

Results of the break-out group: Gulls Data

Group discussion with Emiel van Loon, Jörg-Rüdiger Sack, Kevin Buchin, Maike Buchin, Mark de Berg, Marc van Kreveld, Joachim Gudmundsson, David Mountain

A dataset representing the movement patterns of lesser black-backed gulls (*Larus fuscus*) from a colony based on the island of Texel (Netherlands) has been collected by the Universiteit van Amsterdam. The dataset has a duration of several weeks coincided with the gulls breeding period. In total four gulls were tracked by fitting them with GPS sensors which recorded a timestamp, latitude, longitude and altitude. This dataset was presented to the Dagstuhl seminar by Emiel van Loon, along with a series of research challenges including:

- *finding all recurrent patterns in our gull tracks;*
- *to label these recurrent patterns in an ecologically meaningful way;*
- *investigate the algorithms or metrics that are used for establishing to which recurrent pattern a fix belongs, and try to relate these to what we know from ecological theory and flight energetics.*

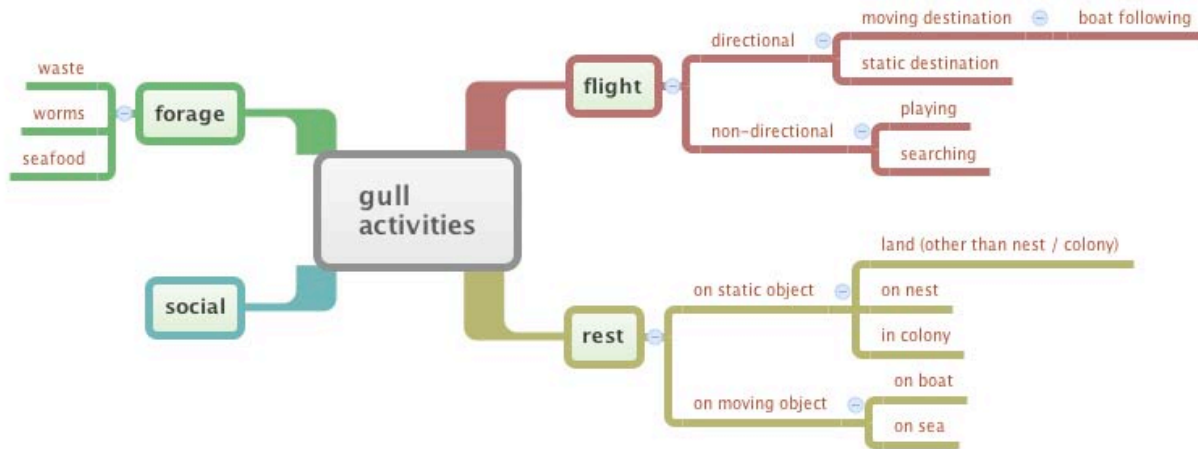
More specific research questions included:

- *When at open sea, can we distinguish whether they are traveling towards a destination, following a fishing vessel, roaming and/or fishing in open water?*
- *Can we distinguish between searching flight and goal oriented flight (e.g. to known food source or previously visited foraging location)*

The gulls data breakout group's task was to discuss methods and strategies that may prove fruitful in meeting these challenges and answering these questions.

A classification of gull behaviour was produced by the group, led by domain expert Emiel van Loon, who provided additional context including that gull trips are typically composed of distinct segments, that gull trips are rarely single purpose, and that there is very little diurnal pattern to activities. The classification produced is not intended to be complete, or non overlapping.

Figure: classification of gull activities



The group explored the idea that this classification is a combination of two distinct concepts:

- gull *behaviour*, as traditionally recorded in time budget analysis. For example, nesting, eating, foraging. It is unclear which behaviours have distinct spatial patterns;
- *spatial patterns*, for example directional flight.

It might be appropriate to split this single classification into two, one representing gull behaviour, and one spatial patterns, and try to identify linkages between behaviour and patterns. It is quite likely that there will be one to one, one to many, and many to many relationships between behaviour and pattern. For example, the pattern *directional flight* maybe associated with returning to the nest following foraging behaviour, or as part of migration behaviour.

Next, the group considered how the attributes in the gulls dataset could be used in algorithms to automatically classify the dataset into distinct spatial patterns, and associate this with gull behaviours. The following attributes were identified as useful for distinguishing between different pattern and behaviour classes.

Table: Attributes appropriate for classifying gull movement dataset into distinct classes

attribute	source	accuracy	sampling interval
x,y	sensor on bird	+/- 2m	3 - 30min
z	sensor on bird	+/- 10m	3 - 30min
t	sensor on bird	+/- 0.1sec	3 - 30min
temp	sensor on bird	+/- 0.1sec	3 - 30min
speed	sensor on bird	+/- 0.5 m/s	3 - 30min
speed cf wind speed	speed, wind speed		
speed cf sea current	speed water speed		

heading	derived from x,y		3 - 30min
heading cf wind direction	heading, wind direction		
heading cf sea current	heading, water direction		
shape	derived from x,y		
duration	from t		
land/sea	contextual info		
landuse	contextual info		
colony location	contextual info		
wind speed / direction	contextual info		6hrs
water speed / direction	contextual info		3 hrs
weather data	contextual info		
tide	contextual info	+/- 5cm vertical	1hr
oil rig locations	contextual info		
fishing boat trajectories	contextual info		
repetitive destination	contextual info		

An algorithm to detect *directional flight* was sketched out by the group.

Algorithm: Directional Flight behaviour detection

1. Run thru all points

2. For each point that is a potential starting point (P1), based on speed (and heading?),

2.1 does subsequent point meet directional flight criteria?

If yes: add to candidate subtrajectory

If not: point is endpoint of candidate subtrajectory (Pn).

3. If duration between start (P1) and end (Pn) is > defined threshold, extract this sub trajectory, and tag as 'directional flight'

The criteria defined for directional flight, based on the attribute table, were:

- P1 speed and Pn speed are between 8m/s and infinity;
- Speed of 80% of points in subtrajectory are within 8m/s and infinity;
- Remaining 20% should be 'well distributed';
- End points sufficiently 'dilated';
- Mean direction towards known location adds confidence;

- Flying against wind adds confidence;
- Detour factor: For any subset of points in subtrajectory, must be within a temporal threshold, based on dilation (and towards goal);
- Sub trajectory must have a minimum duration;

Similar criteria were defined for other classes of behaviour.

A next step in this research would be to implement this algorithm and conduct a qualitative evaluation, led by a domain expert, on the resulting partitioned dataset. It was acknowledged that this approach may be vulnerable to outliers, and may create fragmented subtrajectories. It is anticipated that future work in this area should consider explicit methods are required for handling:

- error and uncertainty in the source data,
- issues related to temporal and spatial scale,
- heterogeneity and tolerance of outliers in the subtrajectories.

References

Shamoun-Baranes J. & van Loon EE (2008) Analysing high-resolution tracks of gulls: short description of a data set and research questions, *Computational Geo- Ecology*