Where does a seagull spend its day? Overcrowded diagrams don’t help you to see it. More cunning designs show it all clearly. Urška Demšar and Emiel van Loon describe how visualising the geography of time and movement supports the study of animal ecology.

James is training for a marathon. On his daily run he takes a bottle of water, a couple of energy bars and his mobile phone. He makes sure that the GPS is turned on. Back at the computer, he logs on to the mapmyrun.com website and uploads the running track from his phone to analyse the distance and time he covered. And he is not the only one. With the increasing availability of positioning technology, such as GPS receivers in every mobile phone, more and more people are collecting data that describe their movement. Similarly, more and more scientists are collecting information about moving objects. Urban planners are interested in how pedestrians are using various routes in the city; transport engineers want to study traffic flow; meteorologists track hurricanes. No matter what the moving object is, data about it comes in the form of trajectories: sequences of times and places, which are measured in either two or three dimensions of space. Improvements in technology allow these measurements to be collected at finer and finer scales – by the hour, by the minute, several times a second if you really want it that way; and it all provides scientists with unprecedented details in the data that can be used for analysing movement behaviour. One of the ways to analyse this information on movements is to display the trajectories on a geographic map. The only trouble is, what if there are too many trajectories?

Figure 1a shows a map of the movements of a single seagull collected over one month. There are 30 separate trajectory lines in it, one for each day. It is very difficult – let us be honest, it is next to impossible – to identify any patterns in its movement. It is not for nothing that such diagrams are sometimes called ‘spaghetti maps’. Imagine having thousands or tens of thousands of trajectories instead – which is a not unusual size for a contemporary trajectory data set. How do you display these whilst still being able to recognise anything from the map?

**Figure 1.** (a) Daily tracks of the movement of one lesser black-backed gull (*Larus fuscus*), breeding on Texel (the Netherlands) in June 2010. For more details, see [http://www.uva-bits.nl](http://www.uva-bits.nl). (b) Space–time cube of same tracks as Figure 1(a). The x–y plane is a landuse map of a part of the Netherlands. The z-axis represents time of day (given in seconds), the bottom and top of the z-axis are midnight and 43 200 s is midday.
Ecology is a discipline where the visualisation of large amounts of movement data is highly important. Organisms move through the environment, either actively or passively, and this movement is a key element in their survival, their ecology and their evolution. This has long been recognised. However, as with many other processes in ecology, the study of movement was, until a decade ago, subject to technological limitations of data collection. It wasn’t easy to track animals’ movements either frequently or precisely. But developments in bio-logging and telemetry equipment have been fast, not to say astonishing – you can put micro-tracking devices on creatures as small as bumble-bees nowadays; and the data limitations of the past have changed into a ‘data deluge’ (Bouten et al. 2013). As a result, in a typical ecological study it is no longer feasible to browse, select, interpret and annotate single observed trajectories. Instead we need new automated and visual tools to deal effectively with the whole mass of them. In particular we need visual tools to prevent misinterpretation of results of automatic algorithms or to explore and learn from the data. This is where collaborations between ecologists, as experts in animal behaviour, and people such as geoinformaticians, who are experts in methods of displaying it, are becoming indispensable.

The challenge for visually exploring data about movement is to highlight those aspects of trajectories that are important while omitting the irrelevant parts. In our study, (http://www.uva-bits.nl) gull trajectories are part of a much larger data set, and are being collected to learn more about their foraging movements, time budgets and habitat preferences. We wanted to find out whether there are any cyclic (specifically here, daily) patterns in the gull’s movements, since these would indicate a regularity in available resources – and would show as well that an individual gull had knowledge of that regularity. This in turn would have an important impact on such things as breeding success.

So we needed an appropriate way to visualise the daily paths of the gull. We built a team of a geoinformatician, a mathematician and two ecologists (Demšar et al. 2013). In our visualisation we combined two approaches: a three-dimensional representation of movement space in a so-called ‘space–time cube’ (STC) and a well-known point-mapping approach called ‘kernel density estimation’ (KDE).

The space–time cube is not new: it was introduced in the late 1960s by a Swedish geographer Torsten Hägerstrand, who is well known for establishing the theory of time geography (Hägerstrand 1970). The cube is a visual representation of the principle that geography – space in other words – and time are inseparable in movement analysis. It is built as a three-dimensional coordinate system, where the x–y plane represents a geographic map and the z axis represents time. Trajectories of moving objects are drawn into this cube as lines connecting observations of location, forming the so-called ‘space–time paths’ (Figure 1b).

Figure 1b shows the trajectories of Figure 1a transferred to a space–time cube. Here, time is represented vertically. The floor of the cube represents midnight, the mid-level (at 43,200 seconds) is midday, and the top surface is the following midnight – after which the next day starts again at the bottom. (There are 86,400 seconds in a day. Hours might have been a more convenient scale.) Each track shows the daily movement of our gull as it flies around north Holland. As before, there are 30 tracks in all, for its movements over a month.

The space–time cube is a great improvement on the two-dimensional spaghetti map; but it still suffers from the same overprinting problem when it tries to show more than a very few trajectories at once. It is slightly easier to see what is happening, but it is still far too complex to grasp it fully. The answer to this problem is to aggregate the trajectories: to combine the 30 different lines into surfaces, or volumes, or clouds.

This is where kernel density estimation comes in. It is not new either; it is a well-known method for aggregating – smearing out, if you like – a set of points on a two-dimensional plane (Silverman 1986) so that the data covers the whole plane. It is often used to make heat maps. Fundamentally, on a heat map the hottest, reddest areas represent places where data-points are most closely clustered together; the coolest, bluest areas are where data-points are scattered far apart. We extended this concept to three dimensions and applied it to our space–time cube. Regions where trajectory lines in the cube run close together are given a high value, or a hot colour; regions of few lines widely spaced get low values.

An analogy would be to imagine each trajectory line in Figure 1b as a wire carrying a current. The magnetic field around the wire falls away with distance from the wire – but where two wires are close to each other, their magnetic fields add up. Adding up all the magnetic fields, from all the trajectory lines, gives an overall picture of the way that the wires are distributed.

That, in effect, is what our kernelisation of the dozens of trajectory lines has done. It has summed them, to give a single value for each point in our cube. Each value represents a density of trajectory lines, or a frequency of the gull being in a particular place at a particular time. Together they make up a density space. We still have the problem of representing those values in our diagram.

We could represent them as a heat map with different colours. Filling a 3-dimensional space with colours so that you can still make sense of it is not straightforward, but it is possible. Figure 2a shows such an attempt. The two columns show that there are two favoured areas where the gull generally likes to be. The red and yellow regions show the times of day that it most frequently visits. The blue clouds linking the columns show that it flies between them several times in the course of each 24 hours.

We could also represent our values as a 3-dimensional equivalent of a contour map, using iso-surfaces – which are surfaces that links all the points in the cube that have the same density value; these are the 3-dimensional equivalent of contour lines. Figure 2b shows one iso-surface, a high-probability one; and here at last the picture becomes beautifully clear. At night-times (top and bottom of the cube) the gull is mainly at its favourite place on the mainland; daytimes it spends on the island.

These representations of course are on paper. On screen we can use software to interact with these three-dimensional densities, rotate them, choose different iso-surfaces and renderings and visually explore them from all angles to detect more easily the patterns in these aggregations of movement.

This new visualisation allows us to see patterns of movement in space and time that cannot be distinguished in a two-dimensional display. Two examples of such patterns are spatio-temporal hotspots and spatial-only hotspots. A
spatio-temporal hotspot is an area where several moving objects come together at the same time and place (or, when aggregating daily trajectories as in our gull example, an area that an animal consistently visits at the same time every day). These appear as areas with highest values in the density volume – the yellow and red parts of Figure 2a. Spatial-only hotspots on the other hand represent areas visited by many objects, but never at the same time. These show up as columns, as in Figures 2a and 2b, but do not overlap enough to build a high-density area. To distinguish between these two types of hotspots is of interest to ecologists, as they can be linked to patterns in the temporal dynamics of space use by an animal.

The pattern for our particular gull was unexpected. There are two spatio-temporal hotspots (Figure 2). We expected the daytime one, on the island of Texel; that is where its colony and its nest is. The other hotspot, the right-hand column, is a nocturnal one. (It is split into the top and bottom parts, which cross at midnight). This shows intensive use by this bird of a location on the mainland around midnight. This was surprising: in previous data explorations visits had appeared much more irregular. This favourite spot was of course a feeding ground, and Figure 2a shows the gull flying several times a day between the feeding ground and the nest, clearly with food for its young. It triggered a more detailed investigation into the synchrony of nest-attendance by this bird and its breeding partner. To be unromantically specific, a field-check was made; this favourite feeding ground was revealed to be an old garbage dump.

Down to earth, perhaps; but a key part of the lives and ecology of gulls, and it was the visualisation that revealed it. These diagrams can identify other unexpected patterns in movements and help new hypotheses about animal behaviour, which field work and statistical models can verify or reject.

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References


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