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A new multi-scale measure for analysing animal movement data

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HIGHLIGHTS

- ► We introduce a new multiscale measure (MSSI) for analysing animal tracking data.
- ► MSSI is a generalisation of 'Straightness Index' over all possible temporal scales.
- ► One major advantage of MSSI is the simplicity of its computation.
- ► We demonstrate the use of MSSI on synthetic and real animal movement data.
- ► MSSI provides information about behaviour over multiple spatio-temporal scales.

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ABSTRACT

We present a new measure for analysing animal movement data, which we term a 'Multi-Scale Straightness Index' (MSSI). The measure is a generalisation of the 'Straightness Index', the ratio of the beeline distance between the start and end of a track to the total distance travelled. In our new measure, the Straightness Index is computed repeatedly for track segments at all possible temporal scales. The MSSI offers advantages over the standard Straightness Index, and other simple measures of track tortuosity (such as Sinuosity and Fractal Dimension), because it provides multiple characterisations of straightness, rather than just a single summary measure. Thus, comparisons can be made among different segments of trajectories and changes in behaviour can be inferred, both over time and at different temporal granularities. The measure also has an important advantage over several recent and increasingly popular methods for detecting behavioural changes in time-series locational data (e.g., state-space models and positional entropy methods), in that it is extremely simple to compute. Here, we demonstrate use of the MSSI on both synthetic and real animal-movement trajectories. We show how behavioural changes can be inferred within individual tracks and how behaviour varies across spatio-temporal scales. Our aim is to present a useful tool for researchers requiring a computationally simple but effective means of analysing the movement patterns of animals.

1. Introduction

Understanding the causes and consequences of animal movement and how it relates to internal states and environmental variability is a subject that over the last decade has captured the attention of many researchers (Holden, 2006; Nathan et al., 2008; Schick et al., 2008). Critical to determining what factors drive the movement patterns of animals are the choice of methods for quantifying and analysing movement trajectories. Recent advances in tracking technologies such as GPS and ARGOS satellite telemetry and light-based geolocation methods now permit remote acquisition of large quantities of movement data at hithertofore almost unimaginable spatio-temporal scales. Corresponding with this progress in data-capture techniques are powerful new means of describing and modelling individual movement tracks. However, many of these new analytical tools are mathematically very complex and can be challenging, especially to laypersons, to understand and implement.

One common reason for analysing animal movement data is to discover latent information about behaviour that cannot be observed directly. That is, observed tracks most typically consist only of a series of time-stamped positional information. From such data we easily can compute measures such as inter-fix speeds and turning angles, but often the real interest focuses on characterisation of different *behavioural states* (e.g., resting, commuting, foraging) and how they change over time. How best to make these inferences remains very much an open question.

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Review of the literature reveals a variety of methods for extracting information about behaviour from animal movement data (Schick et al., 2008; Patterson et al., 2008; Guilford et al., 2004; Gurarie et al., 2009). One of the simplest is the *Straightness Index* (Batschelet, 1981) (also known as Path Efficiency)—the ratio of the beeline distance between the start and end of a trajectory to total distance travelled. Other metrics such as Sinuousity (Bovet and Benhamou, 1988), Tortuosity (Benhamou, 2004) and Fractal Dimension (Dicke and Burrough, 1988; Nams, 1996) are more complicated classifications of 'straightness', but still give a single summary value for a track.

A variety of methods for inferring behaviour, and changes in behaviour, within the movement trajectories of animals, have become increasingly popular in recent years. Many popular examples are based on Markov models and Bayesian fitting techniques (Patterson et al., 2008; Jonsen et al., 2003, 2005; Morales et al., 2004). Other examples include first passage time (Fauchald and Tveraa, 2003), residence time methods (Barraquand and Benhamou, 2008) and wavelet-based approaches (Gaucherel, 2011). Guilford et al. (2004) developed an index they refer to as 'Positional Entropy' to describe the directional variability of individual movement trajectories. This latter measure has the advantage that the number of different behavioural states need not be defined *a priori*. However, both this method and Markov models require complex mathematics and programming skills that likely will be challenging for many potential users. Accordingly, these analyses can be difficult to implement. Indeed, although the Guilford et al. paper (Guildford et al. 2004) has been cited at least 23 times to date, to our knowledge, no other researchers have used this analysis for other tracking data, despite the great value it provides for increasing understanding of behaviour.

In this paper, we propose a new measure, which we term a 'Multi-Scale Straightness Index' (or MSSI) that can be used to extract information about behaviour from animal movement trajectories. The MSSI in many ways is similar to the Straightness Index: the only mathematical calculations required are of the same complexity, that is, computation of ratios of distances. Accordingly, the MSSI has an important advantage over the other methods discussed above in that it is easier to implement and use. The MSSI differs from a simple Straightness Index because it computes the straightness of a track multiple times, over a range of all possible scales for both the temporal 'granularity' (i.e., resolution) and observational 'window'. These attributes permit description of a range of trajectory characteristics. For example, within a track it is possible to identify distinct 'events' representative of different behaviours, through identification of changes in the geometric configuration of position information. Furthermore, because the MSSI simultaneously provides information about behavioural changes over multiple spatio-temporal scales, it is possible to identify scale-dependent variation in behaviour. This is a valuable attribute of the MSSI, as characteristion of behaviour within movement data can be strongly dependent on its spatio-temporal grain and extent (Gaucherel, 2011; Laube and Purves, 2011; Amano and Katayama, 2009; Fryxell et al., 2008; Pinaud, 2008; Wilson et al., 2007).

The remainder of this paper is organised as follows. In Section 2 we explain how the MSSI is calculated, and in Section 2.2 we compare the MSSI with other indices and explain important similarities and differences between them. In Sections 3 and 4 we give examples of the use of the MSSI on various tracking datasets. First, we use synthetic trajectories to show how particular characteristics of the track data can be identified by the MSSI. In particular, we first show how to measure the signal-to-noise ratio in an otherwise straight track, and second, we use the MSSI to identify differences between area-restricted and commuting behaviours. We then use real track data from two animal species to demonstrate how behavioural changes within individual trajectories can be detected, and how behaviour varies across different spatio-temporal scales. Section 5 concludes.

2. Methods

In this section we define the multi-scale straightness index (MSSI). The basic idea is that the MSSI gives a ratio of the beeline distance between two points, and the total distance travelled by an animal between those two points. The difference between the MSSI and the standard Straightness Index (Batschelet, 1981) is that we measure this distance over a variety of spatial-temporal scales. That is, the straightness is computed repeatedly by sub-sampling the track data at all possible temporal granularities. In Section 2.2 we show how the previously defined quantities Straightness Index, Area Interest Index and Fractal Dimension reduce to simplifications of the MSSI. In this sense, the MSSI is a generalisation of all of these measures.

2.1. Definition of MSSI

For simplicity, and ease of calculation, we define the MSSI under the following assumptions. We assume that the location estimates comprising tracks are measured at a fixed time interval, that is, the length of time between any two consecutive data points is constant. Thus, we make the implicit assumption that there are no missing data. Almost certainly, these two assumptions are unlikely to hold for empirical animal-tracking data (because of missed fixes and error-screening procedures), but there are simple means of generalising our method so that these assumptions can be relaxed. Such methods could involve interpolation between fixes when the gaps between data points are small, or simply having corresponding 'missing data' in the resulting MSSI when the gaps between data points are larger than a prescribed threshold.

Let the individual location estimates comprising trajectories be given by triplets (x_j,y_j,t_j), for $j=0,\ldots,N-1$, where N is the total number of position fixes in the track. The point (x_j,y_j) is the location of the animal at time t_j, and without loss of generality we let $t_0=0$. For simplicity (as described earlier) we suppose that the time interval between fixes is a constant, s. That is, that $t_{j+1}-t_j=s$, for all j.

We define the granularity, g, as the interval at which we wish to view the trajectory data, and the window, w, as the length of time or 'term' over which we will compute the MSSI. For simplicity, we take both g and w to be integer multiples of s, and we further require that w is an integer multiple of g. It is possible to allow other values of g and w by interpolating between fixes if so desired.

The track spacing s, granularity g and window w are all defined in units of time, and we define the ratios:

$$s_1=\frac{g}{s},\quad s_2=\frac{w}{g},\quad s_3=\frac{w}{s}. \tag{1}$$

which are all integers. We define distances between two points in a trajectory

$$d_j(z)=\left|(x_{j+z/s},y_{j+z/s})-(x_j,y_j)\right|.$$

where z can be either the granularity, g, or the window, w. The MSSI is then defined as

$$S\left(t_j+\frac{w}{2},g,w\right)=\frac{d_j(w)}{\sum_{k=0}^{s_2-1}d_{j+ks_1}(g)}. \tag{2}$$

The first argument of S gives the time at which the MSSI is defined, the second argument is the granularity, and the third in the window. Note that the time is shifted so that it is in the centre