Movement ecology and human mobility in the GPS tracking era: new opportunities and challenges for remote sensing application

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Abstract.

Recent advances in tracking technology and remote sensing have been shifting the core of movement research. The unprecedented quantity and quality of movement data along with the increasing availability of remotely sensed products allows movement researchers to investigate the role played by the environment in the phenomenon of movement. Environmental triggers of movement can be analysed using Context Aware Analysis (CAMA), a methodology that links trajectories to environmental data. Environmental data in CAMA comes from diverse sources, such as meteorological, weather radar and most often remote sensing data integrates context into movement and creates the so-called semantic trajectories which facilitates context-aware analysis and supports understanding of how environmental situation affects movement behaviour. However, CAMA is challenging due to the 1) complexity of remote sensing data; 2) spatial and temporal incompatibilities between movement and remotely sensed data; 3) multi dimensionality and 4) poor interpenetration between the remote sensing and movement science communities. Hoping to encourage this interdisciplinary dialogue, this paper presents preliminary results of CAMA using remotely sensed data from the NIMROD rainfall radar and gull tracking data which can be downloaded for free. The preliminary results show the potential of remote sensing to help answering movement research questions, as well as the potential of movement research as a new application domain for remote sensing.

Key-words: movement research, remote sensing, trajectories, context aware analysis, annotation, multi-dimensional data.

1. Introduction

Global Positioning Systems (GPS) are widely known by the remote sensing (RS) community and have been extensively used for decades for data collection, georeferencing and orthorectification. Yet movement ecology and location based (LB) human mobility research, as more recent applications, have been revolutionized in the last decade by GPS tracking technologies (Cagnacci et al. 2010).

The recent technological advances and decreasing cost of GPS tracking devices transformed movement research from a data poor science to a big data science. The quantity and quality of movement data currently available is unprecedented (Demšar et al. 2015), so that online data repositories, such as MoveBank (Kranstauber et al. 2011) and ZoaTrack (Dwyer et al. 2015), have been developed specifically for movement data.

Movement data are collected in the form of trajectories, also called space-time paths (Hägerstrand 1970), which are four dimensional spatial entities. A trajectory is a sequence of chronologically ordered fixes with spatial (3D) and temporal coordinates (1D), most often GPS points, representing the movement of a single unit (Long and Nelson 2013). Trajectory fixes can be collected at temporal resolutions varying from milliseconds (Shamoun-Baranes et al. 2006) to hours (Dodge et al. 2014, Safi et al. 2013), and occasionally days.

As a key 4th component, the temporal dimension places movement research at the forefront of Geographic Information Science (GIScience). GIScience has developed and mastered diverse techniques for analyzing and representing static phenomena (3D), but the space-time bond is still a current challenge. Simultaneous analysis of temporal and spatial dimensions

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can lead to a better understanding of inherently chronological processes (Hägerstrand 1970) like movement.

The challenging fourth dimension would be enough to encourage researchers to bind movement research and remote sensing together. The former could benefit greatly from temporal series analysis and the visualization methods established in the latter. However, there are further benefits above and beyond this. The increasing availability of free remotely sensed products has contributed to shifting the core of movement research towards the role played by environmental context in the phenomenon of movement (Brum-Bastos et al. 2016).

It is well known by movement scientists that movement behaviour is influenced by a set of complex external and internal factors which interact at diverse temporal and spatial scales (Lima and Zollner 1996, Nathan and Giuggioli 2013). It is also well known that changes in environmental circumstances, such as wind, temperature and precipitation activate different movement behaviours which are reflected as movement patterns in the data (Nathan and Giuggioli 2013, Brum-Bastos et al. 2016). However, the use of remotely sensed derived products or other sources of environmental data to characterize the environmental context underlying movement is even more novel for these scientists than the use of GPS tracking.

The linkage of environmental context to movement data has been identified as one of the main themes in current movement research (Demšar et al. 2015) and it is known as Context Aware Movement Analysis (CAMA). This is where the strongest intersection between remote sensing and movement research lies, providing many opportunities and challenges for the scientific community (Neumann et al. 2015).

So far trajectory annotation has been the method to approach the challenges posed by CAMA; this method adds environmental information to each GPS fix by linking trajectories to environmental data (Demšar et al. 2015). Currently, it is mostly done by assigning the nearest environmental data value in space and time to the fix; which can be problematic because of the differences in the temporal and spatial resolutions of movement and remotely sensed data sets.

Remotely sensed environmental data has been so recurrent in trajectory annotation that automated annotation systems, such as Env-DATA (Dodge et al. 2013) and STAT (Coyne and Godley 2005) emerged. Nevertheless, the use of remote sensing data is still cumbersome for the majority of the movement research community; this might be justified by the following key challenges which will be detailed later: 1) complexity of remote sensing data; 2) spatial and temporal incompatibilities between movement and remotely sensed data; 3) multi dimensionality and 4) poor interpenetration between the remote sensing and movement science communities.

The integration of RS data into CAMA poses a computational challenge for many movement researchers. Firstly, because spatial and temporal tiling systems, in which RS data is distributed, are seen as highly complex by part of the movement science community (Dodge et al. 2013). Secondly, because the diversity of formats, projections, coordinate systems and processing techniques is enormous when it comes to RS data; so that some movement researchers find it difficult, if not impossible, for anyone other than RS experts to make direct use of the data (Neumann et al. 2015). That is why, movement researchers almost always choose to work with RS products instead of raw or mixed data.

The use of raw and/or mixed RS data could help with the spatial and temporal incompatibilities between movement and RS data. For example in GPS tracking of human mobility (Siła-Nowicka et al. 2015) and some types of animal movement, (e.g. seabird tracking, Stienen et al. 2016), the temporal resolution of environmental data is lower than the frequency with which fixes are registered in a trajectory. In other cases, environmental data are collected more frequently than trajectory points. For example, weather radar data are typically collected at five minute intervals, which is much less than the tracking resolution of

GPS data for larger animals whose movement is potentially affected by precipitation (e.g., roe deer, De Groeve et al. 2015; lynx, Gaston et al. 2016). In all cases, the spatial resolution of environmental data is almost always coarser than the spatial accuracy from GPS tracking (Brum-Bastos et al. 2016).

On top of dealing with the incompatibilities between resolutions, it is perhaps even harder to deal with the multi dimensionality inherent to CAMA. Each one of the derived environmental conditions incorporated into the analysis is a new attribute, i.e., a new dimension to be represented. This probably would not be so troublesome if working in three dimensions, but movement data is in principle four dimensional and quite often nth dimensional, likewise RS temporal multispectral series.

The poor interpenetration between movement research and RS scientific communities has a negative effect on all the aforementioned issues. Most of movement research is published and presented at niche journals and conferences, like *Movement Ecology*. This hampers interaction with the remote sensing community and therefore the expansion and strengthening of a prolific interdisciplinary exchange; which could greatly advance movement research and also benefits the RS community by offering a new application domain.

Hoping to encourage this interdisciplinary dialogue, this paper presents preliminary results of CAMA using remotely sensed data from the NIMROD rainfall radar and gull tracking data which can be downloaded for free (See Stienen et al. 2016).

2. Methodology

The movement database has more than 2.5 million points recorded by 101 GPS trackers coupled with 75 Lesser Black-backed Gulls and 26 Herring Gulls breeding at the Belgian and Dutch coast (Figure 1). We selected the trajectory of Harry, a male Lesser Black-backed Gull *(Larus fuscus)* (See photo from Flicker gallery by Dominic Mitchell at Figure 1). Harry’s flight was over southern England; its trajectory is sampled at intervals varying from 10 minutes to 30 minutes, starting on the 1st of September 2013 at 00:29:00 and ending on the 18th of September 2013 at 16:48:00 (Figure 2). The tracking device was recording the 3D positioning, timestamp, air temperature, speed in the X, Y and Z axis, direction and respective accuracies.

Remotely sensed rainfall rates, provided by the United Kingdom Met Office NIMROD Radar, were used as the contextual environmental data. The data are available in non-standard NIMROD binary format with 1 km spatial resolution and 5 minute temporal resolution (Met Office 2003). The rainfall rates were decoded with a Python module that parses the NIMROD binary format and extracts an ASCII (.asc) image file (See Thomas 2015 for more details).

Movement data and remotely sensed rainfall were both stored in a PostGIS spatial database, the data processing was handled with Python scripts based on the Psycopg module. This module enables the integration of Python and PostGIS.

Figure 1. Gull GPS tracking movement database at the southern North Sea coast. Source: CARTO

We annotated each GPS point by first identifying the nearest earlier (t_1) and the nearest later (t_2) NIMROD image in time, i.e., for a point at 20:53, t_1= 20:50 and t_2 = 20:55; and second intersecting in space the GPS points with the t_1 and t_2 NIMROD images to retrieve the correspondent rainfall rates v_{t_1} and v_{t_2}. The rainfall rate (v_{t_n}) at t_n , time when the GPS point was recorded, was calculated by interpolating the rainfall rates at t_1 and t_2 as follows: we assume that the change rate between t_1 and t_2 is linear and derive a linear function between each pair of values in time (Equation 1) (See Brum-Bastos et al. 2016 for more details).

$$v_{t_n} = \left(\frac{v_{t_2} - v_{t_1}}{t_2 - t_1}\right) . t_n + \left[v_{t_1} - \left(\frac{v_{t_2} - v_{t_1}}{t_2 - t_1}\right) . t_1\right] \quad (1)$$

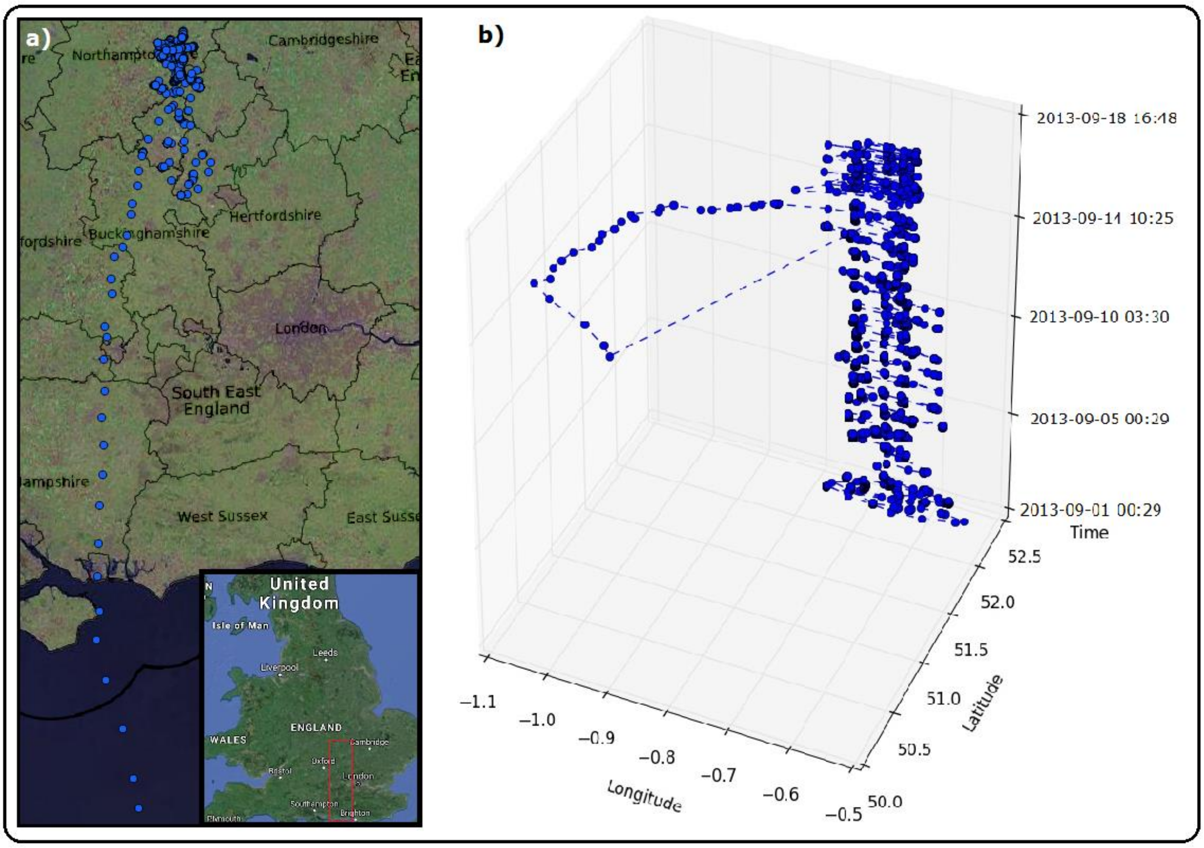

Figure 2. Temporal and spatial location of Harrys' trajectory. a) 2D visualization on UK base map: blue dots represent the recorded GPS points; b) 3D visualization with time dimension (timestamps): blue dots represent the recorded GPS point and the dashed line is the likely trajectory between each point.

In the next step the trajectory was split into subsets according to the following rainfall rate intervals, defined accordingly to the Met Office chart for rain classification: 0 mm/h, between 0.01 mm/h and 2.00 mm/h, between 2.01 mm/h and 4.00 mm/h, between 4.01 mm/h and 8.00 mm/h, between 8.01 mm/h and 16.00 mm/h, between 16.01 mm/h and 32.00 mm/h and > 32 mm/h. Descriptive statistics were calculated for each one of the intervals in order to preliminary assess how rain affects Harrys' flight speed.

3. Results and discussion

Table 1 displays the descriptive statistics for Harry's trajectory and respective rainfall rate bands. The trajectory has 1806 GPS points, of which 86.00% recorded under *Rainfall rate = 0* and presenting the highest maximum speeds for all axes, as would be expected. The remaining points show lower speeds with the increase of the rainfall rate band. It is interesting to note that there is almost no change on the minimum values across the bands, which probably happened because of the presence of not only active GPS points (during flight) but also resting (at nest). The classification of the GPS points into active and inactive or the use of a buffer around the nesting spots could facilitate the analysis of the rainfall rate influence and improve any further CAMA.

Table1. Summary of descriptive statistics for speed and rainfall rates for Harry's trajectory

Rainfall rate = 0					*Rainfall rate between 0.01 and 1.00*				
% of points	0.86				% of points	0.01			
	Average	Min	Max	StD		Average	Min	Max	StD
Speed in X	1.75	0.00	51.97	2.85	Speed in X	3.70	0.07	14.08	4.36
Speed in Y	1.29	0.00	16.14	2.23	Speed in Y	1.79	0.07	8.49	2.41
Speed in Z	1.50	0.00	24.57	2.26	Speed in Z	2.82	0.07	10.68	3.00
Rainfall rate between 1.01 and 2.00					*Rainfall rate between 2.01 and 4.00*				
% of points	0.01				% of points	0.01			
	Average	Min	Max	StD		Average	Min	Max	StD
Speed in X	1.04	0.01	7.90	2.05	Speed in X	3.05	0.04	12.76	3.28
Speed in Y	1.19	0.03	6.76	1.85	Speed in Y	1.67	0.06	7.92	1.99
Speed in Z	1.62	0.11	8.44	2.30	Speed in Z	1.96	0.03	6.94	2.11
Rainfall rate between 4.01 and 8.00					*Rainfall rate between 8.01 and 16.00*				
% of points	0.04				% of points	0.04			
	Average	Min	Max	StD		Average	Min	Max	StD
Speed in X	1.15	0.01	13.49	2.12	Speed in X	0.95	0.00	4.96	0.97
Speed in Y	0.98	0.00	10.02	1.71	Speed in Y	0.74	0.00	5.53	0.92
Speed in Z	1.15	0.00	10.59	1.66	Speed in Z	1.12	0.01	7.03	1.39
Rainfall rate between 16.01 and 32.00					*Rainfall rate > 32.01*				
% points	0.01				% of points	0.03			
	Average	Min	Max	StD		Average	Min	Max	StD
Speed in X	1.65	0.00	16.19	2.61	Speed in X	1.84	0.04	7.52	2.61
Speed in Y	1.02	0.00	8.07	1.49	Speed in Y	1.35	0.02	2.94	1.49
Speed in Z	1.15	0.02	9.15	1.55	Speed in Z	1.76	0.01	7.88	1.55

Despite of the low percentage of points within the Rainfall rate bands > 0, the Maximum speed in all axes show that there is a reduction on the flight speed when it is raining. However, the other statistics are not so conclusive, as they are biased by the resting points.

4. Conclusions

The Maximum speed in all axes show that there is a reduction on the flight speed when it is raining, i.e. the rainfall rate as a contextual environmental variable in CAMA has a negative effect on the Harry's speed. We are aware that the sample size was not enough to generalize the results for the whole species and also this was not our intention with this paper.

We wanted to encourage the interdisciplinary dialogue between remote sensing and movement research, showing once more how RS is powerful in providing environmental data of quality which can be incorporated into CAMA; and how movement research and CAMA are a fertile application domain for well-established and new RS techniques and data. Despite of the apparent high complexity that sometimes put away movement researchers, remote sensing has a lot to offer to a new application domain like movement research. Operations considered really basic for remote sensing experts can solve movement questions that have been posed but still unsolved because of RS technical difficulties. We believe that a better interpenetration between RS and movement scientific community will benefit both sides and helping movement research to grow towards more efficient CAMA and new research questions.

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