Results of the break-out group: Movement Data of Vervet Monkeys

Group discussion with Erik P. Willems, Kevin Buchin, and Urška Demšar

Discussions in this group focused on a particular problem that arises in animal movement ecology: how to link data describing movement (i.e. sequential GPS-coordinates collected on wild and free-ranging animals) with geographical and environmental context (i.e. properties of the internal and external environment within which the animals move). Our case study comprised a spatio-temporal data set on the movement of a group of vervet monkeys (*Cercopithecus aethiops*) over a twelve months observation period. We focused on two topics: context-aware estimation of home range area and multivariate visualisation of context data.

1. Context-aware estimation of home range

The home range of a group of animals is typically calculated by 2D kernel density estimation, taking sequentially collected GPS-coordinates as input. This produces a continuous surface of the estimated probability of the presence of animals, known as the utilisation distribution (Worton, 1989). The home range area is then defined as the contour of some high value of probability of occurrence (typically 95 or 99%) on this surface. However, this treats the GPS-coordinates as independent -i.e. static- observations and ignores the fact that they describe actual movement. This results in biologically counterintuitive artefacts -e.g. “islands of high probability- that are illogical with respect to the movement of animals (fig 1a).

An improvement to this basic point kernel approach that we identified and experimented with in the group was to use line kernel density estimation, which takes linearly inferred trajectory segments between points as input. This approach allows for a more explicit incorporation of the actual movement of animals by no longer treating GPS-coordinates as independent points, but rather, as acquired sequentially. The 99% probability contour of the resulting probability surface, produced an improved estimation of the home range area, where isolated “islands” disappeared (fig. 1b). However, this approach suffers from the disadvantage that the movement between two points is represented by a homogeneous kernel along the linearly inferred movement trajectory. This is not a good representation of animal movement and we therefore explored possible alternatives that would be more consistent with biological observations.

A particularly promising alternative is the calculation of probability surfaces using a Brownian bridge movement model (Horne et al. 2007). This approach takes into account the higher probability of the presence of animals close to the empirically obtained GPS-coordinates and home range area estimates produced with this method are considered to contain far more biologically realistic information.

As an additional innovation, Brownian bridge movement models could be incorporated into an improved visualisation method for animal trajectories. This could be done by expanding the 3D space-time density (Demšar & Virrantaus 2010) with Brownian bridge density in the 2D geographic directions and linear density in temporal direction (since objects always move through time linearly).

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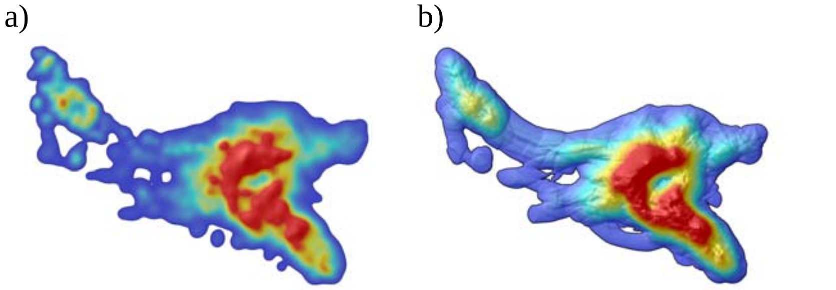

Figure 1: Kernel density of trajectories using a) point density, b) line density.

2. Multivariate visualisations of context data

The second part of the discussion revolved around what the actual context of the observed GPS-coordinates was. We investigated this through a visual exploration of the contextual data using GeoVISTA Studio (Gahegan et al. 2002) and Geoviz Toolkit (Hardisty and Robinson, 2010), both produced by the GeoVISTA Center at the Penn State University (http://www.geovista.psu.edu). We produced Thiessen polygons from point locations and linked these with contextual attributes describing characteristics such as availability of food, presence/distance to certain important features (sleeping trees, river, etc.) and perceived fear of predators (baboons, leopards, snakes, eagles). We explored this newly created dataset visually and identified several patterns in the data that make biological sense. For example, fig. 2 shows a selection of the areas that are in nearest vicinity of sleeping trees – in the Parallel Coordinates Plot in this figure it can be seen that these trees are not in the areas where leopards are perceived to be a large threat, however, the presence of baboons does not necessarily seem to be a problem for monkeys to select a tree as a sleeping tree.

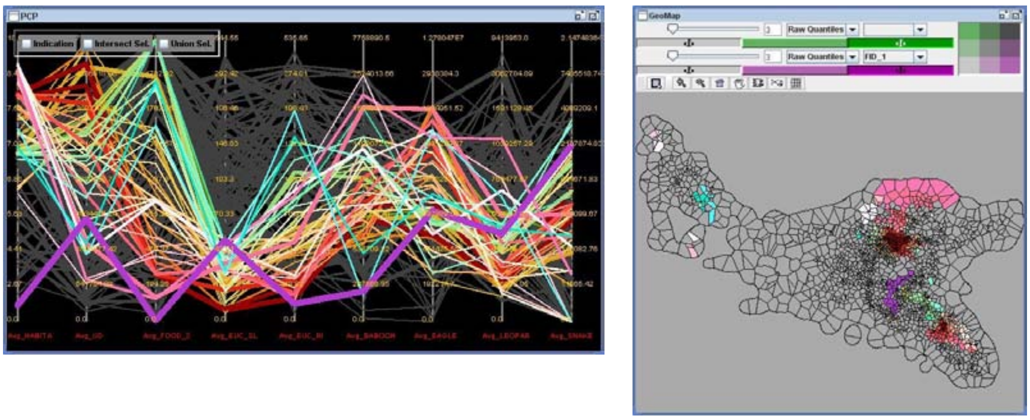

Figure 2: Selecting areas near sleeping trees.

Figure 3 shows another pattern that is interesting biologically: here the perceived fear of predators is shown using star icons plotted on a map (Klippel et al. 2009). Areas with different fears can be easily identifiable from the shape of the icons as well as areas where more than one type of fear is present.

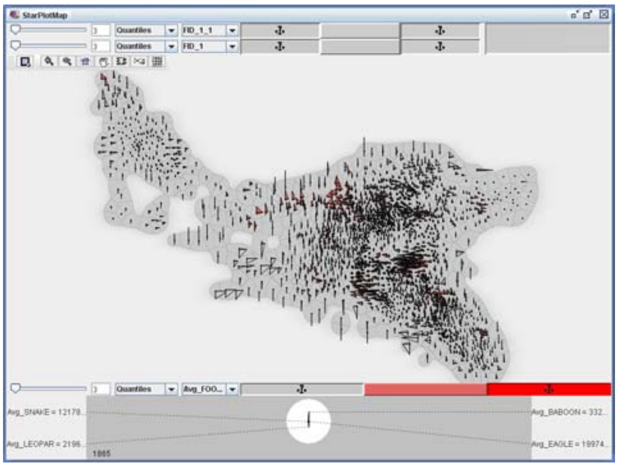

Figure 3: Fear-of-predators types shown with a star map.

These two examples merely illustrate two patterns that we found during group work, but further exploration of this dataset is expected to yield other observations about possible relationships which might be biologically relevant.

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