UC Santa Barbara

UC Santa Barbara Previously Published Works

Title

ORTEGA: An object-oriented time-geographic analytical approach to trace space-time contact patterns in movement data

Permalink

<https://escholarship.org/uc/item/9sr6q7d4>

Authors

Dodge, S
Su, R
Johnson, J
et al.

Publication Date

2021-07-01

DOI

10.1016/j.compenvurbsys.2021.101630

Peer reviewed

ORTEGA: an object-oriented time-geographic analytical approach to trace space-time contact patterns in movement data

Somayeh Dodge^{a,*}, Rongxiang Su^a, Jasper Johnson^b, Achara Simcharoen^c,
Konstadinos Goulias^a, James L.D. Smith^d, Sean C Ahearn^e

^a*Department of Geography, University of California Santa Barbara, USA*

^b*Department of Geography, University of Minnesota, Twin Cities, USA*

^c*Conservation Ecology Program, King Mongkut's University of Technology, Thailand*

^d*Department of Fisheries, Wildlife & Conservation Biology, University of Minnesota,
Twin Cities, USA*

^e*Hunter College – CUNY, New York City*

Abstract

This paper uses movement as a marker to study interactions in humans and animals to better understand their collective behaviors. Interaction is an important driving force in social and ecological systems. It can also play a significant role in the transmission of infectious diseases and viruses as witnessed during the ongoing COVID-19 pandemic. Although a number of approaches have been developed to analyze interaction using movement data sets, these methods mainly capture concurrent and dyadic interaction (i.e. when two individuals have direct contact or move synchronously in the spatial proximity of each other). Less work has been done on tracing interaction between multi-

*Corresponding author: S. Dodge sdodge@ucsb.edu

Email addresses: sdodge@ucsb.edu (Somayeh Dodge), rongxiangsu@ucsb.edu (Rongxiang Su), joh10891@umn.edu (Jasper Johnson), simtom@windowslive.com (Achara Simcharoen), kgoulias@ucsb.edu (Konstadinos Goulias), smith017@umn.edu (James L.D. Smith), sahearn@hunter.cuny.edu (Sean C Ahearn)

URL: <https://somayehdodge.info/> (Somayeh Dodge)

ple individuals, especially when the interaction occurs with a delay or via indirect contact (i.e. when individuals visit the same location asynchronously). This paper introduces a new Object-oriented Time-Geographic Analytical approach (ORTEGA) to extract concurrent and delayed interaction patterns between individuals in space and time. The method leverages the time-geography framework to incorporate the effects of uncertainty and gaps in movement data in the analysis of interaction and tracing contact patterns. Using two different case studies and real GPS tracking data, the method is evaluated in (1) detecting patterns of dyadic, intra and interspecific interactions between two apex predators, tigers and leopards in Thailand; and (2) tracing potential contacts between a large group of individuals of the same and different households in San Jose, California. The results indicate that tigers and leopards have an awareness of each other and their interaction is mainly indirect and delayed. In the human context, the results show that while individuals of the same household have more concurrent interaction, members of different households follow similar patterns asynchronously exhibiting delayed interaction. The delayed interactions and potential asynchronous contacts are often underestimated by the common digital contact tracing technologies. With this study we show how a generic method can be used to identify interesting movement patterns across the human and animal divide.

Keywords: Time geography, contact tracing, interaction analysis, wildlife encounter analysis, delayed interaction, tiger leopard interaction

1. Introduction

Interaction and contact between individuals are important driving factors of many social and ecological systems. Collective behaviors of animals and humans result in complex social dynamics which can be observed through movement of individuals (Potts et al., 2014; Laube, 2014; Dodge et al., 2008). Movement patterns shape urban and natural ecosystem dynamics, structure human and wildlife social networks, and are essential to understanding human and wildlife interactions. There have been advances in the analysis of spatial interactions, but less research has focused on the temporal aspects of interaction between moving individuals. Specifically, approaches to analyzing temporal delays in spatial proximity are lacking. These delayed interactions are critical in virus transmissions and exposure to airborne pathogens. As the decade turned to the 2020s, we witnessed the widespread transmission of Coronavirus disease 2019 (COVID-19) which led to a set of unprecedented non-pharmaceutical interventions (NPIs) implemented by the governments across the globe to mitigate the spread of SARS-CoV-2. Examples of these NPIs include: policies for shelter-in-place, physical distancing, and contact tracing (Flaxman et al., 2020; Ferretti et al., 2020). Similar to influenza viruses, COVID-19 spreads via close contacts and through respiratory droplets that can stay in the air for some time (Centers for Disease Control and Prevention, 2020). Similarly, spatial proximity but delayed temporal response in animals can range up to weeks for scent marks to months for anthrax transmission. Therefore, our ability to analyze delayed interaction and trace contacts in human and animal social networks through their movements is critical to understanding social dynamics (Oliver et al., 2020;

26 Hoover et al., 2020).

27 Movement data, whether obtained from wearable devices equipped with
28 Global Positioning Systems (GPS) such as animal collars, smart watches,
29 activity loggers, smart phones, or other location-aware technologies includ-
30 ing Radio Frequency Identification (RFID) tags, motion sensors, Wi-Fi sen-
31 sors, card readers, Bluetooth sensors, can be used to study the interaction
32 between individuals and their space-time contact patterns. Recently, Apple
33 and Google joined their efforts to include contact tracing functionalities us-
34 ing the Bluetooth technology in their smart phones (Sainz, 2020). Similarly,
35 many other companies have built digital contact tracing apps to track prox-
36 imity between individuals in space and times and inform if a risky contact
37 with an infected individual has occurred (Kitchin, 2020). However, most of
38 these efforts focus on detecting synchronous interactions between individu-
39 als. These technologies rely on the concurrent proximity between moving
40 individuals to detect whether the individuals come within a certain distance
41 of each other in space and at the same time. The proximity is identified ei-
42 ther based on the intersection of Bluetooth signals of mobile devices carried
43 by the individuals or the synchronous distance between individuals. These
44 methods are not well suited to detect delayed interactions when spatial prox-
45 imity occurs asynchronously. This requires techniques capable of estimating
46 the potential paths of individuals and retaining information on their previous
47 locations. Developing computational methods to detect delayed interactions
48 can contribute to animal behavioral studies such as leadership and species
49 competition, as well as research on estimating human exposure risks to air-
50 borne pathogens or hazardous agents.

51 Recent advances in tracking technologies and quantitative techniques have
 52 enabled scientists to analyze more complex patterns of animal and human
 53 movement in relation to environmental and geographic contexts across space
 54 and time (Dodge, 2016; Long et al., 2018; Miller et al., 2019). Among these
 55 techniques, measuring and quantifying interaction and contact between mov-
 56 ing individuals have become a major interest in the areas of movement ecol-
 57 ogy, epidemiology, geographic information science (GIScience), computer sci-
 58 ence, and related disciplines (Potts et al., 2014; Joo et al., 2018). Arguing for
 59 an integrated science of movement, Miller et al. (2019) highlighted the impor-
 60 tance of developing new computational approaches to analyzing the spatial
 61 and temporal patterns of movements that are critical to gaining an under-
 62 standing of the collective movement behavior across the human and animal
 63 divide. This paper responds to this methodological challenge by developing
 64 and evaluating an analytical approach to trace critical space-time contacts
 65 in the social networks of humans and animals. While existing approaches
 66 provide valuable metrics to measure static interaction in space (i.e. the spa-
 67 tial overlap between activity spaces of individuals), our methods to quantify
 68 dynamic and temporally delayed movement interaction in space and time
 69 are less evolved (Miller, 2015). Most dynamic measures focus on quantifying
 70 *dyadic* interactions which occur synchronously (i.e. the proximity between
 71 *two* individuals in space over a time window) (Miller, 2015; Long et al., 2015;
 72 Joo et al., 2018). In a recent study, Hoover et al. (2020) developed a method
 73 to identify asynchronous interactions in animal dyads given a predefined time
 74 lag. As movement data increasingly become available in large volumes and
 75 heterogeneous forms, there is a need for more effective computational ap-

76 proaches to extract and model dynamic and temporally delayed interaction
 77 patterns in movements of multiple individuals.

78 This study focuses on two types of dynamic interaction: *concurrent inter-*
 79 *action* and *delayed interaction*. Concurrent interaction occurs between indi-
 80 viduals when they move synchronously in spatial proximity of each other in
 81 a shared space and at the same time. In concurrent interaction, individuals
 82 can potentially come to a close or direct contact (i.e. interaction at close dis-
 83 tance at the same time). This is a key driver in the transmission of viruses or
 84 shaping social networks in humans and animals. Delayed interaction happens
 85 when individuals visit the same locations in space however asynchronously.
 86 This type of interaction occurs when individuals indirectly interact via a
 87 shared space however with a time lag. It can contribute to virus transmis-
 88 sion, for example, when individuals visit the same infected location with a
 89 time delay. In this work, we introduce and evaluate a novel Object-oRiented
 90 TimE-Geographic Analytical approach (ORTEGA) to trace concurrent and
 91 delayed interaction patterns between individuals in space and time through
 92 their movement trajectories. Our approach builds upon the time-geography
 93 model (Miller, 2005; Long et al., 2015) to measure the probability of con-
 94 tact along the trajectories of two moving entities. We use an object-oriented
 95 scheme to make the time-geography method ‘smart’ by modeling trajectories
 96 as objects with properties and behaviors (actions) which can memorize the
 97 previous locations, potential contacts, and times of interactions with other
 98 individuals along their movement paths. Our main contributions include:
 99 (1) an object-oriented approach which can be used to trace concurrent and
 100 delayed interaction patterns between dyads or multiple individuals; (2) a spa-

101 tial and temporal indexing technique to speed up the computation process;
 102 and (3) an approach to tracing temporally delayed contacts in the context of
 103 human contact tracing. Using GPS tracking data, we show how the proposed
 104 methodology can be applied to identify key interaction patterns among indi-
 105 viduals across the human and animal divide. This is important, as despite
 106 the common interest for studying spatial behavior in movement ecology and
 107 human mobility, there has been little scientific cross-fertilization across these
 108 domains (Miller et al., 2019). We use two case studies to evaluate the pro-
 109 posed methodology: The first study uses tracking data of tigers and leopards
 110 to demonstrate how our method can capture *dyadic* tiger-tiger (intraspecific)
 111 and leopard-tiger (interspecific) interactions. The second study uses human
 112 tracking data to identify concurrent and delayed interactions among *multiple*
 113 individuals of the same and different households in the context of contact
 114 tracing. The case studies also demonstrate how ORTEGA compares to the
 115 proximity-based approaches across different temporal scales.

116 2. Movement Interaction

117 Studying dyadic movement interaction has been a major interest in move-
 118 ment ecology. There are two different types of dyadic interactions: *static*
 119 *interaction* and *dynamic interaction*. Static interaction is when the space
 120 usage (i.e. activity space or home range) of two individuals intersects. Dy-
 121 namic interaction occurs when two individuals move in a shared geographic
 122 space or within the proximity of each other over a certain time interval (Potts
 123 et al., 2014; Miller, 2015).

124 A common technique to quantify interaction spatially is to measure the per-

125 centage of the overlap between the activity spaces of the entities (Benhamou
 126 et al., 2014). The activity space in human context is often measured using
 127 convex hulls or time-geography measures as discussed later in Section 3.1
 128 (Miller, 2005; Long et al., 2015). The activity space in movement ecology
 129 context is computed using home range estimation measures such as convex
 130 hulls, Brownian Bridges, Kernel density estimation (Worton, 1987; Horne
 131 et al., 2007; Powell and Mitchell, 2012; Long et al., 2015). Another static
 132 measure is to compute the proportion of observations (e.g. occurrence or
 133 presence of two species) recorded within the spatial proximity of each other
 134 over the entire sampled locations regardless of observation time (Cole, 1949).
 135 Various measures have been offered to analyze dyadic interaction using tra-
 136 jectories. Long et al. (2014); Miller (2015); Joo et al. (2018) provide extensive
 137 reviews on these measures, including: *the proximity index* (Bertrand et al.,
 138 1996; Doncaster, 1990)—the frequency at which the two entities come near
 139 each other within a certain distance threshold, *the coefficient of association*
 140 (Cole, 1949)—the proportion of proximal fixes, *the coefficient of sociality*
 141 (Kenward et al., 1993)—the ratio of average raw distances between simul-
 142 taneous fixes (i.e. locations recorded at the same timestamps) against the
 143 average distance between non-simultaneous fixes, *the coefficient of interac-*
 144 *tion*—synchronous use or avoidance of a reference area, *the joint potential*
 145 *path area* (Long and Nelson, 2013)—the relative size of the potential en-
 146 counter area, and *the correlation indices* (Konzack et al., 2017)—correlation
 147 between movement parameters of the two individuals such as speed, direc-
 148 tion, step length, turn angle.
 149 Spatial proximity is the most common metric used in the interaction measures

150 described above. It is often computed using a kernel and a distance metric
 151 such as Euclidean distance. The *proximity* measure indicates the average
 152 number of times where the two entities meet within a spatial buffer of a
 153 certain threshold δ . Another way to measure spatial proximity is to compute
 154 the average distance between the entities over a kernel using a similarity
 155 measure (i.e. distance metric) such as the average Euclidean distance over a
 156 kernel, Edit distance, Frèchet distance, Hausdorff distance (Alt and Godau,
 157 1995; Guibas et al., 2000; Konzack et al., 2017).
 158 Existing dynamic measures quantify the closeness of moving entities in space
 159 at the same time using user defined spatial and temporal thresholds (Miller,
 160 2015). This approach involves using a spatial distance buffer around the
 161 individuals' location for a certain time window, and if the buffers intersect
 162 in space and time, it can reasonably be assumed that those two individuals
 163 possibly interacted or came into contact given the uncertainty in their actual
 164 locations during the time window. A similar proximity-based approach is
 165 also applied in current Bluetooth-based contact tracing apps (Sainz, 2020).
 166 These technologies capture if individuals move in close proximity of each
 167 other or come to contacts based on the synchronous intersection between their
 168 Bluetooth signal range areas (i.e. which can be modeled as a spatial buffer).
 169 Long and Nelson (2013) enhances the definition of dynamic interaction by
 170 incorporating movement direction (i.e. azimuth) in addition to the distance.
 171 In their definition, two entities interact when their azimuth shows similarity
 172 over time. These measures require that the movement of individuals to be
 173 recorded simultaneously at the same sampling rates. Konzack et al. (2017)
 174 incorporated a similar measure to identify delayed interaction in trajectories

175 that follow similar paths with a time delay.

176 Dynamic interaction measures which are based on a similarity or distance
177 metric can be less effective when interacting entities do not follow a sim-
178 ilar path simultaneously. These measures are less reliable when movement
179 data are collected at different sampling rates or include gaps due to imperfect
180 tracking or signal loss. Additionally, these approaches have limited capability
181 to identify delayed interactions. In contrast, the potential path area (PPA)
182 using the time-geography framework (Miller, 2005) provides a more robust
183 method for discovering potential interaction between individuals at different
184 time scales (Long et al., 2015; Hoover et al., 2020). The PPA represents
185 possible locations that could be occupied by the individual between known
186 timestamps given its maximum speed and a time budget. Long et al. (2015)
187 showed the intersection of the potential path areas (called “joint PPA”) can
188 identify potential locations for interaction between two entities in space and
189 time. Hoover et al. (2020) further extended the joint PPA measure to identify
190 delayed dyadic interaction (called “temporally asynchronous-joint potential
191 path area (ta-jPPA)”) in animal pairs with a user-defined time-distance win-
192 dow. In this paper, we enhance the PPA measure to quantify concurrent and
193 delayed interactions between dyads and multiple tracked individuals in space,
194 and provide a more flexible search approach to trace interaction patterns.

195 **3. Methods**

196 *3.1. The time-geography framework*

197 This study uses the time-geography framework (Hägerstrand, 1970) to iden-
198 tify potential concurrent and delayed interactions between moving individu-

als (hereafter referred to as ‘entities’ in the description of the methodology). In time geography, the *activity space* of a moving entity (i.e. the locations that are accessible to the entity) is mapped with a *space-time prism* in a three-dimensional space-time cube (Figure 1a). The prism is anchored at two fixed locations P_i and P_j (e.g. representing a pair of origin and destination locations or the locations of two fixed activities). The shape of the prism is a function of the entity’s maximum speed capacity v_{max} and the time budget ($\Delta t = t_j - t_i$) to travel between the two locations (Miller, 2005). The *potential path area (PPA)* is the projection of the space-time prism on a two-dimensional geographic or Euclidean space. The PPA_{ij} ellipse delineates the spatial locations that are accessible to the moving entity during the interval $[t_i, t_j]$. Figure 1 illustrates the space-time prism and the potential path area of a moving entity between two locations P_i and P_j along its trajectory at the time interval $[t_i, t_j]$.

Following Long and Nelson (2015), we modify the space-time prism by dynamically varying the maximum speed at different time intervals instead of using a fixed v_{max} for the entire trajectory. Here, v_{max} for a given time interval $[t_i, t_j]$ is estimated using the speed values v_{ij} during the preceding time intervals in the data. The premise is that an entity does not always move at its maximum speed and the speed varies over time according to the entity’s activity type (i.e. commuting, leisure activity, foraging, hunting) or its transport mode (i.e. walking, biking, driving, etc.). Given a trajectory, $T = \{(x_0, y_0, t_0), (x_1, y_1, t_1), \dots, (x_i, y_i, t_i), \dots, (x_n, y_n, t_n)\}$, the maximum speed capacity v_{max} for the time interval $[t_i, t_j]$ is estimated by a floating average of speed over an exponential kernel (Gijbels et al., 1999) of size m , a

Figure 1: Illustration of (a) the space-time prism in a 3D space-time cube; (b) the computation of PPA_{ij} as the potential path area in a 2D Euclidean space between tracking points $P_i(x_i, y_i, t_i)$ and $P_j(x_j, y_j, t_j)$, where $1 \leq i < j \leq n$ and $i < m < j$. Modified from Miller (2005).

smoothing constant of α , and an additional error term β using Equation (1). In this equation, m is the size of the exponential kernel, i is the index of the current point P_i in the trajectory, k is the location in the kernel. The speed values of m previous trajectory points contribute to the floating average of the speed of the current point s_i . However, their contribution is decreased by a smoothing constant α so that the contributions of the points further from the current location in the trajectory are suppressed multiplicatively in calculating v_{ij} . If $\alpha = 1$ only the speed value of the current point (v_i) is considered. The error term β controls the uncertainty of speed in the estimation of v_{max} enabling the entity to move faster than the previous speed. The parameter β can be set as the maximum rate of speed change (i.e. deviation from average speed) for a given behavior. For example, $\beta = 1.25$ allows 25%

236 deviation from the current average speed.

$$\begin{aligned}
 s_i &= \alpha \sum_{k=0}^{m-1} (1 - \alpha)^k v_{i-k} \quad \text{with} \quad 0 < \alpha \leq 1 \\
 v_{max} &= \beta * s_i
 \end{aligned} \tag{1}$$

237 The potential path area between t_i and t_j , PPA_{ij} , can then be computed
 238 using the estimated v_{max} and the time budget as shown in Figure 1 and
 239 Equation (2), following Miller (2005); Long et al. (2015):

$$\begin{aligned}
 d_{i,m} &= (t_m - t_i) * v_{max} \quad \text{radius of the accessible area during } [t_i, t_m] \\
 d_{m,j} &= (t_j - t_m) * v_{max} \quad \text{radius of the accessible area during } [t_m, t_j] \\
 AA_m &= A_{i,m} \cap A_{m,j} \quad \text{accessible area at time } t_m \\
 PPA_{ij} &= \cup AA_m
 \end{aligned} \tag{2}$$

240 3.2. Mapping interaction as the intersection between space-time prisms

241 Given a trajectory T of length n , a series of space-time prisms between each
 242 pair of consecutive tracking points (i.e. $P_i(x_i, y_i, t_i)$ and $P_{i+1}(x_{i+1}, y_{i+1}, t_{i+1})$,
 243 where $1 \leq i \leq n$) can be used to estimate the locations that are accessible to
 244 the entity along its trajectory. The space-time prisms map the uncertainty
 245 in the activity spaces of the entities between known GPS locations. The
 246 intersection between the space-time prisms along the paths of the two moving
 247 entities can then be used to map the spatiotemporal overlap between their
 248 activity spaces as potential locations for dyadic interaction in space and time

(Long et al., 2015). In a two-dimensional Euclidean space, the intersection of the projected pairs of *PPAs* of the two entities delimits the potential area for a dyadic interaction during the time period over which the *PPAs* are calculated.

Formally, let $PPA_{ij}^{e_1}$ be the potential path area between two consecutive GPS points $P_i(x_i, y_i, t_i)$ and $P_j(x_j, y_j, t_j)$ of entity e_1 , and $PPA_{kl}^{e_2}$ be the potential path area between two consecutive GPS points $P_k(x_k, y_k, t_k)$ and $P_l(x_l, y_l, t_l)$ of entity e_2 . Then, $PPA_{intersect}$ as the potential locations for interaction is quantified following Long et al. (2015) using Equation (3). If the time intervals of the two *PPAs* are the same or overlapped (i.e. $[t_i, t_j] \cap [t_l, t_k] \neq \phi$), then the $PPA_{intersect}$ (Equation 4) indicates a potential direct contact or *concurrent interaction*. It is important to note that, the $PPA_{intersect}$ in this case represents all the locations that the two individuals could potentially come to close contact between the period $[t_i, t_j] \cap [t_l, t_k]$ and does not necessarily mean that the individuals intentionally or directly interacted. However, if the time constraint is relaxed (i.e. $[t_i, t_j] \cap [t_l, t_k] = \phi$ or $[t_i, t_j] \cap [t_l, t_k] \geq t_{lapse}$), the $PPA_{intersect}$ at different time intervals can identify potential *delayed interactions* via indirect contact after a time lapse t_{lapse} (e.g. e_2 goes to the same geographic area where e_1 visited with a delay t_{lapse}).

$$PPA_{intersect} = PPA_{ij}^{e_1} \cap PPA_{kl}^{e_2} \quad (3)$$

$$contact = \begin{cases} \text{no contact,} & \text{if } PPA_{intersect} = \phi \\ \text{concurrent,} & \text{if } PPA_{intersect} \neq \phi \ \& \ [t_i, t_j] \cap [t_l, t_k] \neq \phi \\ \text{delayed,} & \text{otherwise} \end{cases} \quad (4)$$

Although closely related, our method to identify delayed interactions is different from the one presented in Hoover et al. (2020) in two ways: (1) Hoover et al. (2020) consider two additional predefined parameters to set a time window tw (time before and after the tracking point) for a delay (these can be set by the domain expert) to intersect the PPA of entity e_1 at time T_1 ($t_i < T_1 < t_{i+1}$) and the PPA of entity e_2 at time T_2 ($t_i + tw_i < T_2 < t_{i+1} + tw_j$), (2) both Hoover et al. (2020) and Long et al. (2015) consider a finer resolution time-slicing approach to compute the accessible space at each time slice T ($t_i < T < t_{i+1}$) for each individual. However, our method considers the intersection of the PPAs in space over the entire time interval between the consecutive tracking points (e.g. $[t_i, t_{i+1}]$) and does not limit the accessible space to a specific timestamp T . Although the time-slicing approach makes $PPA_{intersect}$ more explicit to a specific timestamp T , it poses several limitations: (a) it requires tracking data of both entities to be of a regular and perhaps an equal sampling rate, so that the interval can be sliced to a set of equal time increments δ (a predefined parameter); (b) it increases the computation cost of recalculating $PPA_{intersect}$ at much higher frequencies per increment δ (i.e. $t_i < T + k\delta < t_{i+1}$ where $k = \frac{t_{i+1} - t_i}{\delta}$) per entity, while ORTEGA only computes one PPA per interval $[t_i, t_{i+1}]$ per entity; and (c) it assumes that the entities always move at constant speed V_{max} between the two consecutive tracking points and therefore the highest probability of interaction always occurs along the beeline between the two consecutive tracking points of each entity. Moreover, in contrast to Hoover et al. (2020), our approach does not require predefined time-distance tw thresholds to identify delayed interaction over a fixed time lag period.

293 As explained later in Section 3.3, we develop a more flexible approach for
294 tracing delayed interaction by incorporating an object-oriented scheme and
295 a space-time index-based search algorithm to store and retrieve calculated
296 PPAs and their intersections regardless of intersection time and without a
297 need for frequent recalculation of $PPA_{intersect}$ on the fly for each specified
298 time lag.

299 3.3. ORTEGA methodology to trace contact patterns in space and time

300 In order to trace contact patterns in the forms of concurrent and delayed
301 interactions in movement data sets, we propose an Object-oRiented TimE-
302 Geographic Analytical method (ORTEGA). First, we apply an object-oriented
303 scheme which constructs trajectories as a set of interacting moving objects
304 (or agents) to facilitate tracing possible PPA intersections (see Section 3.3.1).
305 Then, the interaction analysis is applied using the $PPA_{intersect}$ measure and
306 a spatiotemporal indexing approach to optimize the extraction of concurrent
307 and delayed interactions via potential direct and indirect contacts between
308 trajectories (see Section 3.3.2). The object-oriented model is used as the
309 building block of our method to enhance the capacities of time-geography
310 for a more complex and flexible interaction analysis, especially when more
311 than two entities are involved. For example, it enables storing spatial and
312 temporal characteristics of the PPAs and their intersections in the history
313 of the data and using the information on demand. It can store information
314 on possible interactions between PPAs of multiple agents as their properties
315 (e.g. the time and location of first interaction, duration and number of inter-
316 actions, etc.). The model is flexible, for example, to incorporate ‘behaviors’
317 for the PPA ellipses to take actions when an interaction is detected or when

318 the time lag is too long for a meaningful interaction.

319 3.3.1. The object-oriented scheme

320 The object-oriented model is an important aspect of ORTEGA. Using a set
321 of Class and Object definitions, the model enables moving entities to act
322 like smart agents as self-contained objects with a set of properties and be-
323 haviors that can interact with each other. In this model, a *MovingObject*
324 class (Güting et al., 2000) is used to represent the moving entities. The
325 UML diagram of the proposed object-oriented scheme is provided in Fig-
326 ure 2. Each *MovingObject* can have a *Trajectory* object which itself is a
327 series of *MovingPoint* objects. The proposed scheme models a space-time
328 prism object (*STPO*) as an object class constructed from sequential pairs
329 of *MovingPoint* objects. Each *STPO* has a unique identifier and records
330 the intersections with the *STPO* of other *Trajectory* objects as an array
331 of intersected *STPOs* (or in short *iSTPO*). The array *iSTPO* stores all
332 possible intersected *PPA* ellipses for each *STPO* along the *Trajectory* of
333 each *MovingObject* in the data set. This way, the information about the
334 location and time of intersected *PPAs* are stored and can be retrieved when
335 needed.

336 3.3.2. Interaction analysis algorithm

337 Figure 3 presents the algorithm for tracing possible contacts in movement
338 data of multiple entities to identify concurrent and delayed interactions.
339 Given a database of GPS tracking data including M moving objects, the
340 *Trajectory* objects are first constructed using the object-oriented model de-
341 scribed in Section 3.3.1, following a trajectory preprocessing step (Dodge

Figure 2: The object-oriented model applied in ORTEGA for moving object interaction analysis.

et al., 2009) to eliminate outliers and erroneous data. Next, the space-time prisms and their corresponding potential path areas are calculated along the *Trajectory* of each *MovingObject*. These are stored as arrays of *STPO* and *PPA* objects embedded in *Trajectory* objects. In order to optimize the computation in large tracking data sets, a spatial and temporal indexing method, a ‘compressed kd-tree’ or CKD-tree (Caro et al., 2016; Bentley, 1975), is applied based on the centroid points of the calculated *STPOs*. This way, only the *PPA* objects that are closer in space and within a given temporal interval are considered for interaction analysis.

In order to trace contacts between M moving entities, one entity is considered as a reference *MovingObject* (e.g. MO^r) (Figure 3). Then using the CKD-tree indexing, potential *STPOs* that are proximate to the *STPOs* of the reference MO^r are retrieved. Once potential *STPOs* are retrieved, their

Figure 3: Workflow of the interaction analysis algorithm used in ORTEGA.

355 PPA ellipses are intersected with the PPA ellipses of the references MO^r .
 356 For any pair of PPA_{ij}^r (i.e. the PPA of the reference MO^r at interval $[t_i, t_j]$)
 357 and PPA_{kl}^m (i.e. the PPA of the m^{th} entity at interval $[t_k, t_l]$) that their
 358 intersection is not *null* ($PPA_{intersect} \neq \phi$), the intersecting PPA_{kl}^m is stored
 359 in the *iSTPO* array for further analysis. The advantage of this approach
 360 as compared to the existing dyadic interaction analysis techniques is that, it
 361 can be applied simultaneously to multiple entities and enhanced using parallel

362 computing. Since the identifiers, time and location of the intersected areas
 363 (i.e. $PPA_{intersect}$) are stored in the $iSTPO$ array as properties of a $STPO$
 364 object, the approach is flexible enough to retrieve all possible intersections
 365 among a group of moving entities. This is also useful for the detection of
 366 different types of movement patterns such as leader and follower, avoidance,
 367 or divergence.

368 To detect concurrent interaction, the intersected $PPAs$ for which $[t_i, t_j] \cap$
 369 $[t_k, t_l] \neq \phi$ are selected. These can be further analyzed to calculate the length
 370 of contact, the number of *MovingObjects* that the individual came into close
 371 contact, and the frequency of contacts. Delayed interaction can be extracted
 372 from the intersected $PPAs$ stored in $iSTPO$ using a time window. For
 373 example, we can retrieve all *MovingObjects* that visited the same location
 374 within a certain time of each other.

375 **4. Case Study I: Analysis of Dyadic Interactions in Animal Move-** 376 **ment**

377 We evaluate the proposed performance of the methodology on mining dyadic
 378 interaction patterns between tigers and leopards in the Western Forest Com-
 379 plex in Thailand. The purpose of this case study is twofold: (1) to evaluate
 380 ORTEGA in analyzing dyadic movement interaction in a Euclidean space,
 381 (2) to conduct a comparative evaluation of ORTEGA and the proximity-
 382 based approach on GPS tracking data that are collected at relatively coarse
 383 frequencies and different sampling rates (15 min to 1 hour).

384 4.1. Animal GPS tracking data set

385 Four tigers and one leopard were captured and fitted with VECTRONIC
 386 Aerospace GmbH collars (Simcharoen et al., 2014). Location data were ac-
 387 quired at 1 hour or 15 minute intervals over a period of four months as
 388 summarized in Table 1.

Table 1: The duration and temporal intervals of tiger tracking data.

animal ID	No. points	temporal resolution	start date	end date	home range area (km^2)
tiger 20080	1798	1 hour	2016-04-30	2016-09-16	57.12
tiger 20083	2751	1 hour	2016-04-30	2016-09-17	56.35
tiger 22901	4529	variable	2018-09-27	2019-02-02	49.68
tiger 22904	1998	1 hour	2018-09-27	2019-02-02	60.67
leopard 31898	7170	15 min	2018-09-27	2019-02-02	40.57

389 4.2. Tiger-tiger interaction

390 A delayed interaction occurs when a tiger scent marks a tree and that mark
 391 is subsequently inspected hours or days later by another tiger. Tigers have
 392 large home ranges and scent marks serve as message boards to alert other
 393 tigers of territorial boundaries, and in the case of a female, her reproductive
 394 status. A female tiger scent marks intensively starting a week before she
 395 comes into estrous (Smith et al., 1989). A male patrolling a large territory
 396 encompassing several females is alerted that the female will soon be receptive.
 397 When the female becomes receptive, she reduces scent marking and begins
 398 repeated calling. The male response then brings them together (Ahearn
 399 et al., 2001). Scent marks that are detected and often over-sprayed up to
 400 three weeks later serve to demarcate territorial boundaries while reducing

401 the likelihood of direct encounters that can result in serious injuries to both
 402 animals and sometimes mortal injuries to the loser.
 403 Here, we demonstrate the applicability of the method to study the interac-
 404 tion between two female tigers (IDs: 20080 and 20083) sharing a boundary
 405 along one side of their home ranges. Figure 4a illustrates the GPS data and
 406 home ranges of the two tigers during the tracking period between April and
 407 September 2016. The home ranges are calculated as the convex hulls of 95%
 408 of GPS points (Worton, 1987). As seen in the 3D space-time cube repre-
 409 sentation of the tracking data in Figures 4a-b, the two tigers patrol their
 410 shared boundary often asynchronously, and rarely have direct encounters.
 411 These asynchronous messages reduced the likelihood of costly aggressive en-
 412 counters (Smith et al., 1989). We applied our method to extract concurrent
 413 and delayed interactions between the two tigers. The yellow PPAs in Figure
 414 4c illustrate the interactions between the two tigers allowing three hours.
 415 Figure 4d visualizes the frequency of detected interactions over a range of
 416 time lags from 30 minutes up to five weeks. To be specific, each bar repre-
 417 sents the frequency of the first visit of one tiger to the same location visited
 418 by the other tiger (i.e. first ellipse intersection) with a certain time delay.
 419 There are 53 close encounters within 3 hours out of a total of 6756 detected
 420 spatially intersected *PPA* pairs (Table 2). As the histogram shows, most of
 421 the interactions between the two tigers occur within one or two days of each
 422 other when the tiger scent appear to be the strongest. Few yellow marks
 423 in Figure 4c and low frequencies in Figure 4d within three hours indicate
 424 the small likelihood of tigers directly encountering each other. The visits to
 425 the same locations increase after one week and last until week three. Our

findings here support field observations in Thailand using camera traps and by human observers which indicate that tigers appear to detect scent marks only at a close spatial range (several meters at the most). In our field observations, we can detect a mark for up to 21 days. However, the olfactory acuity of tigers is clearly much higher than humans; therefore, we see visits to the same locations up to even five weeks.

Figure 4: Interaction analysis of two female tigers (IDs: 20080 shown in blue and 20083 shown in red) sharing a boundary: (a) 2D representation of GPS tracking data and home ranges; (b) 3D space-time cube representation of the tigers' tracking data; (c) Intersected PPAs highlighted in yellow indicates interaction allowing three hours of delay; and (d) the frequency of interactions (first visits to the same locations) detected between the two tigers over a range of time lags.

Table 2: The total number of detected PPA intersections (spatial) among tigers and leopards and the number of close encounters (interaction allowing three hours).

animal 1	animal 2	total PPA intersections	close encounters
tiger 20080	tiger 20083	6756	53 (0.784%)
tiger 22901	tiger 22904	40260	31 (0.077%)
leopard 31898	tiger 22901	41410	2 (0.005%)
leopard 31898	tiger 22904	41255	107 (0.259%)

4.3. Tiger-leopard interaction

This experiment uses GPS tracking data of two tigers 22901 (young male) and 22904 (female) and a leopard 31898 (male) over the period between September 2018 and February 2019. Figure 5a (in the middle) illustrates the tracking data and home ranges of the three carnivores. The two tigers, a resident, breeding female and a subadult, non-reproductive male, share a portion of their home ranges. The leopard’s home range overlaps with both tigers, but is completely within the home range of tiger 22904. The two tigers were originally tracked with a sampling interval of one hour; however, the tracking frequency of tiger 22901 was increased later to 15 minutes. These data help to analyze the impact of temporal granularity (i.e. sampling rates) of tracking on the analysis of animal interaction. With this experiment, we demonstrate that in contrast to a simple proximity-based approach, in which tracking data must be of the same sampling rate and collected synchronously, our method is capable of handling tracking data of variable sampling rates. The results of interaction analysis using a three hour window between tigers 22901 and 22904 indicate that these two animals only came into close contact 31 out of 40260 times when their spatial path crossed (Figure 5b). This limited direct interaction over a period of four months may be explained by

451 the fact that there is no territorial competition between tigers of the opposite
 452 sex. Also, the male is not yet of breeding age and the female is raising young
 453 so she is not receptive. In contrast, females 20080 and 20083 are territorial,
 454 breeding females each defending a territorial boundary. They show a much
 455 higher rate of potential concurrent interactions, as they patrolled and likely
 456 marked their common boundary (see Section 4.2 and Table 2).

457 The interaction analysis applied on this data set suggests that the leopard
 458 tends to avoid the two tigers in the area. The number of delayed interac-
 459 tions is much higher between the leopard and the two tigers with very few
 460 close encounters detected (Figure 5c-d). Out of the total of 41410 spatially
 461 intersecting *PPA* pairs, only two incidences of close contacts (i.e. encounter
 462 in space and time allowing three hours) were detected between tiger 22901
 463 and the leopard (Figure 5c). Figure 5d highlights 107 close contacts within
 464 a three hour window which occurred in the shared home range areas of tiger
 465 22904 and the leopard, out of the total of 41255 spatially intersecting *PPA*
 466 pairs. It is interesting to note that the number of near-concurrent inter-
 467 actions of the leopard with tiger 22904 is relatively higher than with tiger
 468 22901, as the leopard's home range is contained within the home range of
 469 tiger 22904. Therefore, the larger shared space increases the probability of
 470 having close encounters between the two animals. The histograms in Figure
 471 5b-c represent the frequency of intersecting *PPAs* over a range of time lags
 472 from 30 minutes to 24 hours. The histogram suggests that the animals hap-
 473 pen to visit the locations visited by the other animal with a delay of 24 hours,
 474 while they keep distance for at least a few hours of each other. Based on
 475 biological observations delayed interaction between tigers and leopards after

Figure 5: Results of tiger-leopard interaction analysis using (a) GPS tracking data of two tigers 22901 (in red) and 22904 (in green) and one leopard 31898 (in blue). Map and the frequency of interactions over a range of time lag (b) between tigers 22901 and 22904; (c) between tiger 22901 and leopard 31898; and (d) between tiger 22904 and leopard 31898. The PPA intersections allowing three hours of delay are highlighted in yellow.

more than several hours does not have a significant meaning. In contrast, avoidance, quantified as little to no concurrent interaction or close contact within few hours, which is also confirmed in our interaction analysis, is key to the survival of the leopards when sharing the same geographic space with tigers.

481 As a simple experiment to compare ORTEGA to the proximity-based ap-
 482 proach and their sensitivity to data granularity, we applied both techniques
 483 on the 15-min data set of tiger 22901 and leopard 31898 and re-sampled
 484 the data to reduce its granularity (see Table 3). As the results suggest, the
 485 proximity-based approach is more sensitive to the sampling rate, while both
 486 approaches result in more false negatives as the sampling rate decreases.

Table 3: Delayed interaction between tiger 22901 and leopard 31898 within 4 hours over different sampling rates. A buffer size of 428 meters is used for the proximity-based approach to detect the same number of interactions as in the ORTEGA approach using the original data.

Data completeness (data granularity)	ORTEGA	proximity
100% (15-min)	54	54
50% (30-min)	32	8
25% (1 hour)	4	0

487 5. Case study II: Tracing Contacts Among Multiple Individuals

488 In this case study, we evaluate the performance of the methodology on trac-
 489 ing contacts between a group of people from the same or different households
 490 using fine resolution GPS tracking data in a network space. We further in-
 491 vestigate the impact of varying temporal scales on the outcomes and evaluate
 492 the results in comparison to the proximity-based approach. As compared to
 493 the previous case study in which dyadic interactions of only two individuals
 494 were analyzed at the time, here we evaluate the method in identifying con-
 495 current and delayed interactions in a larger network of people. This can be
 496 useful in contact tracing applications when detection of possible encounters
 497 between individuals is critical to monitor and estimate infection exposure.

498 5.1. Human GPS tracking data set

499 This study uses the GPS component of the 2012-13 California Household
500 Travel Survey (CHTS) (NuStats, 2013), which includes human movement
501 tracking data over a three-day period at a temporal resolution of three sec-
502 onds. The data were collected using GlobalSat GPS Data Loggers that can
503 be worn on the waist, clipped to a purse or backpack, or dropped in a pocket.
504 From the CHTS data set, which covers most of California, we only used the
505 data of respondents from San Jose as a test case. This subset contains GPS
506 traces of 402 persons from 176 households and spans from February 3, 2012
507 to January 31, 2013 (total of 75,770 GPS tracking points). Each GPS record
508 contains information including: a person’s anonymous ID, location in longi-
509 tude and latitude format, and local time. We only considered the GPS data
510 from 5 am to 23:59 pm because humans mainly stay at home during the
511 night and we were interested in day-time interactions. The original data are
512 in much finer resolution than what is needed for the purposes of interaction
513 analysis (i.e. human movement over three seconds might not be significant).
514 Therefore, we down-sampled the data into 1-minute intervals. The original
515 3-second sampling rate data result in very narrow *PPAs* which are basi-
516 cally equivalent of using a beeline between the consecutive GPS points. Such
517 fine resolution GPS tracking data can perhaps improve the performance of
518 the proximity-based interaction analysis methods, but it is very expensive
519 (computationally and financially) to collect tracking data at this very fine
520 sampling rate. Our method does not require such fine sampling rate as the
521 potential path area inherently incorporates the uncertainty of positioning
522 and the accessible locations at times that the GPS data are not recorded.

Table 4, summarizes the results of applying interaction analysis on this data set. The results are described in the following sections. The first three experiments present the outcomes of ORTEGA on tracing concurrent interaction (defined as contacts within 5 minutes) as compared to a proximity-based approach (see Section 5.2). The last four experiments summarize the outcomes of delayed interaction analysis using ORTEGA for a range of time lags from 30 minutes to 3 hours (see Section 5.3).

Table 4: Number of concurrent and delayed interactions detected among individuals of the same and different households. As a reference for comparison to ORTEGA, the outcomes of the proximity-based approach for concurrent interaction analysis using two buffer sizes are provided.

Exp.	method	type	parameters	within house- hold	outside house- hold	total
1	proximity	concurrent	5 min, 100 m	187	12	190
2	proximity	concurrent	5 min, 500 m	198	59	257
3	ORTEGA	concurrent	5 min	202	149	351
4	ORTEGA	delayed	30 min	250	376	626
5	ORTEGA	delayed	1 hour	279	542	821
6	ORTEGA	delayed	2 hours	299	708	1007
7	ORTEGA	delayed	3 hours	306	820	1126

5.2. Tracing concurrent interactions and comparison to the proximity-based approach

The goal of this experiment is to compare ORTEGA to the proximity-based approach in detecting concurrent interactions between the 402 participants in the data set, and investigate the influence of temporal scale (i.e. sampling rate) on both methods. The proximity-based approach is implemented by intersecting spatial buffers of a certain distance threshold around synchronous GPS tracking points. In practice, often a user-defined time threshold is

538 considered to relax the restriction of requiring synchronous fixes which can
539 be hard to achieve in real tracking data. Here, a five-minute time lag is
540 considered to extract concurrent interactions using both approaches. In these
541 experiments, two buffer sizes (i.e. 100 meters in Exp. 1 and 500 meters in
542 Exp. 2) are considered (see Table 4). These buffer sizes are considered to
543 account for average distance traveled by intermittent or continuous walking
544 over a five-minute interval. The average distance traveled by walking is 100
545 meters over one minute. Our proposed ORTEGA approach is not reliant
546 on a buffer threshold or a set time window. Although in this experiment
547 we considered the same 5-min time window to make it comparable to the
548 proximity-based approach.

549 Figure 6 represents two networks generated using Gephi (Bastian et al., 2009)
550 based on the detected concurrent interaction (close contacts allowing 5 min-
551 utes delay) among all individuals using (a) the proximity-based approach
552 (with a buffer size of 100 m), and (b) the ORTEGA approach. The networks
553 include 402 nodes (i.e. each node represents one person). The edges repre-
554 sent the interactions between every pair of two persons. The lighter pink to
555 beige represent less to no interactions, while more saturated pink to purple
556 colors represent higher number of interactions. A comparison between the
557 two networks (Figure 6 and Table 4) suggests that our approach is capable
558 of finding more potential direct contacts between individuals, while a higher
559 degree of concurrent interaction is detected among individuals of the same
560 household. The network generated using ORTEGA unveils some clusters
561 grouping people who interacted more with their own household members,
562 while they had less close contacts with people outside their households. This

563 may indicate households with children who mainly traveled together and had
 564 fewer encounters with other individuals in the data set. A closer look into
 565 the generated network using ORTEGA reveals more details on the frequency
 566 of interactions between individuals within the same households and their
 567 connections to individuals of other households. For example, the zoomed-
 568 in network of person H01P01 (from household H01) in Figure 6 illustrates
 569 that she/he interacted closely with three of her/his household members and
 570 came into close contacts with four other persons from different households
 571 over the course of the three days tracking period (see also Table 5). The
 572 histograms in Figure 6 indicate that the proximity-based approach in this
 573 case missed most of the close contacts among people outside households as
 574 compared to our approach. Therefore, it resulted in a less structured and
 575 more homogeneous network with more isolated nodes. It is worth mentioning
 576 that the proximity-based approach resulted in a higher number of individ-
 577 uals with no direct contact as compared to our approach (isolated nodes in
 578 the middle of the networks). However, based on the CHTS survey data we
 579 know that most of these individuals lived and interacted with at least one
 580 other person. The data include 154 (out of 176) households with at least two
 581 persons. According to the histograms in Figure 6, ORTEGA also identified
 582 a higher number of possible close contacts between individuals of different
 583 households. This result indicates a higher chance of encountering more peo-
 584 ple from other households in a shared location at the same time (e.g. a
 585 grocery shop). However, the proximity-based approach could only identify
 586 close contacts between a handful of outside household individuals.
 587 The results indicate that in general the proximity-based approach detects

(a) Direct interactions applying the proximity-based approach

(b) Direct interactions applying the ORTEGA approach

Figure 6: Illustration of the networks of individuals who came into close contacts (allowing five minutes time lag) extracted applying (a) the proximity-based approach (using a buffer size of 100 m) (b) the ORTEGA approach. The histograms show the frequency of the concurrent interaction incidences detected between people of different households. ORTEGA detects more concurrent interactions between people of different households as compared to the proximity-based approach. The zoomed-in network shows that person H01P01 interacted concurrently the most with person H01P04 from their own household. They also came into close contact with four other people from three different households.

588 a smaller number of interactions as compared to our approach. The de-
589 tected number of interactions increases when a larger buffer size is used. For
590 example, with a buffer size of 500 meters (which is quite large for a meaning-
591 ful human interaction), the proximity-based approach can detect almost the
592 same number of interactions as ORTEGA did in terms of concurrent contacts

among individuals of the same households. However, household members tend to stay in close proximity to each other over a period of time when they travel together. These outcomes show that the proximity-based approach can significantly under-estimate the number of contacts given the buffer size. However, ORTEGA detects more potential concurrent interactions as it considers possible accessible locations to the moving entities. This comparison indicates that ORTEGA may be better suited to detect potential concurrent interactions (or close encounters) between individuals of different households as it extracts all possible cases for potential interactions. This observation is especially important in the context of contact tracing for infectious diseases and risk exposure in which an over-estimation might be more desired than the under-estimation of potential risky contacts. ORTEGA enables detection of possible contacts between individuals who may not travel together over an extended period of time and only come into contact for a short period of time. For example, when two individuals from different households happen to be in the same location (e.g. a grocery store or a gas station) at the same time for a few minutes. This is a key advantage of using a time-geographic approach over the proximity-based approach, which can under-estimate contacts given the selected buffer size and time threshold. The proximity-based approach might miss contacts when the locations of individuals have not been recorded at exact time when they happened to be close to each other or when a small buffer distance is used to represent the proximity (see Section 6 for more information). Using a larger temporal threshold and bigger buffer size may alleviate this problem but increases the uncertainty in contact tracing. The difference between the two approaches becomes even more pronounced

618 when the GPS sampling rate decreases (i.e. coarser temporal granularity).
 619 Figure 7 demonstrates the influence of temporal scales on concurrent in-
 620 teraction analysis (allowing 5 minutes) using both approaches for sampling
 621 rates of 1 min, 5 min, 10 min, 20 min, and 30 min. The proximity-based
 622 approach seems to be more prone to data granularity for outside household
 623 interaction when individuals are not tracked synchronously. The number of
 624 direct contacts identified by the proximity-based approach slightly decreases
 625 within households (Pearson’s $R = -0.77$, $P - value = 0.1$) and drops to zero
 626 outside households (Pearson’s $R = -0.58$, $P - value = 0.3$) as the sampling
 627 rate decreases. In contrast, the potential path area used in ORTEGA takes
 628 into account the potential locations accessible to the individuals between
 629 known GPS recordings. And therefore, while the number of identified con-
 630 tacts stays the same for people within households using ORTEGA (Pearson’s
 631 $R = 0.05$, $P - value = 0.9$), the chance of identifying potential interactions
 632 between individuals of different households becomes higher, although not
 633 significantly, as the sampling rate decreases due to larger PPAs (Pearson’s
 634 $R = 0.79$, $P - value = 0.1$).

635 5.3. *Tracing delayed interaction through indirect contacts*

636 Using ORTEGA and a range of time lags, the delayed interactions were
 637 computed in Table 4. The networks representing delayed interactions are
 638 provided in Figure 8. As the time lag increases, more distinct clusters are
 639 detected and the networks become more fragmented. These clusters represent
 640 individuals of both inside and outside households who share the same spatial
 641 patterns (i.e. spatial interaction) but may not necessarily encounter at the
 642 same time. The longer tails in the histograms resulting from longer time lags

Figure 7: The influence of temporal scale on identifying concurrent interactions (allowing 5 min) using ORTEGA and the proximity-based approach (of 100 m buffer) between individuals of the same household and outside households.

643 represent the higher number of interactions detected among individuals of
 644 different households. This result indicates individuals of different households
 645 might visit similar locations over longer delays. That is, the chance of using
 646 the same space by more individuals becomes higher over a longer time period.
 647 The clusters in the fragmented network may indicate the households from the
 648 same neighborhoods who tend to use the same geographic space for their daily
 649 activities. With these clusters, we can detect a set of individuals that have
 650 similar spatial patterns but not necessarily following the same schedule. For
 651 example, people who go to the same gym or the same grocery shop but at
 652 different times of the day. This is the powerful aspect of our method which
 653 is capable of tracing delayed spatial interactions.
 654 A closer look into the network of person H01P01 (as shown in Figure 6) can
 655 inform us about how many individuals this person came into contact syn-
 656 chronously or visited the same location as other individuals asynchronously

Figure 8: Illustration of the networks of individuals who had delayed interaction (i.e. visited the same location) over a range of time lags (30 min, 1 hour, 2 hours, 3 hours). The histogram shows the frequency of different number of delayed contacts between individuals outside households.

657 (Table 5). The outcomes indicate that this person interacted mostly with
 658 person H01P04 from the same household and person H02P02 from household
 659 H02. Overall, person H01P01 was in close contact (met with or visited the
 660 same locations at the same time) with four individuals outside the household
 661 (from households H02, H04, and H06) over the course of a three day tracking
 662 period. She/he visited the same locations as 10 other individuals from six
 663 other households after a temporal lag of 30 minutes to three hours. This is
 664 significant for finding possibility of exposure to viruses or other hazardous
 665 conditions that may last in the air for a period of time. In total, this per-
 666 son had concurrent or delayed contacts with 13 members of seven different
 667 households including their own household.

Table 5: Cumulative number of concurrent and delayed interactions detected between
 person H01P01 and other individuals within a range of time lags. The three individuals
 above the horizontal line are from the same household as person H01P01, while the others
 are from six different households (H02-H07).

interacted with	within 5min	within 30min	within 1hour	within 2hours	within 3hours
H01P02	29	142	190	280	327
H01P03	9	40	69	173	303
H01P04	408	755	1059	1372	1476
H02P01	0	22	40	44	56
H02P02	15	19	63	104	137
H03P02	0	15	21	34	41
H04P01	0	0	25	46	48
H04P03	6	12	15	28	28
H04P04	0	0	11	11	15
H05P01	0	4	4	7	12
H06P01	5	8	27	34	49
H06P02	3	6	56	61	64
H07P01	0	9	9	17	17

668 6. Discussion

669 In this section, we discuss the performance and efficacy of the developed
670 methods in light of the results described above. The strengths and weaknesses
671 of the approach are presented in comparison with the classic proximity-based
672 interaction analysis approach which is commonly used in the contexts of
673 animal interaction and human contact tracing.

674 6.1. Method parametrization

675 Computation of the potential path area requires two parameters which can
676 be derived from data: the time budget Δt (which is typically calculated
677 from the timestamps of known GPS points) and the maximum speed capac-
678 ity V_{max} . Our proposed approach calculates the maximum speed parameter
679 based on the data itself by applying a floating average over an exponential
680 kernel instead of using a predefined fixed value for maximum speed. There-
681 fore, the PPAs are computed with the actual (data-driven) speed capacity
682 of the individual for different behavioral modes and at each given time. The
683 maximum variation from the average speed can also be calculated from the
684 data itself. We allowed 25% variation from the computed average speed.
685 This avoids having unreasonably large PPAs by setting a fixed large V_{max}
686 for the entire data set, which may result in more false positives in tracing
687 potential contacts.

688 The proximity-based approach requires setting a predefined distance thresh-
689 old as the buffer size, as well as a user-defined time threshold for the search
690 window to relax the requirement of having synchronous fixes. Setting larger
691 distance and time thresholds result in a higher number of contacts. This is

692 a major limitation of the proximity-based approach. In contrast, ORTEGA
 693 is not reliant on a distance threshold or a set time window. Although in
 694 the experiments we considered the same five minutes time window for con-
 695 current interactions to make ORTEGA comparable to the proximity-based
 696 approach. Figure 9 schematically demonstrates the difference between buffer
 697 intersection in the proximity-based approach versus the PPA intersection
 698 used in ORTEGA in terms of sensitivity to buffer size and data granularity.
 699 Figure 9a shows a smaller buffer size might lead to more false negatives and
 700 under-estimation of contacts in the proximity-based approach.

Figure 9: Illustration of method sensitivity to (a) buffer size and (b) data granularity. The proximity-based approach is highly sensitive to the buffer size and temporal resolution of the data. The ORTEGA approach does not rely on a buffer size and it outperforms the proximity-based approach when the data is collected at lower frequencies.

701 In comparison to previous time-geographic approaches (Hoover et al., 2020;
 702 Long et al., 2015), ORTEGA is flexible to retrieve delayed interactions using
 703 any time window in the history of the data and does not depend on several
 704 time slicing and time window thresholds to compute concurrent and delayed
 705 interactions.

706 6.2. Data granularity and temporal scale considerations

707 The original proximity-based approach is only able to detect proximate points
708 collected at synchronous intervals unless this restriction is relaxed through
709 a search window or kernel. Depending on the search window size, it might
710 miss interactions that happened between known GPS points. For example,
711 it might miss the cases where the individuals were close to each other but
712 moved away from each other between two GPS fixes or when individuals
713 move at different rates. In contrast, ORTEGA does not require synchronous
714 sampling. The overlap of potential path areas of two individuals indicates
715 their potential interaction between consecutive GPS recordings.

716 Overall, both approaches are sensitive to the temporal resolution used in
717 data collection (Figure 7). However, the proximity-based approach results in
718 more underestimation or false negatives when data of coarser sampling rate
719 is used. In Figure 9b notice the missed proximate points at time T_2 after
720 re-sampling using the proximity-based approach.

721 A weakness of ORTEGA is that for data of coarser sampling rates (e.g. 1
722 hour) it generates larger *PPAs* as compared to higher-resolution tracking
723 data (e.g. 15 min) (Figure 5d). Although it is possible to intersect *PPA*
724 pairs of different resolutions—which itself is a strength when compared to
725 the proximity-based approach, their intersections results in a higher level of
726 uncertainty in the detection of interaction. This situation may lead to more
727 overestimation or false positive cases for interaction as explained in Section
728 5.2. For example, the larger *PPA* of one hour duration for tiger 22904 might
729 contain or intersect with several smaller 15-min *PPAs* of the leopard and it
730 might not be possible to determine actual interaction time over the one hour

731 period.

732 6.3. Computation consideration

733 The efficiency of ORTEGA lies in lowering the computation cost that is as-
734 sociated with the retrieval of potential concurrent and delayed interactions
735 among multiple individuals. This is incorporated via two key elements of
736 the methodology: (1) ORTEGA applies an object-oriented model to create
737 *MovingObjects* as ‘smart agents’ which can retain information about the
738 PPAs and their intersections along the trajectories of individuals. This way,
739 the PPA polygons of *MovingObjects* only need to be computed and inter-
740 sected between different tracks once. The $PPA_{intersects}$ and their associated
741 time intervals are also stored as properties of PPAs for efficient retrieval of
742 delayed intersections. (2) Using a CKD-tree indexing technique, ORTEGA
743 applies space-time indexing to limit the search area for potential interactions
744 to smaller regions and restricted time windows when needed, so the search
745 does not incorporate the entire trajectories of all *MovingObjects*. This of-
746 fers a more efficient approach as compared to the method proposed in Hoover
747 et al. (2020), by reducing the need for on-the-fly and redundant computation
748 of pairwise PPA intersections over long trajectories at finer time increments
749 and for different time windows to identify potential delayed interactions. OR-
750 TEGA retains all possible spatial intersections between PPAs, and therefore,
751 potential delayed interactions can be retrieved on demand using an optimized
752 search through the CKD-tree indexing.

753 In comparison with the proximity-based approach which relies on a distance
754 threshold comparison, the time-geographic interaction analysis approaches
755 (as in ORTEGA) are overall more computationally intensive as they rely

756 on PPA ellipse computation and polygon intersection. To give a sense of
757 the computation speed of both approaches, the interaction analysis between
758 two GPS tracks (total of 265 points: track #1 with 183 GPS points and
759 track #2 with 82 points) takes 3.88 seconds using ORTEGA (allowing 5 min
760 delay) and 423 milliseconds using the proximity-based approach (allowing 5
761 min delay, 100 m buffer) to run using a Macbook Pro laptop with 2.3 GHz
762 8-Core Intel Core i9 processor, 16 GB RAM. In practice, the computation
763 speed of the proximity-based versus PPA approaches can greatly vary based
764 on the indexing methods used and the distribution of GPS points in the data.
765 Though spatial and temporal indexing on larger data sets are necessary for
766 both proximity-based approaches and PPA approaches to avoid exponential
767 runtime growth, the indexing of simple radius proximity-based approaches
768 is much simpler than index creation and index querying of multi-sized PPA
769 polygons.

770 For both ORTEGA and proximity-based approaches, first the GPS tracking
771 data sets need to be preprocessed to remove erroneous points and outliers.
772 The proximity-based approach involves a search through the list of points to
773 pick the proximate points with a time difference of less than the minimum
774 search window threshold. The search can be improved using an indexing ap-
775 proach, especially for larger data sets. The ORTEGA approach involves cre-
776 ating PPA ellipses for consecutive GPS points in the path of each trajectory.
777 These collections of PPAs are then intersected while the computation is opti-
778 mized by taking advantage of the characteristics of object-oriented program-
779 ming and the CKD-tree indexing as described in the methodology. In our
780 experiments both the proximity-based and ORTEGA approaches were con-

781 ducted in an object-oriented fashion to retain information about the points
782 that interacted in the history of the data. This approach provides advan-
783 tages and flexibility over a non-object-oriented approach, when dealing with
784 delayed interactions.

785 *6.4. Application considerations and the context of interaction*

786 As shown, ORTEGA is a powerful tool to trace not only concurrent interac-
787 tions, but also delayed interactions via indirect contacts in movement data
788 of both animals and humans. However, it is important to note that the out-
789 comes require a careful interpretation and perhaps consultation with domain
790 experts. For example, it is important in any case study to contemplate a
791 meaningful set of the conditions or criteria for concurrent and delayed in-
792 teractions prior to the analysis. Here, we used domain expertise of a tiger
793 biologist and an expert in travel behavior and transportation to set meaning-
794 ful parameters and interpret the results. Moreover, we used field observations
795 to back up the selected parameters. For example, we knew how long a tiger
796 scent might last in nature for a meaningful delayed interaction.

797 It is important to note that depending on the setting of the case study
798 and data granularity, the detected concurrent interactions or close contacts
799 might not actually mean that the individuals met or socially interacted. For
800 example, if there is a busy coffee shop and two individuals arrive at the coffee
801 shop within 5 minutes of each other, stay for an hour or so, then leave at the
802 same time, it can reasonably be assumed that they interacted because they
803 planned a meeting with each other for a set time. This is in contrast to two
804 individuals who may have been in a coffee shop together for an hour or so
805 of overlapping time, but arrived and left at totally different times, indicating

806 they were strangers who coincidentally were in the same coffee shop and
807 did not interact. Other points to consider when analyzing interaction or
808 tracing contacts are the impact of mode of transportation, physical or natural
809 barriers, and 3D spaces in detecting meaningful contacts. For example, the
810 interaction might not be meaningful when movement happens in separate
811 cars on the same road or when moving individuals are separated by walls or
812 different floors in multistory buildings or when animals are separated by a
813 natural barrier such as a river.

814 **7. Conclusion and Future work**

815 This study presented a new object-oriented time-geographic analytical ap-
816 proach (ORTEGA) to trace space-time contact patterns in movement data.
817 The method is capable of detecting direct and indirect contacts to identify
818 concurrent and delayed interactions between humans or animals in space and
819 time. In contrast to existing approaches which are limited to the interaction
820 analysis of two individuals, ORTEGA enables tracing interaction patterns
821 among a group of moving individuals. Our approach uses the potential path
822 area between GPS fixes to measure potential exposures that might have been
823 missed due to small data gaps or irregular sampling rates. These are ma-
824 jor problems in the proximity-based approaches which are employed in most
825 existing contact tracking technologies using Bluetooth or GPS in cellphones.
826 We applied and tested the proposed method on two different case studies
827 using real GPS tracking data of animals (tigers and leopards) and humans
828 (people of the same and different households) of different resolutions. The
829 results showed that the proposed ORTEGA method performs better than

830 the classic proximity-based approach in tracing concurrent and delayed con-
831 tact patterns in movement data, although at a higher computation cost. The
832 outcomes suggest that the proximity-based approach underestimates contacts
833 when individuals do not move together or are not tracked synchronously. As
834 compared to the proximity-based approach, ORTEGA requires less param-
835 eterization and is less sensitive to data granularity. By incorporating the
836 time-geography framework, ORTEGA incorporates movement data uncer-
837 tainty and potential accessible areas between known locations, and hence it
838 is a more powerful approach. The proximity-based approach is more sensitive
839 to the selected distance buffer size, tracking frequency, and the search time
840 window. For future extensions, ORTEGA can be strengthened by embedding
841 information on the context of movement and incorporating a probabilistic
842 method to better represent movement across the potential path areas. Cur-
843 rently, following the traditional time-geography model, ORTEGA assumes
844 that the entire potential path area is accessible to the moving entity. To
845 further extend the methodology it will be important to identify the duration
846 of contacts which is a critical factor in the analysis of social interactions for
847 both humans and animals. ORTEGA also opens the possibility of adding
848 context-awareness (Ahearn et al., 2017) to interaction analysis by incorpo-
849 rating behavioral, environmental, and geographic parameters that influence
850 movement interaction patterns. Using ORTEGA and sample weights expan-
851 sion it is possible to estimate the total number of persons that interact in a
852 specific place. This approach can be used not only for disease transmission
853 but also congestion and crowding management.

Acknowledgment

This work was supported in part by the National Science Foundation Award No.1853681, the University of California Santa Barbara Office of Vice Chancellor for Research COVID-19 Seed Grants. J. Johnson’s contribution to this work was supported by the University of Minnesota Office of the Vice Provost for Research’s Grant-in-Aid of Research, Artistry, Scholarship Program. J.L.D. Smith’s contribution to this research was supported by the USDA National Institute of Food and Agriculture.

References

- Ahearn, S.C., Dodge, S., Simcharoen, A., Xavier, G., Smith, J.L.D., 2017. A context-sensitive correlated random walk: a new simulation model for movement. *International Journal of Geographical Information Science* 31, 867–883. URL: <http://dx.doi.org/10.1080/13658816.2016.1224887>, doi:10.1080/13658816.2016.1224887.
- Ahearn, S.C., Smith, J.L., Joshi, A.R., Ding, J., 2001. TIGMOD: An individual-based spatially explicit model for simulating tiger/human interaction in multiple use forests. *Ecological Modelling* 140, 81–97. doi:10.1016/S0304-3800(01)00258-7.
- Alt, H., Godau, M., 1995. Computing the Fréchet distance between two polygonal curves. *International Journal of Computational Geometry & Applications* 05, 75–91. doi:10.1142/S0218195995000064.
- Bastian, M., Heymann, S., Jacomy, M., 2009. Gephi: an open source software

- for exploring and manipulating networks, in: Proceedings of the International AAAI Conference on Web and Social Media.
- Benhamou, S., Valeix, M., Chamaillé-Jammes, S., Macdonald, D.W., Loveridge, A.J., 2014. Movement-based analysis of interactions in african lions. *Animal Behaviour* 90, 171–180.
- Bentley, J.L., 1975. Multidimensional binary search trees used for associative searching. *Communications of the ACM* 18, 509–517.
- Bertrand, M.R., DeNicola, A.J., Beissinger, S.R., Swihart, R.K., 1996. Effects of parturition on home ranges and social affiliations of female white-tailed deer. *The Journal of Wildlife Management* 60, 899–909.
- Caro, D., Rodríguez, M.A., Brisaboa, N.R., Fariña, A., 2016. Compressed kd-tree for temporal graphs. *Knowledge and Information Systems* 49, 553–595. doi:10.1007/s10115-015-0908-6.
- Centers for Disease Control and Prevention, 2020. How Coronavirus Spreads. URL: <https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/how-covid-spreads.html>.
- Cole, L.C., 1949. The measurement of interspecific association. *Ecology* 30, 411–424.
- Dodge, S., 2016. From Observation to Prediction: The Trajectory of Movement Research in GIScience., in: Onsrud, H., Kuhn, W. (Eds.), *Advancing Geographic Information Science: The Past and Next Twenty Years*. GSDI Association Press. chapter 9, pp. 123 – 136.

- Dodge, S., Weibel, R., Forootan, E., 2009. Revealing the physics of movement: Comparing the similarity of movement characteristics of different types of moving objects. *Computers, Environment and Urban Systems* 33, 419–434. doi:10.1016/j.compenvurbsys.2009.07.008.
- Dodge, S., Weibel, R., Lautenschütz, A.K., 2008. Towards a taxonomy of movement patterns. *Information Visualization* 7, 240–252. doi:10.1057/palgrave.ivs.9500182.
- Doncaster, C.P., 1990. Non-parametric estimates of interaction from radio-tracking data. *Journal of Theoretical Biology* 143, 431–443.
- Ferretti, L., Wymant, C., Kendall, M., Zhao, L., Nurtay, A., Abeler-Dörner, L., Parker, M., Bonsall, D., Fraser, C., 2020. Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing. *Science* 368. doi:10.1126/science.abb6936.
- Flaxman, S., Mishra, S., Gandy, A., Unwin, H.J.T., Mellan, T.A., Coupland, H., Whittaker, C., Zhu, H., Berah, T., Eaton, J.W., Monod, M., Perez-Guzman, P.N., Schmit, N., Cilloni, L., Ainslie, K.E., Baguelin, M., Boonyasiri, A., Boyd, O., Cattarino, L., Cooper, L.V., Cucunubá, Z., Cuomo-Dannenburg, G., Dighe, A., Djaafara, B., Dorigatti, I., van Elsland, S.L., FitzJohn, R.G., Gaythorpe, K.A., Geidelberg, L., Grassly, N.C., Green, W.D., Hallett, T., Hamlet, A., Hinsley, W., Jeffrey, B., Knock, E., Laydon, D.J., Nedjati-Gilani, G., Nouvellet, P., Parag, K.V., Siveroni, I., Thompson, H.A., Verity, R., Volz, E., Walters, C.E., Wang, H., Wang, Y., Watson, O.J., Winskill, P., Xi, X., Walker, P.G., Ghani, A.C., Donnelly, C.A., Riley, S.M., Vollmer, M.A., Ferguson, N.M., Okell,

- L.C., Bhatt, S., 2020. Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. *Nature* 584, 257–261. doi:10.1038/s41586-020-2405-7.
- Gijbels, I., Pope, A., Wand, M.P., 1999. Understanding exponential smoothing via kernel regression. *Journal of the Royal Statistical Society. Series B: Statistical Methodology* 61, 39–50. doi:10.1111/1467-9868.00161.
- Guibas, L.J., Alt, H., Guibas, L.J., 2000. Discrete Geometric Shapes: Matching, Interpolation, and Approximation, in: Sack, J.R., Urrutia, J. (Eds.), *Handbook of Computational Geometry*. North-Holland, Amsterdam, pp. 121–153. doi:10.1016/B978-044482537-7/50004-8.
- Güting, R.H., Böhlen, M.H., Erwig, M., Jensen, C.S., Lorentzos, N.a., Schneider, M., Vazirgiannis, M., 2000. A foundation for representing and querying moving objects. *ACM Transactions on Database Systems* 25, 1–42. doi:10.1145/352958.352963.
- Hägerstrand, T., 1970. What about people in Regional Science? *Papers of the Regional Science Association* 24, 6–21. doi:10.1007/BF01936872.
- Hoover, B.A., Miller, J.A., Long, J., 2020. Mapping areas of asynchronous-temporal interaction in animal-telemetry data. *Transactions in GIS* 24, 573–586. doi:10.1111/tgis.12622.
- Horne, J.S., Garton, E.O., Krone, S.M., Lewis, J.S., 2007. Analyzing animal movements using Brownian bridges. *Ecology* 88, 2354–2363. doi:10.1890/06-0957.1.

- Joo, R., Etienne, M.p., Bez, N., Mahévas, S., 2018. Metrics for describing dyadic movement : a review. *Movement Ecology* 6, 1–17. doi:<https://doi.org/10.1186/s40462-018-0144-2>.
- Kenward, R.E., Marcström, V., Karlbom, M., 1993. Post-nestling behaviour in goshawks, *Accipiter gentilis*: II. sex differences in sociality and nest-switching. *Animal Behaviour* 46, 371–378.
- Kitchin, R., 2020. Using digital technologies to tackle the spread of the coronavirus: Panacea or folly? *The Programmable City Working Paper* 44, 1–24.
- Konzack, M., McKetterick, T., Ophelders, T., Buchin, M., Giuggioli, L., Long, J., Nelson, T., Westenberg, M.A., Buchin, K., 2017. Visual analytics of delays and interaction in movement data. *International Journal of Geographical Information Science* 31, 320–345. doi:10.1080/13658816.2016.1199806.
- Laube, P., 2014. *Computational Movement Analysis*. SpringerBriefs in Computer Science. 1 ed., Springer International Publishing. doi:10.1007/978-3-319-10268-9.
- Long, J., Nelson, T., 2015. Home range and habitat analysis using dynamic time geography. *Journal of Wildlife Management* 79, 481–490. doi:10.1002/jwmg.845.
- Long, J.A., Nelson, T.A., 2013. Measuring Dynamic Interaction in Movement Data. *Transactions in GIS* 17, 62–77. doi:10.1111/j.1467-9671.2012.01353.x.

- Long, J.A., Nelson, T.A., Webb, S.L., Gee, K.L., 2014. A critical examination of indices of dynamic interaction for wildlife telemetry studies. *Journal of Animal Ecology* 83, 1216–1233. doi:10.1111/1365-2656.12198.
- Long, J.A., Webb, S.L., Nelson, T.A., Gee, K.L., 2015. Mapping areas of spatial-temporal overlap from wildlife tracking data. *Movement Ecology* 3, 1–14. doi:10.1186/s40462-015-0064-3.
- Long, J.A., Weibel, R., Dodge, S., Laube, P., 2018. Moving ahead with computational movement analysis. *International Journal of Geographical Information Science* 32, 1275–1281. doi:10.1080/13658816.2018.1442974.
- Miller, H.J., 2005. A Measurement Theory for Time Geography. *Geographical Analysis* 37, 17–45. doi:10.1111/j.1538-4632.2005.00575.x.
- Miller, H.J., Dodge, S., Miller, J., Bohrer, G., 2019. Towards an integrated science of movement: converging research on animal movement ecology and human mobility science. *International Journal of Geographical Information Science* 33, 855–876. doi:10.1080/13658816.2018.1564317.
- Miller, J.A., 2015. Towards a Better Understanding of Dynamic Interaction Metrics for Wildlife: a Null Model Approach. *Transactions in GIS* 19, 342–361.
- NuStats, 2013. 2010-2012 California Household Travel Survey Final Report. Technical Report. California Department of Transportation.
- Oliver, N., Lepri, B., Sterly, H., Lambiotte, R., Delataille, S., De Nadai, M., Letouzé, E., Salah, A.A., Benjamins, R., Cattuto, C., Colizza, V.,

- de Cordes, N., Fraiberger, S.P., Koebe, T., Lehmann, S., Murillo, J., Pentland, A., Pham, P.N., Pivetta, F., Saramäki, J., Scarpino, S.V., Tizzoni, M., Verhulst, S., Vinck, P., 2020. Mobile phone data for informing public health actions across the COVID-19 pandemic life cycle. *Science Advances* 6. doi:10.1126/sciadv.abc0764.
- Potts, J.R., Mokross, K., Lewis, M.A., Dina, P., 2014. A unifying framework for quantifying the nature of animal interactions. *Journal of the Royal Society Interface* 11. doi:10.1098/rsif.2014.0333, arXiv:1402.1802.
- Powell, R.A., Mitchell, M.S., 2012. What is a home range? *Journal of Mammalogy* 93, 948–958. doi:10.1644/11-MAMM-S-177.1.
- Sainz, F., 2020. Apple and Google partner on COVID-19 contact tracing technology. URL: <https://nr.apple.com/d2s6h070n0>.
- Simcharoen, A., Savini, T., Gale, G.A., Simcharoen, S., Duangchantrasiri, S., Pakpien, S., Smith, J.L., 2014. Female tiger panthera tigris home range size and prey abundance: important metrics for management. *Oryx* 48, 370–377.
- Smith, D.J.L., McDougal, C., Miquelle, D., 1989. Scent marking in free-ranging tigers, *Panthera tigris*. *Animal behavior* 37, 1–10.
- Worton, B.J., 1987. A review of models of home range for animal movement. *Ecological Modelling* 38, 277–298. doi:10.1016/0304-3800(87)90101-3.