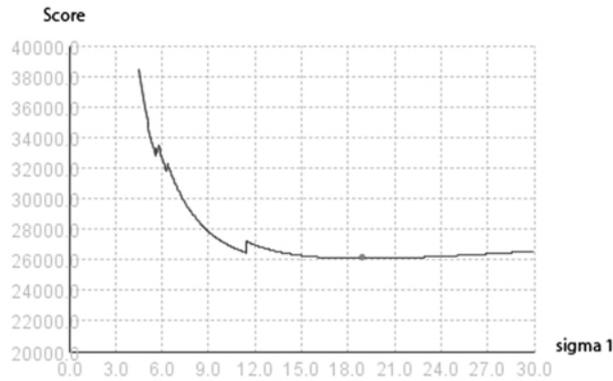


Figure 3. Reaching the numerical limits for 32-bit computers causes jumps in the graph for the Brownian Bridge score value calculations. The dot in the middle marks the minimum score value that determines parameter σ_1 .

Software Distribution

The Home Range Analysis and Estimation (HoRAE) toolbox for OpenJUMP is distributed under the GPL license (www.gnu.org), a free and open source license (Steiniger and Hay 2009). Hence, the source code is delivered with the toolbox and the toolbox can be modified and re-distributed under the GPL license terms. This also gives others the option to test and improve existing functionality and to contribute new functions. For instance, (i) the newly developed Geo-Ellipse for density estimation by Downs (2010) could be implemented, (ii) auto-correlation measures should be added (Blundell et al. 2001, Fieberg 2007), and (iii) the integration of movement pattern analysis methods from Laube et al. (2005) may be useful as well.

As the HoRAE toolbox needs the Sextante libraries we generated a pre-packaged version of OpenJUMP that can be downloaded from <http://sourceforge.net/userapps/mediawiki/mentaer/>. Information on the use of the toolbox can be found on the related wiki. However, as there is no comprehensive introduction yet for home range estimation and analysis with our toolbox we refer the reader to the ABODE documentation by Laver (2005) (also on the wiki).

Acknowledgments

Parts of this work have been funded by a Canadian Phase IV GEOIDE project, #03, to Andrew Hunter and a Swiss National Science Foundation grant to Stefan Steiniger (PBZH2-1211004). We thank the Foothills Research Institute, Alberta, Canada, and Greg McDermid's team, U. of Calgary, for providing grizzly bear GPS data and land-cover data for testing. Our sincere thanks go also to the authors of the free software packages *adehabitat* for R, Clement Calenge & others, the authors of the *Sextante* toolbox, Victor Olaya & other, and to Peter Laver who developed *ABODE* for ArcGIS. Without access to the source code of those packages we could not have accomplished our work.

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