A time-geographic approach to quantify the duration of interaction in movement data

Rongxiang Su
Department of Geography, University of California, Santa Barbara
Santa Barbara, CA, USA
rongxiangsu@ucsb.edu

Somayeh Dodge
Department of Geography, University of California, Santa Barbara
Santa Barbara, CA, USA
sdodge@ucsb.edu

Konstadinos Goulias
Department of Geography, University of California, Santa Barbara
Santa Barbara, CA, USA
goulias@ucsb.edu

ABSTRACT

Interaction between moving individuals is a critical factor in shaping social dynamics and human networks. Recent advancements in trajectory analytics have resulted in promising methods to identify and extract spatio-temporal patterns of interaction using movement tracking data. However, methodologies to quantify the duration of interaction remain limited. In the present work, we advance the existing time-geographic based approach that mainly relies on potential path area computation and polygon intersection to quantify the duration of potential concurrent interactions (i.e. synchronous interaction in space and time) between mobile individuals. Two case studies using real human GPS tracking data in California reveal that in general, the proposed time-geographic based approach outperforms the proximity-based approach which is commonly used in digital contact tracing technologies. Our method is more effective in the identification of potential continuous interactions, especially when individuals do not move together. In addition, the results show that the proposed method can estimate the duration of contacts more accurately and can identify more complete interactions over a continuous time period, while the proximity-based approach underestimates contacts which may result in more intermittent interactions with shorter durations.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Interaction analysis, Interaction duration, Time geography, Human mobility

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1 INTRODUCTION

Interaction between moving individuals in space and time is an important contributing factor to urban dynamics and shaping human social networks [9, 16, 22, 26]. Identifying and quantifying dynamic interactions between moving individuals attracts scholars from geographic information science (GIScience), computer science, movement ecology, epidemiology, and related disciplines [16, 27]. While existing approaches have advanced our ability to identify and trace patterns of interaction in movement tracking data, they fall short in estimating the duration of interaction. Quantifying duration of interaction or the amount of time over which interacting individuals stay in close contacts with one another can contribute to our understanding of social dynamics and human exposure to potential risks. For example, in the context of contact tracing for infectious diseases such as COVID-19, the probability of a contagion event between a susceptible and an infected individual highly relies on the degree of proximity and the duration of contact [30, 32]. Estimating the duration of interaction between individuals can assist identifying critical risky contacts to inform non-pharmaceutical interventions (NPIs) and related policies [7].

Recent advancements in trajectory analytics have resulted in promising methods to identify and extract spatio-temporal patterns of interaction using movement tracking data. Existing methods quantifying interactions mostly rely on the spatial proximity between two individuals and many of them require user-defined spatial and temporal thresholds [16, 21, 27]. However, these proximity-based approaches may be limited when individuals are not recorded at simultaneous points in time. Simultaneous tracking of multiple individuals usually is hard to achieve due to limited battery life and capacity concerns [23]. To address this issue, several studies leverage the time geography framework [14] modeling a Potential Path Area (PPA) [5, 19, 25] to measure the accessible locations between two consecutive tracking points. The PPAs of different individuals are then intersected to determine whether a potential interaction is possible [9, 15, 22]. These time-geographic or PPA-based approaches incorporate the uncertainty of positioning and gaps in movement data. They are shown to be more effective to identify potential interactions when individuals do not move together. Also, they can be used to quantify delayed interactions when individuals visit the same locations asynchronously with a time lag [9, 15].

The main contribution of this article is to introduce a new technique to estimate the duration of interaction using movement trajectories of interacting individuals. Specifically, our work advances the time-geographic based interaction analysis approaches to trace and compute the duration of concurrent contacts (i.e. synchronous interaction in space and time) between mobile individuals.

The proposed approach is implemented by first identifying potential concurrent interactions between moving individuals using the method introduced in [9], followed by extracting subsequences of continuous interaction segments to estimate the duration of contacts. The proposed technique is evaluated on two use cases using real human GPS tracking data in California. In addition, we evaluate the efficacy of our method against the commonly-used proximity-based approach and show that the proposed method can estimate the duration of contacts more accurately and can identify more complete interactions over a continuous time period, while the proximity-based approach underestimates contacts which may result in more intermittent interactions with shorter durations. While we evaluate the method in the context of human mobility, the proposed approach can apply to identify duration of interaction in interspecific and intraspecific interactions of animals.

2 MOVEMENT INTERACTION ANALYSIS

Interaction analysis has been a major interest in biology and ecology to study dyadic interaction in animal movement [16, 27]. In computational geography and GIScience, scholars have focused more on modeling and mapping spatial interaction in collective movement of humans and movement flows [26, 34]. However, with the increasing availability of fine-grained human movement data and following the demand for digital contact tracing technologies, new computational approaches to analyze human interaction at more granular levels are needed. While the study subjects remain different, the methods of interaction analytics in both movement ecology and human mobility domains are often interchangeable and can support each other to facilitate a more holistic approach to understand movement [26]. Interaction can be classified as *static* or *dynamic* [11]. *Static interaction* occurs when individuals' activity spaces intersect in space but not necessarily in time. *Dynamic interaction* happens when individuals move in close proximity at the same time. In human movement, the latter type of interaction attracts more attention due to its crucial role in understanding a wide range of phenomena such as human social behavior, risk exposure, and social network dynamics [9, 26, 33]. Considering the occurrence of interaction in time, dynamic interaction can be classified as *concurrent (or direct/synchronous) interaction* or *delayed (or indirect/asynchronous) interaction* [9]. According to [9], "Concurrent interaction occurs between individuals when they move synchronously in spatial proximity of each other in a shared space and at the same time; delayed interaction happens when individuals visit the same locations in space however asynchronously with a time lag".

Various measures have been used to quantify dynamic interactions. Examples of these measures include: the proximity index [3, 11], the coefficient of association [8], the coefficient of sociality [17], the correlation indices [18], the half-weight association index (HAI) [4], the coefficient of interaction [28], the cross sampled entropy (CSE) [1, 12, 31], and the dynamic interaction index [20]. Most of these measures rely on the spatial proximity between two individuals with pre-defined spatial and temporal thresholds [16, 21, 27]. In addition, many of these methods require moving entities to be tracked simultaneously in time, which is hard to achieve in real applications when individuals do not always move together or due to imperfect tracking and signal loss [23]. Hence, the proximity-based approach may be less effective when individuals are not recorded at simultaneous points in time or when the interactions are delayed (e.g., two individuals visit the same location at different times). In order to address this issue, more recent approaches incorporate the time geography framework [14] to consider the accessible locations to the moving individuals between a pair of consecutive tracking points. This area is called the Potential Path Area (PPA) which delimits the areas that a moving entity can potentially reach given a time budget and the maximum speed [25]. The time-geography framework has been widely used to study joint accessibility and potential interactions between moving entities [9, 13, 15, 22]. By intersecting the PPAs of different moving entities along their trajectories, potential areas for interaction can be identified as shown in [9, 15, 22].

The time-geographic methods for interaction analysis share a common assumption that potential concurrent interactions between two individuals can occur when their PPAs intersect or overlap spatially and temporally. Specifically, the joint potential path area (jPPA) approach proposed by [22] generates and intersects PPAs for two moving entities at a predefined δ increment by slicing the time between their consecutive GPS points to delineate the common areas between the two entities where potential concurrent interaction is possible. The temporally asynchronous-joint potential path area (ta-jPPA) proposed by [15] extends the jPPA approach to identify potential areas of delayed interaction by allowing a user-defined temporal lag parameter. The object-oriented time-geographic analytical approach (ORTEGA) developed by [9] shares a similar approach but does not require several time slicing and time lag thresholds compared to previous two time-geographic based approaches. ORTEGA optimizes the search for potential interactions through an object-oriented scheme and space-time indexing. It also can be applied to identify interaction among a group of individuals (two or more moving entities). Overall, these time-geographic approaches are shown to be a more robust framework to identify both concurrent and delayed interactions between mobile individuals compared to common proximity-based approaches [9, 15, 22]. One advantage is that PPA can incorporate the positioning uncertainty and gaps in movement data collected using location-aware technologies (LATs) by considering the accessible locations to a moving entity between consecutive tracking points. In this way, PPA can relax the strict requirement of simultaneously tracking of moving entities when determining if a potential interaction is possible.

Despite the extensive existing work on computational methods for movement interaction analysis as described in this section, there remains a research gap to quantify the duration of interaction between moving individuals or the amount of time that individuals stay in close contact. The present research fills this gap by advancing the time-geographic based approach to estimate the duration of potential concurrent interactions between mobile individuals.

3 METHODOLOGY

This section presents our proposed method to quantify the duration of interaction using human movement trajectory data. The method involves two processes: (1) to apply a time-geographic technique to identify potential concurrent interactions between two moving individuals, and (2) to trace continuous segments of interactions and quantify their durations.

3.1 Identifying concurrent interactions

In time geography, the activity space of a moving entity can be measured by a space-time prism which is shaped by a pair of origin and destination locations, a time budget, and the maximum speed capacity for the travel mode [14, 24]. As presented in Figure 1, the projection of a space-time prism onto a two-dimensional Euclidean space is called the potential path area (PPA), which delineates the accessible locations to the moving entity over a given time budget (for further details about the definition and formalization, the readers are referred to [24, 25]). According to recent studies, the potential interactions between moving entities can be identified by intersecting their PPA ellipses and/or space-time prisms along their trajectories over small time increments [15, 22] or between two consecutive tracking points [9]. In this paper, we adopt and extend ORTEGA, an object-oriented time-geographic based approach introduced in [9], to identify continuous segments of potential concurrent interactions between moving individuals and quantify their duration.

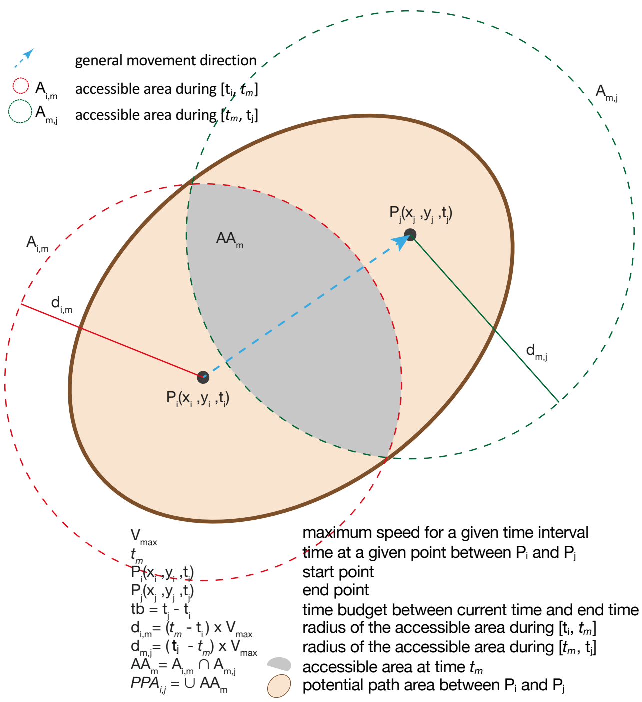

Figure 1: Illustration of the potential path area in a two-dimensional Euclidean space (modified from [25])

Figure 2 presents the overall workflow of the object-oriented time-geographic based approach to identify concurrent interactions between moving individuals. This workflow uses the same Class and Object definitions from ORTEGA: A moving entity is considered as a $MovingObject$ (MO) with a set of properties and methods. The properties of the $MovingObject$ class include a $Trajectory$ object which itself holds a series of PPA objects along the trajectory. The PPA object can be intersected with the $PPAs$ of other entities to create $PPA_{intersect}$ regions marking areas of potential interaction. The readers are referred to [9] for more detail on the description of the object-oriented scheme used in ORTEGA. The advantage of using an object-oriented scheme is that we can store information about the PPA intersections (i.e. location and time) as the properties of the $Trajectory$ objects and hence facilitate tracing of continuous segments of potential interactions in the history of the data.

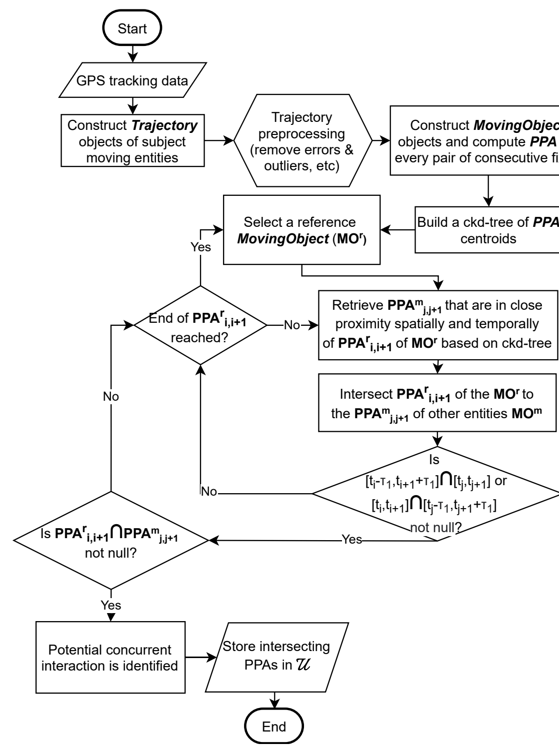

Figure 2: Workflow of identifying concurrent interactions in human movement

The first step of the workflow is to construct the $MovingObject$ and $Trajectory$ objects based on the original tracking data. A $Trajectory$ object of length n can be expressed as a series of $T = \{(x_0, y_0, t_0), (x_1, y_1, t_1), ..., (x_i, y_i, t_i), ..., (x_n, y_n, t_n)\}$, where x_i and y_i denote the geographical location and t_i denotes the time. This is followed by excluding outliers and erroneous data through trajectory preprocessing. Next, we calculate $PPAs$ along the trajectory of each MO. Formally, for each pair of consecutive tracking points (x_i, y_i, t_i) and $(x_{i+1}, y_{i+1}, t_{i+1})$ of the $MovingObject$ e (denoted by MO^e), the PPA between the two points can be denoted by $PPA^e_{i,i+1}$. It is necessary to note that, very large PPAs that are generated as the result of gaps in the data (i.e. larger than three times the standard deviation of the sampling intervals), occurring due to long stops or signal loss are eliminated from the data [10].

To trace concurrent interactions between a group of moving entities, every $MovingObject$ entity is selected in turn to be reference entity MO^r. To accelerate the computational speed for large data sets of tracking data of multiple individuals, a spatial and temporal indexing method named Compressed KD-tree or CKD-tree [2, 6] is implemented on the centroid of each PPA for every *MO*. Applying CKD-tree substantially reduces the computation by retrieving only the PPAs that are in the spatial and temporal proximity of the PPA of the selected reference moving entity MO^r. Next, the PPA of the selected reference MO^r denoted by $PPA^r_{i,i+1}$ is intersected spatially and temporally with the other retrieved PPAs of the mth moving entity in the data set, denoted by $PPA^m_{j,j+1}$. For any pair of $PPA^r_{i,i+1}$ and $PPA^m_{j,j+1}$, if $[t_i, t_{i+1}] \cap [t_j, t_{j+1}] \neq \phi$, a synchronous intersection between the two PPAs is determined. However, if this condition is relaxed by allowing a reasonable time lag τ_1, namely, if $[t_i - \tau_1, t_{i+1} + \tau_1] \cap [t_j, t_{j+1}] \neq \phi$ or $[t_i, t_{i+1}] \cap [t_j - \tau_1, t_{j+1} + \tau_1] \neq \phi$, the two PPAs are still considered to be overlapping temporally within the allowable time lag τ_1. The time lag parameter τ_1 can be defined by the user depending on the application scenarios (e.g., for human interaction analysis using tracking data of 1 min sampling rate, a time lag of 5 min may be reasonable to identify potential concurrent interactions [9]). If $PPA^r_{i,i+1} \cap PPA^m_{j,j+1} \neq \phi$, the two PPAs are overlapping spatially. That is, the accessible areas to the two *MO*s overlap, and they could potentially interact with each other at the same time. The output of this algorithm will be a list of PPA intersections (a list of $PPA_{intersect}$s) denoted by $\mathcal{U}$ which includes the unique IDs of the two *MO*s and the start time and end time of the two intersecting PPAs (an example of this list is provided in Table 1).

The present workflow is different from ORTEGA in two aspects. First, the objective of ORTEGA is to identify both concurrent and delayed interactions between moving entities, while in this study we only consider concurrent interactions within a reasonable time lag. Here, the goal is to quantify the duration of concurrent interactions or contacts between individuals, and 'duration' is not meaningful if the interaction is delayed (i.e. the individuals were not in the same location synchronously). Delayed interactions occur in a synchronous space but at asynchronous times. Second, the two steps of determining if two PPAs overlap spatially and temporally are swapped because judging if two ellipses intersect (i.e. $O(n+m)$ for intersection of two ellipses where n and m are the number of vertices for each ellipse) can take longer than judging if two time intervals overlap (i.e. $O(1)$ for computing time distance).

3.2 Quantifying the duration of interactions

The algorithm in the previous section can identify a set of spatially and temporally intersecting PPAs for every two moving individuals if they come into close contacts synchronously. However, it does not consider the temporal order of the intersecting PPAs and lacks the ability to identify continuous segments of interaction, which is important for quantifying the frequency and the duration of interactions between moving individuals. In this section, we present a new algorithm as an extension to ORTEGA that can extract subsequences of continuously intersecting PPAs of two moving individuals derived from the output from the previous stage (i.e. $\mathcal{U}$) and then measures the duration of potential contacts.

Table 1 presents an illustration of the identified set of $PPA_{intersect}$s between the reference individual MO^r and a selected individual MO^a in the output data $\mathcal{U}$ from the previous stage. The MO^r and

Table 1: A list of PPA intersections and their times identified between two moving individuals in the database. The columns of t^r_s and t^r_e are the start time and end time of the intersecting PPA of the reference individual MO^r with a unique identifier id^r, and the columns of t^a_s and t^a_e are the start time and end time of the intersecting PPA of a selected moving individual MO^a with a unique identifier id^a. N is the total number of identified PPA intersections between the two individuals.

$PPA_{intersect}$#	MO^r	MO^a	t^r_s	t^r_e	t^a_s	t^a_e
1	id^r	id^a	$t^r_s(1)$	$t^r_e(1)$	$t^a_s(1)$	$t^a_e(1)$
2	id^r	id^a	$t^r_s(2)$	$t^r_e(2)$	$t^a_s(2)$	$t^a_e(2)$
...	...	...	...	...	...	...
i	id^r	id^a	$t^r_s(i)$	$t^r_e(i)$	$t^a_s(i)$	$t^a_e(i)$
...	...	...	...	...	...	...
N	id^r	id^a	$t^r_s(N)$	$t^r_e(N)$	$t^a_s(N)$	$t^a_e(N)$

MO^a columns are the unique identifiers of the two moving individuals who have potential contacts determined by the algorithm described in the previous section. Let $[t^r_s(i), t^r_e(i)]$ and $[t^a_s(i), t^a_e(i)]$ denote the time intervals of the PPAs of the ith intersection between MO^r and MO^a. The notation i here only denotes the row number in the list of $PPA_{intersect}$s, but not the sequential order in the original PPA sequence. Note that one PPA of MO^r can overlap with multiple PPAs of MO^a as we consider two PPAs temporally overlap as long as the intersection between the two time intervals of the two *MO*s is not null given an allowable time lag τ_1, as described in the previous section. For example, in Table 1, if the two PPAs of MO^r in the first two rows are the same (i.e. $[t^r_s(1), t^r_e(1)] == [t^r_s(2), t^r_e(2)]$), the corresponding two PPAs of MO^a must be different (i.e. $[t^a_s(1), t^a_e(1)] \neq [t^a_s(2), t^a_e(2)]$).

Algorithm 1 presents the computation process of extracting continuous subsequences of intersecting PPAs of two moving individuals and estimating the duration of continuous interaction. The main steps of this algorithm are as follows:

(1) Take the $PPA_{intersect}$ list (e.g. Table 1) between the reference individual MO^r and a selected MO^a obtained from $\mathcal{U}$.
(2) Sort the $PPA_{intersect}$ list based on the start times of the PPAs of the two individuals (i.e. t^r_s and t^a_s).
(3) Trace continuous subsequences of intersecting PPAs using a for loop: identify consecutive records that share the same start time (i.e. $t^r_s(i) == t^r_s(i+1)$) or the end time is the same as the start time of the next record (i.e. $t^r_e(i) == t^r_s(i+1)$). Otherwise, the end of a continuous interaction segment is determined.
(4) Append all start times and end times of MO^r and MO^a (i.e. the records in the four columns of $t^r_s, t^r_e, t^a_s, t^a_e$) over the identified time interval of the continuous interaction segment to a candidate set $\Theta^{r,a}$.
(5) Determine the start time and end time of the continuous interaction segment using the minimum and maximum time of the derived $\Theta^{r,a}$.
(6) Compute the duration of the continuous interaction segment as $duration = max\{\Theta^{r,a}\} - min\{\Theta^{r,a}\}$.

(7) Continue the search for continuous subsequences until the end of the $PPA_{intersect}$ list is reached.

Algorithm 1: Quantifying the duration of interactions

Input: a list of $PPA_{intersect}$s between the reference individual MO^r and a selected MO^a obtained from $\mathcal{U}$
Output: a list of the start time, end time, and duration of the continuous interactions between MO^r and MO^a

```
Let Θ^{r,a} and L be new arrays
N ← length of the PPA_intersect list
for i = 0 to N-1 do
    if t_s^r(i) == t_s^r(i+1) then
        Θ^{r,a}.insert[t_s^r(i), t_e^r(i), t_s^r(i+1), t_s^a(i), t_e^a(i), t_s^a(i+1), t_e^a(i+1)]
    end
    else if t_e^r(i) == t_s^r(i+1) then
        Θ^{r,a}.insert[t_s^r(i), t_e^r(i), t_s^r(i+1), t_s^a(i), t_e^a(i), t_s^a(i+1), t_e^a(i+1)]
    end
    else
        if |Θ^{r,a}| == 0 then
            Θ^{r,a}.insert[t_s^r(i), t_e^r(i), t_s^a(i), t_e^a(i)]
        end
        starttime ← min{Θ^{r,a}}
        endtime ← max{Θ^{r,a}}
        duration ← max{Θ^{r,a}} − min{Θ^{r,a}}
        L.insert([starttime, endtime, duration])
        Θ^{r,a} ← empty list
    end
end
if |Θ^{r,a}|! = 0 then
    starttime ← min{Θ^{r,a}}
    endtime ← max{Θ^{r,a}}
    duration ← max{Θ^{r,a}} − min{Θ^{r,a}}
    L.insert([starttime, endtime, duration])
end
return L
```

4 EXPERIMENTS

4.1 Data description

This study uses several trajectories from the 2012-13 California Household Travel Survey (CHTS)[29]. The data set contains a single-day travel diary and three days of GPS tracking including the same single-day during which a travel diary was collected. The single-day travel diary records every survey respondent's household membership information (i.e. in the same or different household), trip start time and end time, transport mode, origin and destination coordinates (in longitude and latitude format) and corresponding location types (e.g., home, work, school, other). The GPS tracking data contains a unique ID of each participant, location in longitude and latitude, and local time and date when the person was tracked. It is noteworthy that due to the battery and storage capacity, the device will automatically deactivate when the movement speed is lower than one mile per hour, which means that only people's movements are tracked and the data do not include stops. Several tracks of 1 min sampling rate from the 2012-13 CHTS data are used to illustrate the proposed approach to identify and measure the duration of potential concurrent interactions.

4.2 Case studies

Using the information of household composition and several GPS trajectories from 2012-13 CHTS, we conduct two case studies to demonstrate the effectiveness of the proposed approach in identifying and quantifying the duration of continuous concurrent interaction events between mobile individuals of the same or different households. Guided by [9], in these two case studies, we define the concurrent interactions between mobile individuals as potential contacts within 5 min (i.e., $\tau_1 = 5$ min). In addition, we also evaluate the efficacy of our proposed approach in comparison with the commonly-used proximity-based approach in this section. It is worth noting that the identified continuous interaction events by both approaches can only be considered as 'potential' interactions [9]. In other words, individuals may or may not have socially or physically interacted when they come into close contact spatially and temporally.

4.2.1 *Interaction within household.*

The first case study focuses on the interactions occurring between mobile individuals from the same household or between individuals who most probably traveled and were tracked together. The premise is that people who live in the same household are more likely to move together during the day. For example, parents escort their children to school, couples may go grocery shopping or for a walk/ride together, a family goes out for dinner and so forth. Many of the joint activities within the same household tend to associate with joint travels.

Figure 3 illustrates the complete one-day GPS tracking of two persons from the same household ("H1P1" and "H1P2" herein) in the main map. The traces of H1P1 are presented in red dash-dotted line and H1P2 is in blue dash-dotted line. As presented in Table 2, 100% of their GPS fixes identified using PPA intersections, which indicates potential joint trips by the two individuals throughout the diary day. To give a sense of the identified interactions using our PPA-based approach, a portion of the interactions (i.e., PPAs of the two individuals overlap or intersect) are highlighted using yellow ellipses as shown in the inset map in Figure 3. Table 3 summarizes the identified continuous concurrent interaction events between two moving individuals. The results reveal six potential concurrent interaction events between person H1P1 and person H1P2 on November 20th in 2012.

We next verify the results by assessing the travel diary collected on the same day for the tracked individuals. Since the travel diary of H1P1 and H1P2 are exactly the same, Table 4 only presents the travel diary of H1P1. During the assigned survey day, these two persons from the same household traveled together and made in total six trips. The six continuous interaction events identified by the proposed approach match the travel diary almost perfectly (Tables 3 and 4). The total absolute difference between the diary and the identified results is 1,203 seconds (20.05 min). For each individual trip, the average absolute difference is 3.34 min. The slight time differences are reasonable since a conventional travel diary is completed at the end of the day and is purely based on people's memory

Table 2: Summary of the total # of fixes in the tracking data and the total # of fixes identified using PPA intersection. The percentage of overlap is quantified as the ratio between the two numbers.

Date	Person	# of total fixes	# of overlapped fixes(%)
Nov.20, 2012	H1P1	98	98(100%)
	H1P2	99	99(100%)
Oct.11, 2012	H2P1	60	13(21.67%)
	H3P1	79	14(17.72%)

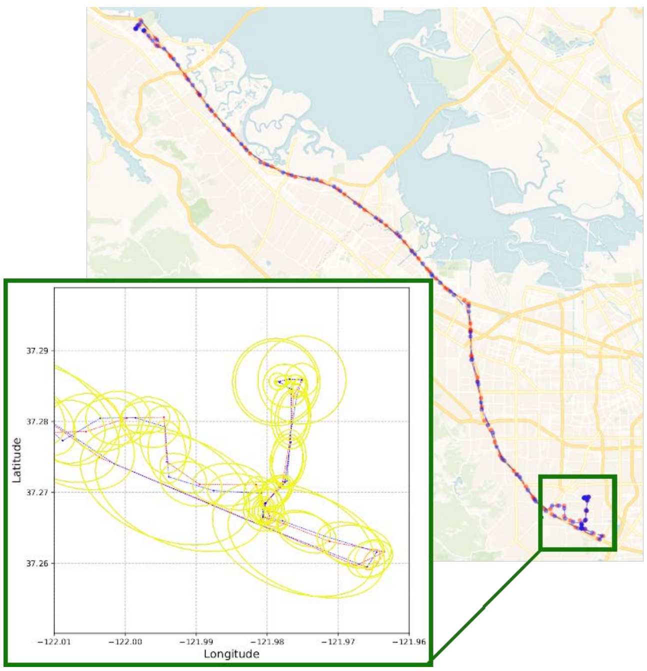

Figure 3: Complete single-day tracks of H1P1 (red dash-dotted line) and H1P2 (blue dash-dotted line) who are from the same household. The inset map shows a subset of intersecting PPAs between the two persons using yellow ellipses. The basemap is hidden in the inset map to protect participants' privacy.

of their schedules. In general, our proposed method is capable of accurately identifying the concurrent interaction events between individuals of the same household.

4.2.2 Interaction outside household. The second case study uses GPS tracking data of two persons who live in different households to illustrate the efficacy of the proposed approach in identifying continuous interaction events outside households when people not necessarily move together. The two persons are denoted by H2P1 and H3P1. Figure 4 depicts the complete trajectories of the two selected persons (in blue/red dash-dotted lines) during the same assigned survey day, and the intersected PPAs are highlighted in yellow in the inset map. Overall, as shown in Table 2, only

Table 3: The identified continuous interaction events between individuals from the same or different households using the proposed PPA-based approach.

Persons	Event#	Start time	End time	Duration (min)
H1P1&H1P2	1	14:16:29	14:52:57	36.5
	2	15:00:58	15:04:46	3.8
	3	15:47:49	16:29:39	41.8
	4	18:16:25	18:23:07	6.7
	5	18:34:11	18:37:16	3.1
	6	18:44:53	18:50:05	5.2
H2P1&H3P1	7	18:34:47	18:50:28	15.7

21.67% (H2P1) and 17.72% (H3P1) of their respective total number of fixes were identified using PPA intersection, indicating a few short segments for potential concurrent interactions. This is reasonable, as people from different households are most likely strangers and the potential contacts between them are usually more occasional and random, unless they are related or work together. Table 3 summarizes in detail the identified continuous interaction event (i.e. interaction event #7) between H2P1 and H3P1 which begins at 18:34:47 and ends at 18:50:28. Based on the visualization of their tracks presented in Figure 4, this interaction event #7 occurred when the two individuals stayed in two different vehicles moving along the same direction and came into close contact on the same road segment.

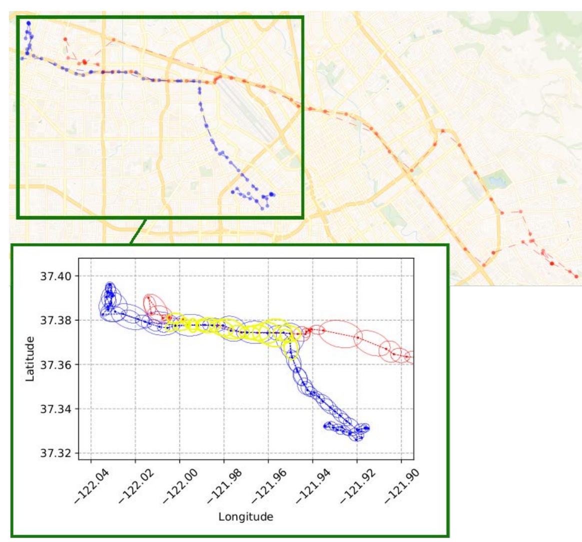

Figure 4: The identified continuous interactions #7 (yellow ellipses) between H2P1 (red) and H3P1 (blue) from different households. The basemap is hidden in the inset map to protect participants' privacy.

Next, the travel diary and the trajectories of the two individuals are used to interpret the identified potential continuous interaction event on the assigned survey day. The one-day travel diary of H2P1 and H3P1 on October 11th, 2012 shows that during the time

Table 4: Travel diary of H1P1

Trip #	Date	Start time	End time	Duration (min)	Origin	Destination
1	Nov.20, 2012	14:17:00	14:52:00	35	Home	Liquor store
2	Nov.20, 2012	15:02:00	15:04:00	2	Liquor store	Parent's home
3	Nov.20, 2012	15:48:00	16:29:00	41	Parent's home	Home
4	Nov.20, 2012	18:16:00	18:23:00	7	Home	Restaurant A
5	Nov.20, 2012	18:34:00	18:35:00	1	Restaurant A	Restaurant B
6	Nov.20, 2012	18:37:00	18:45:00	8	Restaurant B	Home

when the two persons came into close contacts, H2P1 was on a car leaving from the workplace to a supermarket while H3P1 was driving home after work. Therefore, it is reasonable to state that the two individuals of different households actually came into close contact for 15.7 min when they stayed in different vehicles during the same survey day. For the purpose of contact tracing in disease transmission, this identified interaction event between H2P1 and H3P1 should not be considered as a risky contact because the two individuals did not necessarily travel together and only happen to pass each other when potentially in different vehicles.

4.3 Comparison to the proximity-based approach

Figure 5 illustrates the implementation of the proximity-based approach to identify potential concurrent interaction events between two moving individuals. A potential interaction can be identified by intersecting spatial buffers centered on synchronous GPS tracking points of two individuals. In this experiment, a buffer size of 100 m is used. Increasing the buffer size allows a higher chance of intersection between the tracks, especially when synchronous or high resolution tracking data are not available [9]. In the hypothetical example shown in Figure 5, the spatial buffer at time t_3 for moving object #1 and the buffer at t_2 for moving object #2 intersect spatially. Although they are at different times (i.e. $t_3 > t_2$), if $|t_3 - t_2| < \hat{\tau}$ where $\hat{\tau}$ is a parameter of the allowable time difference, the two moving objects can be considered as having a potential concurrent contact between the time interval $[t_2, t_3]$ [9]. To make the two approaches comparable, the same 5-min threshold (following Section 4.2) is applied for the proximity-based approach to identify concurrent interaction events (i.e. $\hat{\tau} = \tau_1 = 5min$). The same tracking data sets from the above two case studies are used to discuss the difference between the two approaches in identifying and measuring the duration of continuous interaction events.

The number of intersecting GPS fixes (i.e. buffers) identified by the proximity-based approach are summarized in Table 5. Only 38.78% and 31.31% of their respective total number of GPS fixes of H1P1 and H1P2 (from the same household) are identified as potential interactions. Presumably, even though the two individuals come from the same household are very likely to move together, their locations were not tracked completely synchronously, since each used an individual tracker. Therefore, compared to our approach which considers the potential path area between GPS fixes, the proximity-based approach resulted in many missing concurrent interactions along their movement paths. This underestimation problem is even more pronounced for individuals from different

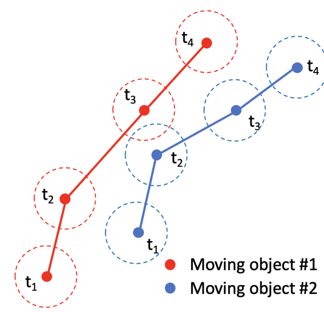

Figure 5: Illustration of the proximity-based approach to identify potential interactions between two moving individuals. The solid points and lines between them represent the tracking points and moving trajectories of the two individuals. The dashed circle around the tracking point represents the spatial buffer with a user-defined size.

households when individuals are not necessarily tracked together. Table 5 shows that only 5% and 2.53% buffers of the total number of GPS fixes of H2P1 and H3P1 intersected. This observation suggests that the proximity-based approach is less effective to identify close contacts when people are not traveling together or when short contacts occur. Table 6 summarizes the timeline and duration of the identified continuous interactions between people of the same or different households by applying the proximity-based approach. As compared to our PPA-based approach, for the pair of individuals of the same household (H1P1 and H1P2), the proximity-based approach results in more intermittent interactions with shorter durations of contacts, which doesn't align with the actual observations based on the diary logs as shown in Table 4. In the case of outside household interaction (H2P1 and H3P1), the results show that the proximity-based approach can only identify a portion of a potential continuous interaction event compared to the proposed time-geographic based approach.

5 CONCLUSIONS AND FUTURE WORK

This paper introduced a technique to trace and estimate the duration of continuous interactions between moving individuals. In doing so, it advanced the existing time-geographic approaches to movement interaction analysis. The proposed method relies on the spatial and temporal intersection of potential path areas to determine possible concurrent interactions between moving individuals in space and time. By taking into account the temporal

Table 5: Summary of the total # of fixes in the tracking data and the total # of fixes identified using buffer intersection. The percentage of overlap is quantified as the ratio between the two numbers.

Date	Person	# of total fixes	# of overlapped fixes(%)
Nov.20, 2012	H1P1	98	38(38.78%)
	H1P2	99	31(31.31%)
Oct.11, 2012	H2P1	60	3(5%)
	H3P1	79	2(2.53%)

Table 6: The identified continuous interaction events using the proximity-based approach

Persons	Event#	Start time	End time	Duration
H1P1&H1P2	1	14:16:29	14:20:42	4.2 min
	2	14:49:36	14:51:33	1.95 min
	3	15:00:58	15:04:46	3.8 min
	4	15:48:09	15:51:42	3.6 min
	5	16:07:33	16:07:42	9 s
	6	16:19:53	16:20:00	7 s
	7	16:22:03	16:25:57	3.9 min
	8	18:16:25	18:23:05	6.7 min
	9	18:34:11	18:34:16	5 s
	10	18:35:36	18:37:14	1.6 min
	11	18:44:53	18:50:02	5.2 min
H2P1&H3P1	12	18:37:30	18:41:58	4.5 min

order of the identified intersecting PPAs, the proposed technique is capable of extracting subsequences of continuous potential interaction segments to estimate the duration of potential contacts. Two case studies were conducted to examine the proposed approach in identifying and quantifying interactions between individuals of the same or different households. The results showed that the proposed approach can identify almost perfectly the interactions and the duration of the interactions between individuals who move together. In addition, the proposed approach can also identify potential concurrent interactions between individuals who do not move together. The results are also evaluated against the commonly-used proximity-based approach (i.e. based on point-to-point distance) which is often used in contact-tracing applications. The comparison indicates that using the proximity-based approach to quantify the duration of interactions may yield very erroneous results, while the proposed time-geographic based approach can identify the duration of contact more accurately. In addition, unlike the proximity-based approach, our proposed approach does not rely on arbitrary buffer size. Although the time-geographic based approach is computationally more intensive than the proximity-based approach, the proposed method can estimate the duration of contacts more accurately and identify more complete interactions over a continuous time period, which outperforms substantially the proximity-based approach. The proposed approach can also apply to trace the duration of interaction in interspecific and intraspecific interactions of animals.

There are several directions for future research. The identified continuous interactions can be enriched by incorporating contextual information such as surrounding geographic environment, travel behavior and people's socio-demographic characteristics. This can help better understand and interpret the identified interaction patterns. For example, by incorporating contextual information, it may be feasible to distinguish close contacts between individuals in indoor and outdoor settings which might pose different risk levels in the transmission of diseases such as COVID-19. In addition, by taking into account travel mode, contacts that occurred on the road where individuals stayed in different vehicles can be differentiated from more risky contacts when individuals passed by each other in the street.

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