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Editor

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Editor

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Wavefront Deformation Particle Tracking

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Waypoint Detection

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Synonyms

[Landmark detection](#); [Key point detection](#)

Definition

Animals are frequently required to navigate accurately from one location to another. The means an animal uses to perform a navigational task depends on the available environmental cues, their specific sensory systems, and particularly whether they are in a familiar or unfamiliar area. A *familiar area* can be defined as one of which the animal has extensive experience, leading to detailed knowledge of the environment and available navigational cues.

Waypoints are geostationary locations used by an animal to navigate in a familiar area. Specifically they are small-scale regions of space that the animal returns to as part of the navigational task. A waypoint may be

associated with a memorized *landmark* which allows the animal to identify the waypoint from a distance and direct itself toward it. Navigation toward an eventual goal may involve visiting an ordered succession of waypoints finishing at the final location – this mechanism is generally referred to as *pilotage*. Alternatively waypoints may be a by-product of navigational constraints imposed by the environment; if, for example, the goal can be reached only by passing through a narrow passage, that passage will act as a waypoint.

While waypoints may be associated with landmarks – recognizable sensory features such as prominent visual cues or memorable odors – the task of waypoint detection is not in general synonymous with landmark detection. Landmarks may be identified and used by the animal at a distance, without necessarily visiting the landmark's true location. Conversely, as noted above, a waypoint may exist independently of any memorable feature. Instead, waypoints are more accurately defined as importance regions of space and segments of movement paths, whose salience may be the result of a variety of cues and constraints, which cause discernable effects upon the animal's movement.

Waypoint detection is the task of identifying waypoints from observations of the animal's movements. Since the definition of a waypoint requires the animal to return to the specific area, this therefore constitutes a classification task, identifying the segments of the animal's movement trajectory, or *path*, that correspond to waypoint locations. This entry gives an overview introduction to the purpose and methods of waypoint detection, examining three methods for isolating particularly salient elements of movement paths.

Purpose

The principle purpose of detecting waypoints is to understand what drives and facilitates navigation. It is a way of identifying important areas which may contain salient information the animal uses to recall a memorized path or important resources the animal must utilize. Examples of this might include visually striking features, high food concentrations, or unseen constraints on the animal's movement (strong wind patterns acting on flying creatures, for instance). Waypoint detection can be useful for biomimicry, allowing both an understanding of how animals use key features to navigate and replication of this process in artificial navigating agents such as robots.

In the literature, waypoint detection has been used as the basis for understanding which features animals attend to in the landscape [6, 7, 10], determining the extent of an animal's knowledge of the area [5] and determining where animals forage [1, 4]. The technique of isolating important regions of the path for further analysis is a basis for linking animal movement behaviors and the surrounding environment, such as the landscape, sensory cues, and other animals, by determining what the environmental conditions are in the spatial and temporal vicinity of the detected waypoints.

Three Methods for Detecting Waypoints

Specific identification of waypoints from recorded animal movements is a novel task, and there are consequently few formalized examples in the scientific literature that deal explicitly with this problem. However, the likely existence of waypoints in specified regions of space is implicit in several analyses of movement paths. The three principle methods for identifying these spatial regions can be broadly classified as:

- Localized variability *between* multiple movement paths – *Path similarity*
- Changes in speed and direction *within* a single path – *Path complexity*
- Information content of a path segment – *Path predictability*

This entry describes these methods largely in the context of experiments on homing pigeons, where the use of global positioning satellite (GPS) devices has

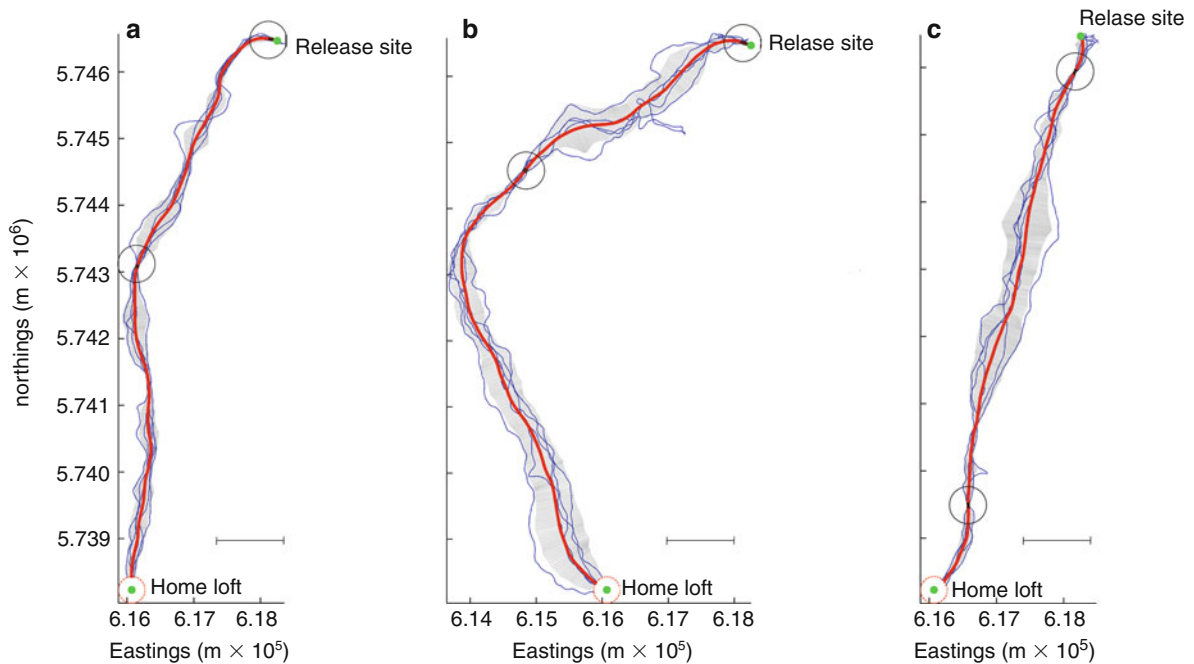
created a huge amount of data calling for novel analysis. This has led to the development of methods for path analysis, which are generalizable and applicable to movement paths from other species.

Path Similarity

Path similarity presents an intuitive method for waypoint detection. The principle property of a waypoint is that it is a *restricted* region of space which the animal will pass through on its way to the objective. A waypoint therefore is likely to present itself as a relatively small region of space to which the animal repeatedly returns. In this case it is likely, though not guaranteed, that the movement paths of the animal will be significantly more similar in the vicinity of the waypoint, since their freedom to vary is constrained, than outside these regions where the animal's movements may vary more widely. Increasing path similarity over time has been linked to the emergence of detailed visual memories of the landscape and the use of pilotage as a navigational strategy [2, 3, 12].

To use path similarity objectively requires an algorithmic measure of the variability between different paths. To identify specific regions of space demands a *localized* measure – one that varies through space – rather than a *global* measure which relates the overall similarity of the paths. Here several options present themselves. None can be considered the sole correct way to measure variability, nor are these options exhaustive. Different measures of variability are necessarily highly correlated but the specific choice depends on the exact nature of the analysis. The basic principle is to measure the spatial separation between paths within some localized region. For this purpose it is helpful to define the concept of the *nearest-neighbor distance* (NND). This is the distance from a point on one path to the closest point on another. Using this distance allows the path separation to be determined in a purely spatial manner. The alternative approach of measuring the distance between paths *at the same point in time* measures a spatiotemporal separation. Ordinarily it is purely spatial separation that best describes the expected effect of waypoints.

A simple means of calculating path separation is to measure the NND from every point on a path to every other path. The value of the separation can then be taken as the mean, median, minimum or maximum of



Waypoint Detection, Fig. 1 Five flights each from three pigeons (light blue) showing the calculated mean path (bold red), variance around the mean path (grey band), and location of areas of peak route similarity (black circles). The peak similarity regions correspond to variance below a threshold value.

Each peak similarity region can contain multiple successive points, but for clarity only one circle is shown per region (Reprinted from [5], Copyright [2010], Creative Commons open access license)

these values as desired, giving a value for separation at every position along the path. This provides a measure of separation along each path, but not a single description of the overall separation of all the paths as a single variable, which may make it difficult to identify single points where variation is low. This may be ameliorated by the fact that areas where the separation is low will also be areas where the paths are very close, so regions of low variability will be spatially restricted.

It is also possible to measure a single value of separation, using variation around a constructed *mean path*. A mean path is a single path that is representative of the full set of paths. As with path separation there is no absolute way to construct such a path. In analogy with the mean of a set of scalar variables, a mean path can be constructed to minimize a particular measure of separation relative to the original paths, much as the scalar mean minimizes the square distance between itself and the original variables. This approach is used, for example, by Freeman et al. [5], where a mean path is generated which minimizes the total nearest-neighbor separation from itself to the true paths. Constructing such a path may require an iterated

approximation method rather than a direct calculation. See Fig. 1 for examples of constructed mean paths and mean path similarity in relation to the original paths. Similarly to the case where path similarity is calculated along each route, the mean path will be most representative of the true paths in regions of peak similarity, which correspond to waypoint locations. Therefore, having calculated similarity along the mean path, one can be sure that the waypoints identified from this similarity will be in approximately the correct spatial location.

A related approach is that used by Lipp et al. [8], for investigating the propensity of pigeons to follow roads and other linear features. Here the spatial area containing the paths is segmented into a two-dimensional grid. The number of paths passing through each grid element is recorded and compared with a null hypothesis for the distribution of paths (see [8] for an example of generating an appropriate null hypothesis). In the original paper, the analysis demonstrates that grid elements containing roads also contain significantly more paths than expected. The converse argument can also be applied – grid elements

containing more paths than expected (judged by some significance test) are likely to contain waypoints. The disadvantage of this method is the difficulty in striking a balance between the size of the grid and the density of paths. If the grid elements are too small there will be few paths in any single element and it will be impossible to distinguish from the null hypothesis. If the grid elements are too large, the resolution will be limited to the size of the element, making it difficult to pinpoint the location of the waypoint accurately.

Path Complexity

Less intuitive than path variability, but applicable even when only a single path is observed, path complexity segments the movement path into regions of high and low localized complexity. Increased complexity can be an indicator of waypoint location since waypoints may be associated with decision points, where the animal must first adjust its heading to reach the waypoint and subsequently readjust again to direct itself toward the next objective. Conversely when the animal is far from any known locations, it would be expected to follow a smooth path since there is no external cue available to correct the heading and any other variation would lead to unnecessary energy loss.

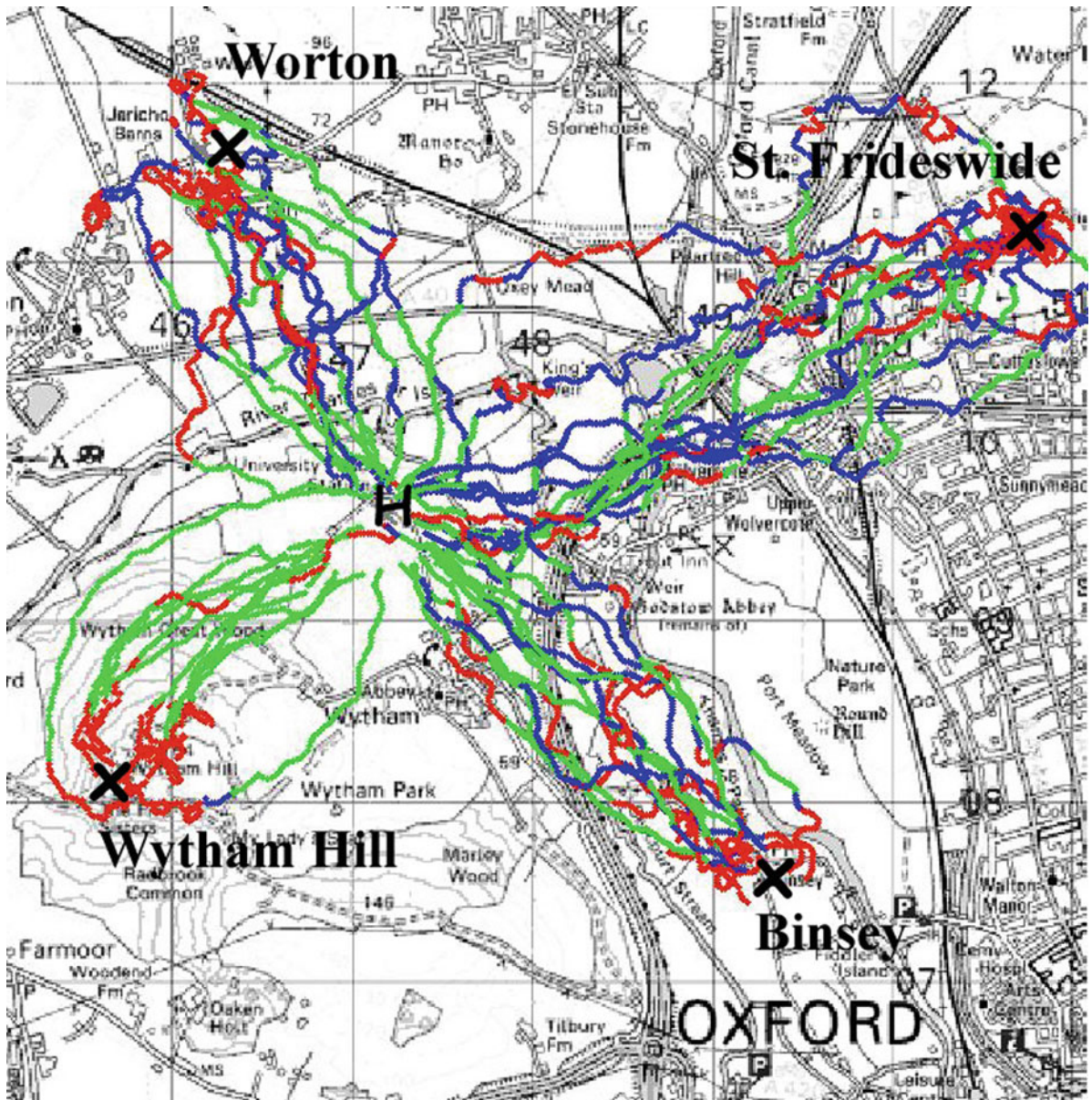
The complexity of a path segment can be viewed as a measure of how much information is required to describe it. A straight line or a very smooth curve can be described simply by stating the end points and the degree of curvature. A segment whose curvature is constantly changing, which may change direction discontinuously or which returns back to a previously covered point (looping) will require far more information to adequately describe. To understand the relationship between complexity and information, imagine having to describe a path segment to someone who is unable to see it, well enough that they could draw it themselves. The more details that are required to convey that path segment, the more complex it is.

As with path similarity, path complexity can be measured in a variety of ways, which are similarly highly correlated with each other. These range in abstractness from *tortuosity*, the local degree of inefficiency in the path, to the highly abstract concept of spatiotemporal positional entropy introduced by

Roberts et al. [13]. Figure 2 shows a plot of a number of recorded movement paths, color-coded by the local degree of complexity, to demonstrate how high complexity and low complexity path segments present themselves visually. Each path is segmented into low-, medium-, and high-complexity regions, using positional entropy as a measure of complexity. In the figure, it can be clearly seen that low complexity (green) regions are smooth, with low curvature and few if any sharp changes of direction. High-complexity (red) regions often include loops, sharp turns, and many changes of direction. The medium-complexity (blue) regions lie between these extremes. The figure also shows that high-complexity regions are often short, indicating some local effect on the path, and occur particularly around the release point, when the pigeons are deciding on a heading to take.

Another similar measure that has been used to detect foraging within movement paths is *passage time*. This is amount of time taken by an animal from the moment when it enters a (typically circular) region of space to the moment when it leaves. This can be measured as the first passage time [4, 11] – the time from first entering to first leaving the region or total passage time [1] – the time from first entering to the final time leaving. This is strongly related to path complexity, since highly complex, inefficient path segments with lots of changes of direction will have high passage times. The use of passage time to detect foraging within directed movement is broadly analogous to waypoint detection, since foraging stops within a directed path will form waypoints by virtue of the concentration of the food source.

Complexity measures have associated spatiotemporal scales which must be appropriate for the detection task. Tortuosity is measured as the inefficiency of a path segment, the length must be selected. Likewise positional entropy measures the complexity of a moving segment of the path. Passage time is measured with respect to a spatial region whose size must be chosen. These scales must bear in mind the classic trade-off between resolution and signal-to-noise ratio; the smaller the scale, the more fine structure will be detected and the more tightly determined will be the position of identified waypoints. Longer scales improve the signal-to-noise ratio by filtering out high-frequency noise from the behavior but also reduce the resolution of the measurement.



Waypoint Detection, Fig. 2 Identified regions of low (green), medium (blue), and high (red) complexity in a variety of homing pigeon flight paths, as determined by positional entropy (Reprinted from [6], Copyright [2004], with permission from Elsevier)

Variation in complexity measures has been suggested to correlate with changes in the animal's behavioral state [1, 2, 4, 6, 11] and to segment the path into distinct behavioral phases [1, 6, 13] supporting the use of complexity to identify key path segments that may correspond to waypoint locations. Path complexity has also been linked to the surrounding visual environment [7], indicating

that the waypoints identified may correspond to visual landmarks, as expected under the pilotage hypothesis.

Path Predictability

Path predictability differs distinctly from the previous two approaches since it uses complete movement paths

in a global analysis, rather than examining only localized properties of the paths. Waypoints are selected as those segments of the path that can be used to provide the best prediction of the complete path and other paths (where these exist). The logic of this approach depends on the hypothesis of navigation by *pilotage*. This hypothesis claims that the animal makes its way from its original position to its final objective by successively visiting an ordered sequence of fixed waypoints, as per the definition above. The path predictability method argues that if this hypothesis is accurate, the path(s) of the animal must be defined by the locations of those waypoints, the segments between waypoints being subject to constraints such as energy minimization and random variation from environmental and internal factors. These waypoints are thus analogous to the fixed positions in a curve-fitting exercise, with the constraints given above acting similarly to the constraint of curvature minimization in spline fitting. The upshot of this is that those segments of the path(s) close to the waypoints should provide the maximum amount of information about the rest of path(s).

Similarly to path complexity, path predictability is intimately linked to information. Consider trying to convey to someone not just a path segment but instead a set of complete paths. Now imagine that the only information you are allowed to send is the position of the paths at a small set of times. If your friend subsequently “joins the dots” to link these points, how well will they approximate the true paths? The most informative, or predictive, locations are those that allow the best estimate of the real paths using this technique.

Technically, the information contained in a path can be defined how it affects the probability of another path. If path B is informative about path A then the probability of path A will increase as a result of knowing path B. Mathematically, the information contained in path B about path A is related to the ratio of probability of path A, conditional on knowing path B through some model M, compared to the probability of path A when B is unknown. Information is defined as the log of this probability ratio:

$$\begin{aligned} \text{Information}(A | B)/\text{bits} &= \log_2 \\ & \frac{P(\text{path A} | \text{path B}, M)}{P(\text{path A} | M)} \end{aligned} \quad (1)$$

The probability $P(\text{path A} | \text{path B}, M)$ depends on the choice of model. A simple model might be that each point

on path A should be the same as on path B at the equivalent point in time, give or take some amount of Gaussian noise to account for natural variation. More realistic models should take account of the correlations over time that lead to the spatial structure of the path. Mann et al. [10] provide a more sophisticated model choice implemented via the use of Gaussian processes, allowing for autocorrelation within the path over time as well as the correlations between paths. In this implementation, all paths are assumed to be samples from a distribution centered on a mean path – similar to the mean path defined as part of the path similarity measure. Constructing a model to describe the probability distribution of movement paths is a complicated task which is not readily reducible to a simpler scheme. This task is necessary, however, to specify the mutual information contained between paths and between elements of the same path and thus to be able to use path predictability as a measure. See Mann et al. [10] for guidance on model construction.

Having defined a model and therefore a probability distribution from one path to another, the task of identifying the waypoints can be clarified as follows. Path B will be a recorded path, with positions recorded at a set of time points, t . Let t' be a subset of those timesteps such that path B' is the recorded positions at times t' . The information in those positions is calculated as

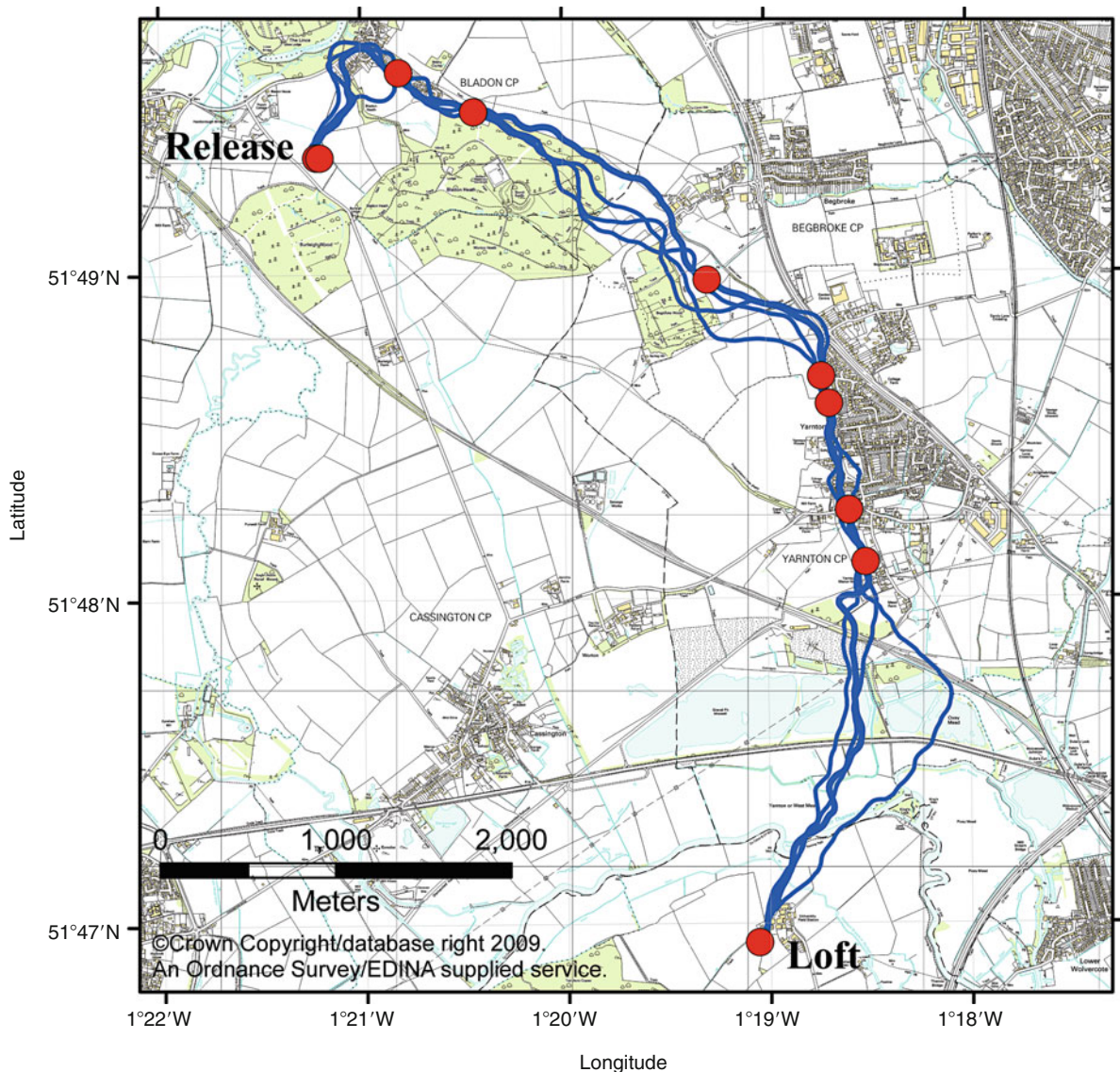
$$\begin{aligned} \text{Information}(t') &= \text{Information}(A | B') \\ &= \log_2 \frac{P(\text{path A} | \text{path B}', M)}{P(\text{path A} | M)} \end{aligned} \quad (2)$$

Having hypothesized that waypoints correspond to the most informative segments of the path, the task is now rephrased as finding the subset of t , t^* , that maximizes Eq. 2,

$$t^* = \text{argmax}_{t'} \text{Information}(t') \quad (3)$$

Finding a limited number, m , of waypoints can be accomplished simply by searching for the t^* restricted to subsets of size m . Optimization of Eq. 2 can be accomplished by “greedy” forward selection, gradient ascent, Monte Carlo sampling, or other established optimization techniques. Standard texts on learning algorithms, for example, [9], can provide comprehensive details of optimization algorithms.

Predictability between different paths tends to be maximal under two circumstances. The first is in regions



Waypoint Detection, Fig. 3 Ten waypoints identified from five flight paths from a single homing pigeon, using path predictability as a criterion. The waypoints are identified preferentially in flight segments that a similar between paths, where the

path exhibits high complexity and where the path is far from the most efficient straight “beeline” between start and finish (Reprinted from [10], Copyright [2010], Creative Commons open access license)

where the two paths are very similar. Here knowing one path gives good information about the likely location of the other. This then is similar to the path similarity criterion. The other case is where the location of the path is highly unpredictable either a priori, or conditional on the other chosen waypoints. Locally this bears a resemblance to the path complexity measure, but also takes account of the global unpredictability – for example finding path segments that are locally smooth but

globally far from the straight-line path between start and finish. This corresponds to an intuitive analysis of the path. If the bird consistently flies to a location far from the most efficient route this is unlikely to be due to chance; there must be a waypoint at this location.

Figure 3 shows an example of waypoints selected by maximizing the path predictability, taken from Mann et al. [10]. In this demonstration, the number of selected waypoints is ten and the information in Eq. 2

is maximized by forward selection. It can be seen from this example that the selected waypoints each exhibit at least one of the three properties that maximize information content. Many of the waypoints are located where the paths coalesce into narrow corridors, exhibiting high path similarity. Others are located where the paths turn sharply, which correspond to high path complexity. Finally there are waypoints located in the regions furthest from the most efficient beeline path, at the apex of the curve, which is the most unlikely area for the pigeons to visit a priori.

Summary

Detection of waypoints in recorded movement paths is a novel problem that has potential future applicability in studies of animal movement and biomimicry. The methods described in this entry constitute a basis for identifying important regions of the movement path based on hypotheses about the likely effects of waypoints upon the animal's movement. These methods span a range of mathematical complexity and intuitive applicability. More recent developments such as the path predictability tend toward higher levels of abstraction. The methods explored in this entry are not mutually exclusive and combinations should be explored to achieve the best detection results. With animal movement tracking still developing as an experimental field, methods for the analysis of recorded data are being created in parallel and the development of further methods for identifying salient regions from movement paths can be expected in the near future.

Cross-References

- ▶ [Biomimetics](#)
- ▶ [Nanoparticle Tracking Analysis](#)

References

1. Barraquand, F., Benhamou, S.: Animal movements in heterogeneous landscapes: identifying profitable places and homogeneous movement bouts. *Ecology* **89**, 3336–3348 (2008)
2. Biro, D., Guilford, T., Dell'Omo, G., Lipp, H.-P.: How the viewing of familiar landscapes prior to release

- allows pigeons to home faster. *J. Exp. Biol.* **205**, 3833–3844 (2002)
3. Biro, D., Meade, J., Guilford, T.: Familiar route loyalty implies visual pilotage in the homing pigeon. *Proc. Nat. Acad. Sci.* **101**(50), 17440–17443 (2004)
4. Fauchald, P., Tveraa, T.: Using first-passage time in the analysis of area-restricted search and habitat selection. *Ecology* **84**, 282–288 (2003)
5. Freeman, R., Mann, R., Guilford, T., Biro, D.: Group decisions and individual differences: route fidelity predicts flight leadership in homing pigeons (*Columba livia*). *Biol. Lett.* **7**(1), 63–66 (2010). Advance online publication
6. Guilford, T., Roberts, S., Biro, D., Rezek, I.: Positional entropy during pigeon homing II: navigational interpretation of Bayesian latent state model. *J. Theor. Biol.* **227**(1), 25–38 (2004)
7. Lau, K.-K., Roberts, S., Biro, D., Freeman, R., Meade, J., Guilford, T.: An edge-detection approach to investigating pigeon navigation. *J. Theor. Biol.* **239**(1), 71–78 (2006)
8. Lipp, H.-P., Vyssotski, A.L., Wolfer, D.P., Renaudineau, S., Savini, M., Tröster, M., Dell'Omo, G.: Pigeon homing along highways and exits. *Curr. Biol.* **14**, 1239–1249 (2004)
9. Mackay, D.: *Information Theory, Inference and Learning Algorithms*. Cambridge University Press, Cambridge (2003)
10. Mann, R., Freeman, R., Osborne, M., Garnett, R., Armstrong, C., Meade, J., Biro, D., Guilford, T., Roberts, S.: Objectively identifying landmark use and predicting flight trajectories of the homing pigeon using Gaussian processes. *J. Roy. Soc. Interface.* **8**, 210–219 (2011)
11. McKensie, H.W., Lewis, M.A., Merrill, E.H.: First Passage time analysis of animal movement and insights into the functional response. *Bull. Math. Biol.* **71**(1), 107–129 (2009)
12. Meade, J., Biro, D., Guilford, T.: Homing pigeons develop local route stereotypy. *Proc. Roy. Soc. B.* **272**(1558), 17–23 (2005)
13. Roberts, S., Rezek, I., Guilford, T., Biro, D.: Positional entropy during pigeon homing I: application of Bayesian latent state modelling. *J. Theor. Biol.* **227**(1), 39–50 (2004)

Wear

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