Inferring Relationships from Trajectory Data

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Abstract. *Devices like smart phones and GPS navigators are very popular nowadays. These equipments can save the location of an object with an associated time, generating a new kind of data, called trajectories of moving objects. With these data it is possible to discover several interesting patterns, among which is the interaction between individuals, allowing to infer their relationship. This work addresses the discovery of relationship degree between moving objects based on their encounters. To calculate the relationship degree we propose different measures based on frequency, duration, and area of the encounters. These measures were evaluated in experiments with a running example and real trajectory data, and show that the method correctly infers relationships.*

1. Introduction and Motivation

The price reduction of mobile devices such as GPS and mobile phones, as well as advances in satellite and wireless sensor technologies, has enabled a significant increase in the use of these mechanisms. These devices allow recording people's movement. Accordingly, any individual who carries a mobile device, while moving, generates a trace, in which each time point corresponds to a location in space. This trace is called trajectory of the moving object. There are several works dealing with such data, as the one that describes avoidance of trajectories [Alvares et al. 2011], chasing [de Lucca Siqueira and Bogorny 2011], outliers [de Aquino et al. 2013], flocks, leadership, convergence, and encounter [Laube et al. 2005].

Although there are numerous works on patterns in trajectories, only a few address the encounter/meeting patterns, and even less works infer friendship relationships from trajectories or consider encounters for relationship inference. The first work to define encounter was [Laube et al. 2005], where encounters happen when a set of objects have points in a specific given radius. [Gudmundsson et al. 2007] defined the encounter pattern with a minimum number of entities inside a given radius. [Bak et al. 2012] proposed an algorithm to detect encounters between two trajectories, where all points that are close in space and time are connected forming a line. The work of Bak focuses on visual analysis of encounters. The most formal definition of encounter is given by [Dodge et al. 2008], which defines encounter as a convergence where objects arrive at a place at the same time.

Existing works do only define the concept of encounter, and have neither go deeper in the encounter pattern analysis nor use them for relationship inference among moving objects. The inference of relationships is an important issue for several application domains. In biology, for example, we can discover how much time the pandas A and B

stayed together in the last summer, and which areas they visited together and alone. For investigative applications, we can verify the total time that a group of individuals stayed close in the last month, and how much time two objects Y and Z of this group stayed together and which areas they visited with a bigger group of objects. We strongly believe that the relationship of objects is directly related to amount of time they spend together. For instance, a married couple stays more time together than a couple that is dating, and the couples, in turn, stay more time together than a couple of friends.

To infer relationships from encounter patterns is not a trivial task. Let us consider the example shown in Figure 1, where Louis met Marie and then both met John, and after they met Susan, at day 5th May. For this day we have four encounters, each one with duration of one hour. The first encounter is between Louis and Marie (from 9 to 10). The second encounter is between Louis, Marie and John (from 10 to 11). The third encounter is between Louis and Marie alone (from 11 to 12), and the fourth encounter is between Louis, Marie and Susan (from 12 to 13). This example illustrates three important things when we reason about measuring the relationship degree based on encounters: the number of objects present on each encounter, the frequency, and the duration. In this example, still considering 5th of May, the duration of the encounter is higher for Louis and Marie, corresponding to 4 hours in total. So we can consider that Louis and Marie have a stronger relationship degree among each other than with John and Susan. When considering the encounter of Louis and Marie alone, their encounter has 2 hours of duration. Considering the whole time they stayed together at 5th of May, the duration is 4 hours. This example shows that it is very complex to analyze encounters and relationships between moving objects, and that we must analyze every different encounter and with all different objects.

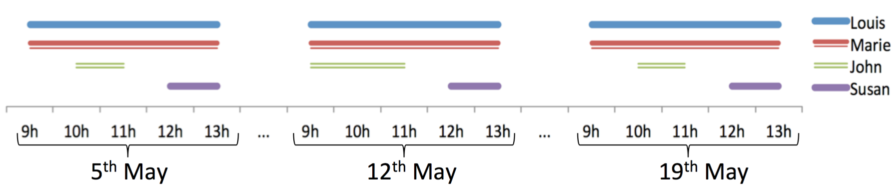

Figure 1. Temporal Representation of encounters between the same individuals

In this paper we propose a new definition of level-wise encounter patterns. From these encounters we propose an algorithm to infer relationships, called MORE (Moving Objects Relationship inference from Encounters). The main contribution of our approach is the definition of level-wise encounter patterns and the inference of moving object relationships, considering their encounters, the frequency of the encounters, the duration, and the encounter area. In this work we go one step further to existing approaches, which do only detect encounters from trajectory data and do not infer objects relationships, making the following contributions: (i) define encounter patterns as well as the encounter area from trajectory data; (ii) define different measures to compute the relationship of individuals based on the frequency, the duration, and the area of their encounters; (iii) propose an efficient algorithm to infer the relationship degree of individuals from their trajectories.

The rest of the paper is organized as follows. In section 2 we summarize the related work. In Section 3 we present the main definitions and the algorithm $MORE$. In

Section 4 we present preliminary experiments to evaluate the algorithm, and finally, the conclusions are presented on Section 5.

2. Related Work

In this section we summarize the works that define encounters and flocks, and since there are only a few works that infer relationships from GPS trajectories, we present some methods that infer relationships from other types of spatio-temporal data, as phone logs/calls and social networks.

2.1. Encounters

Among the few existing studies in the literature that directly address the encounter between trajectories we can highlight the work of [Laube et al. 2005], which defines a set of patterns considering geographic and temporal aspects. Between these patterns are flock and encounter. The flock pattern can be detected from the REMO (RElative Motion Pattern) matrix, which relates the time and the direction of objects movements. When objects are moving in the same direction at the same time, and within a certain area, they present a flock behavior. The encounter pattern cannot be detected from the REMO matrix, because objects come from different directions until they meet. To detect encounters, [Laube et al. 2005] proposed a division of the space in cells of a given size, and the trajectories that intersect the same cells in a similar time have an encounter pattern.

Gudmundsson in [Gudmundsson et al. 2007] defines encounter as a minimal number of objects m that ”stay” inside an area of size r at a certain time. A flock is defined as a set of m objects that ”move” inside a spatio-temporal cylinder of size r for a certain time, and objects may leave or enter the flock. In this work both encounter and flock are considered as different patterns, while in our proposal we assume that objects that are together, either stopped or moving, are having an encounter. Indeed, while in [Gudmundsson et al. 2007] objects enter and leave a flock, we create a *different* encounter every time the group changes.

Bak in [Bak et al. 2012] proposed an algorithm to detect encounters focused on visual analysis. The main idea of the algorithm is to connect with a line two points of different objects that are close in space and time. The user can vary the space and time threshold, visualizing the connected dots and evaluating the results.

In our work, we consider as an encounter the whole time that the objects remain together, does not matter if they are stopped or moving. Usually, a whole encounter is separated in two patterns to fit in the definitions of encounter and flock. For example, a walk with a friend followed by a visit to a restaurant is separated in two parts: the walk is a flock pattern and the staying in a restaurant, an encounter.

The works about encounters and flocks focused only on detecting the pattern, not on the inference of relationships between level-wise objects, which is the objective of our work. Indeed, the area of the encounters and flocks is not defined.

2.2. Relationship Inference from GSM and Social Network

Before describing these works we must highlight that the task of relationship inference in social network is only an affine topic, and it is more trivial since much information about friendship is available in the data. In the domain of social network analysis there are several works that try to infer the relationship between pairs of objects. Some of these works use information of phone logs and calls like [Eagle et al. 2009], others use only social network data where the user makes a check-in at some place, or shares a geo-tagged picture [Crandall et al. 2010], [Pham et al. 2013] and [Wang et al. 2014].

A friendship network structure based on mobile phone data was proposed in [Eagle et al. 2009]. A group of students answered if another member of the group is a friend or not. In a first step, each pair of objects is classified as "Reciprocal Friends", "Non-Reciprocal Friends" and "Reciprocal Non-Friends". Then, the friendship relations are inferred using proximity information of the mobile phones, based on phone logs, calls, and Bluetooth connections. Finally, the proximity of these persons is evaluated based on the day of the week and the kind of place the objects met. The output is a friendship network, where each node is an individual and the edge corresponds to a score based on two factors: the first one is based on the proximity at place of work, and the second is based on the proximity outside the work environment.

Crandall, in [Crandall et al. 2010], proposed a model to infer social ties between pairs of users, where spatio-temporal co-occurrences are detected based on shared photos of the site Flickr. First, the space is divided in cells, then if both users shared a photo within t days in the same cell, a co-occurrence is detected. Finally, the number of different cells visited by the same pair is counted. Based on the number of different co-locations between the pair of objects a probabilistic model is used to compute the friendship.

A model to infer social strength called EBM (Entropy-Based Model) was proposed by Pham in [Pham et al. 2013]. It analyses information from the social network Gowalla, that allows the users to make check-ins when they are in a known place. First, the co-occurrences are computed for each pair of objects. The co-occurrences are coincident check-ins of the objects, considering space and time. Finally, the relationship is calculated considering the entropy of the places and the frequency of the co-occurrences.

Another model to infer relationship strength between pairs of users based on check-ins from location-based social networks was recently proposed by Wang in [Wang et al. 2014]. This approach is based on personal, global, and temporal factors. The personal factor considers an individual user's probability to visit a certain location. The global factor captures the popularity of a location to the general public. The temporal factor considers the time gaps between consecutive meeting events.

Even though check-ins from social networks are useful to infer relationships between people, when we want to measure the relationship among animals or people which do not use social networks (e.g. house arrest criminals), GPS trajectories are the most appropriate data.

2.3. Relationships in Trajectories of Moving Objects

Only a few works use GPS data to infer relationships, like [Brilhante et al. 2012], that infers relationships among places. Because GPS data are more complex and lack in relationship information, [Brilhante et al. 2012] use summarized trajectories, i.e., stops or stay points to reduce the complexity. In our approach we use raw trajectories, first computing encounters/flocks and from these encounters propose a method to infer relationships.

Brilhante [Brilhante et al. 2012] proposed a methodology to discover communities of interesting places, using as input the trajectories of moving objects and known POIs (Point of Interest). The first step is to detect stops at the given POIs. If a group of trajectories has short stops on a pair of POIs, these POIs are connected. This work does not infer relationships among users, only between points of interest.

In summary, none of the related work infer a relationship degree based on encounters of groups of multiple objects, and none of them consider area, duration and frequency of encounter as measures to determine the relationship degree.

3. Main Definitions and the Proposed Algorithm

In this section we first present the main concepts to define an encounter pattern, the encounter area, and the relationship degree between objects (Section 3.1). In Section 3.2 we present the algorithm $MORE$ (Moving Objects Relationship inference from on Encounters), an algorithm to infer the relationship degree between a group of objects.

3.1. Main Concepts

We start our definitions with the well known concepts of *point*, *trajectory*, and *subtrajectory*, inspired by the definitions presented in [de Lucca Siqueira and Bogorny 2011] and [Bogorny et al. 2014].

Definition 1 *Point. A point p is a tuple (x,y,t), where x and y are geographic coordinates that represent a position in space and t is the timestamp in which the point was collected.*

A trajectory is an ordered list of points that correspond to the position of the object in space at a time, as presented in Definition 2.

Definition 2 *Trajectory. A trajectory $T_o = \langle p_1, p_2, p_3, ..., p_n \rangle$ is an ordered list, where o is the object identifier, $p_j = (x_j, y_j, t_j)$ and $t_1 < t_2 < t_3 < ... < t_n$.*

It is well known that several trajectory patterns do not hold for an entire trajectory, but only in a trajectory part. For the encounter pattern it is not different. Two trajectories may not be together during all their life, but only in parts of their movements, and this parts are called subtrajectories. The definition of subtrajectory is given in Definition 3.

Definition 3 *Subtrajectory. A subtrajectory s of T is a list of consecutive points $\langle p_k, p_{k+1}, ..., p_{k+l} \rangle$, where $p_i \in T$ and $k + l \leq n$.*

[Laube et al. 2005], [Gudmundsson et al. 2007] and [Dodge et al. 2008] define an encounter as a set of objects that are close in space and time. Our definition for encounter is a bit different, where we compute encounters of every object in the database in relation to other objects which stay close in space and time, for a minimal amount for time. For example, in Figure 1, we compute the encounters between Louis and Marie, between Louis, Marie and John, and between Louis, Marie and Susan. We do not require a minimal number of objects, since we are, in fact, interested in all possible encounters of any number of two or more objects.

In this work we do not distinguish stationary and moving encounters, since we want to know when two or more objects stay together. Definition 4 presents the concept of encounter. For the sake of simplicity, in the following we will restrict the definitions for two moving objects, but note that the generalization to more than two objects is straightforward.

Definition 4 *Encounter. Let $T_1 = \langle p_1, p_2, p_3, ..., p_n \rangle$ and $T_2 = \langle q_1, q_2, q_3, ..., q_m \rangle$ be two trajectories. Let $s_1 = \langle p_a, p_{a+1}, ..., p_{a+u} \rangle$ and $s_2 = \langle q_b, q_{b+1}, ..., p_{b+v} \rangle$ be two subtrajectories of T_1 and T_2, respectively. T_1 and T_2 have an encounter at two maximal subtrajectories s_1 and s_2 w.r.t a spatial threshold Δ_d, a temporal threshold Δ_t and a minimum duration $minTime$ IIF the following conditions hold:*

- $\forall p_i \in s_1, \exists q_j \in s_2|$ *spatialDist(p_i,q_j)* $< \Delta_d \wedge$ *temporalDist(p_i,q_j)* $< \Delta_t$
- $\forall q_j \in s_2, \exists p_i \in s_1|$ *spatialDist(q_j,p_i)* $< \Delta_d \wedge$ *temporalDist(q_j,p_i)* $< \Delta_t$
- *(min($p_{a+u}.t$,$q_{b+v}.t$) - max($p_a.t$,$q_b.t$))* $>$ *minTime*

where the functions $spatialDist()$ and $temporalDist()$ compute, respectively, the Euclidean distance and the temporal distance between the points p_i and q_j.

To the best of our knowledge, there are no works in the literature which take into account the area where two or more objects have an encounter to infer relationships. In this work, as we want to measure the relationship degree for all combinations (sets) of objects, just assuming that objects should stay together (close) in space for a certain amount of time is not enough. However, if we consider meetings at different places, we reduce the fact that they meet only by coincidence. For instance, objects that leave in a nearby area and work at a nearby place (e.g. in a shopping center), will be detected as having encounters, even if these encounters represent a coincidence. Although the coincidence may generate several encounters, we cannot ignore them, because for several applications, mainly for security, objects that came close in space and time may have a contact, and this contact should be considered for relationship inference. However, by considering that these objects that have frequent encounters at the same places (e.g. nearby homes and working place) also have encounters in different areas, the probability of coincidence will be reduced, and the confidence that these objects know each other will increase the relationship degree.

We define encounter area as the union of the subtrajectories of all trajectories involved in the encounter. More formally,

Definition 5 *Encounter area. Let e be an encounter between the subtrajectories s_1 and s_2, w.r.t Δ_d, Δ_t and $minTime$. The encounter area a_e is given by the formula:*

$$a_e = buffer(makeLine(s_1), \Delta_d/2) \cup buffer(makeLine(s_2), \Delta_d/2) \tag{1}$$

where $makeline()$ is a function that transforms a set of points of a subtrajectory s in a line and $buffer()$ is a function that builds a polygon of size $\Delta_d/2$ around s.

To take into account the area of an encounter, hereafter we refer to encounter as a tuple e = (O, $beginTime$, $endTime$, a), where O is the set of objects involved in the encounter, $beginTime$ and $endTime$ are, respectively, the begin and end time of the encounter, and a is the spatial area of the encounter.

To define the relationship degree between two or more objects based on their encounters, we consider three main criteria: the *frequency* of the encounters, the *duration*, and the *different areas* where the encounters take place.

The frequency reveals how many times two or more objects meet.

Definition 6 *Frequency-Based Relationship Degree. Let* $DB = e_1, e_2, ..., e_n$ *be a set of encounters w.r.t.* Δ_d*,* Δ_t *and* $minTime$*, of all sets of moving objects in a trajectory database. Let* $E(o_i, o_j)$ *denote the set of all encounters between any objects* o_i *and* o_j*. The frequency- based relationship degree between a pair* (o_1, o_2) *is given by:*

$$R_f(o_1, o_2) = \frac{|E(o_1, o_2)|}{max(|E(o_i, o_j)|)} \tag{2}$$

where $|X|$ *represents the cardinality of X.*

The duration of an encounter tells how much time two objects spend together. We assume that the higher the duration of an encounter is, the higher will be the relationship between the objects. The duration based relationship degree is given in Definition 7.

Definition 7 *Duration-Based Relationship Degree. Let* $DB = e_1, e_2, ..., e_n$ *be a set of encounters w.r.t.* Δ_d*,* Δ_t *and* $minTime$*, of all sets of moving objects in a trajectory database. Let* $E(o_i, o_j)$ *denote the set of all encounters between* o_1 *and* o_2*. The duration based relationship degree between* o_1 *and* o_2 *is:*

$$R_d(o_1, o_2) = \frac{\sum_{z=1}^{z=|E(o_1,o_2)|}(endTime_z - beginTime_z)}{max\left(\sum_{z=1}^{z=|E(o_i,o_j)|}(endTime_z - beginTime_z)\right)} \tag{3}$$

The first idea when we think about defining a relationship degree between a group of several objects is to use the duration and frequency. However, in downtown areas we can find different objects close to each other in space and time. In these cases, people who get the same bus everyday together could have a strong relationship, when they not even know each other. To reduce this problem we define that a group that has encounters in different areas has a higher relationship degree. The more different areas two or more objects have an encounter, the higher is the probability that the objects know each other. Therefore, we define the area-based relationship according to Definition 8.

Definition 8 *Area-Based Relationship Degree. Let* $DB = e_1, e_2, ..., e_n$ *be a set of encounters w.r.t.* Δ_d*,* Δ_t *and* $minTime$*, of all sets of moving objects in a trajectory database. Let* $E(o_1, o_2)$ *denote the set of all encounters between* o_1 *and* o_2*. Let* $A(o_1, o_2) = \{a_1, a_2, ..., a_r\} | a_1 \cap a_2 \cap ... \cap = \emptyset$ *be the set of different encounter areas between* o_1 *and* o_2*. The area-based relationship degree between* o_1 *and* o_2 *is:*

$$R_a(o_1, o_2) = \frac{|A(o_1, o_2)|}{max(|A(o_i, o_j)|)} \tag{4}$$

Considering duration, frequency, and encounter area, the final relationship degree between two or more objects is computed by the sum of the degrees, as shown in Definition 9.

Definition 9 *Relationship Degree. Let* $DB = e_1, e_2, ..., e_n$ *be a set of encounters w.r.t.* Δ_d*,* Δ_t *and* $minTime$*, of all sets of moving objects in a trajectory database. Let* $E(o_i, o_j)$ *denote the set of all encounters between* o_1 *and* o_2*. The final relationship degree between* o_1 *and* o_2 *is computed as:*

$$R(o_1, o_2) = (R_f(o_1, o_2) + R_d(o_1, o_2) + R_a(o_1, o_2))/3 \tag{5}$$

In the following section we present an algorithm to infer the relationship degree between moving objects, called MORE (Moving Objects Relationship inference from Encounters)

3.2. MORE (Moving Objects Relationship inference from Encounters)

The input of the algorithm $MORE$, shown in Listing 3, is: a set of trajectories T, the time tolerance Δ_t, the distance threshold Δ_d, and the minimum time for detecting an encounter $minTime$. The output is a list with the relationship degree of the moving objects R.

Listing 1. MORE Algorithm

```
1  Algorithm MORE
2  Input:  T //set of trajectories
3        Δt //Time Tolerance
4        Δd //Distance Threshold
5        minTime //Minimum Encounter Tolerance
6  Output: R //list of objects, with their relationship degree
7
8  E = BeingTogether(T, Δt, Δd, minTime)
9  E = computeArea(E, Δd)
10 encountersPerObjects = retrieveEncountersPerObjects(E)
11 max_f = getMaxFrequence(encountersPerObjects)
12 max_d = getMaxDuration(encountersPerObjects)
13 max_a = getMaxDiffAreasCount(encountersPerObjects)
14 for each set of objects o ∈ encountersPerObjects.values do
15    R_f = getFrequencyOf(encountersPerObjects.get(o)) / max_f
16    R_d = sumDurationsOf(encountersPerObjects.get(o)) / max_d
17    R_a = getDistinctsAreasOf(encountersPerObjects.get(o)) / max_a
18    result.R = (R_f + R_d + R_a)/3
19    R.put(e.O, result)
20 end for
21 return R
```

The first step is to compute the encounters (according to Definition 4), using the function $BeingTogether()$ (line 8). Since we have the set of encounters E, it is possible to compute the encounter area (according to Definition 5), using the function $computeArea()$ (line 9). Two encounter areas are considered as only one if their intersection is higher than 75%.

In order to compute the frequency, the duration, and the distinct areas of the encounters, the algorithm transforms the set of encounters E into a list that contains each different group of objects with their respective encounters (line 10). Figure 2 shows this transformation for the encounters between Marie ($o1$), Louis ($o2$), John ($o3$) and Susan ($o4$), according to Figure 1. Since we have the groups of objects and their respective

id	O	area	beginTime	endTime
e_1	{1,2}	a_1	5th May 9h	5th May 10h
e_2	{1,2,3}	a_2	5th May 10h	5th May 11h
e_3	{1,2}	a_3	5th May 11h	5th May 12h
e_4	{1,2,4}	a_4	5th May 12h	5th May 13h
e_5	{1,2,3}	a_5	12th May 9h	12th May 11h
e_6	{1,2}	a_6	12th May 11h	12th May 12h
e_7	{1,2,4}	a_7	12th May 12h	12th May 13h
e_8	{1,2}	a_8	19th May 9h	19th May 10h
e_9	{1,2,3}	a_9	19th May 10h	19th May 11h
e_{10}	{1,2}	a_{10}	19th May 11h	19th May 12h
e_{11}	{1,2,4}	a_{11}	19th May 12h	19th May 13h

oids	encounters
{1,2}	{e_1, e_2, e_3, e_4, e_5, e_6, e_7, e_8, e_9, e_{10}, e_{11}}
{1,2,3}	{e_2, e_5, e_9}
{1,2,4}	{e_4, e_7, e_{11}}

Figure 2. (left) list of encounters and (right) encounters grouped by objects

encounters, the next step of the algorithm is to get the maximum values for the frequency (line 11), duration (line 12), and the distinct area of the encounters (line 13). Then, for each group of objects (line 14) the algorithm computes the frequency (line 15), the duration (line 16) and the area of the encounters (line 17) according to Definitions 6, 7 and 8, respectively. Finally, the relationship degree is computed (line 18) and added to a list (line 19).

The complexity of the algorithm $MORE$ is given by the complexity of the function to transform the encounter list $retrieveEncountersPerObjects$ plus the number of different sets of objects, represented by the variable $encountersPerObjects$. In the iteration are computed frequency, duration, and different areas for each different group of objects, having a cost of $O * m$, where O is the size of the transformed list and m is the number of encounters.

4. Preliminary Experiments

In this section we present two preliminary experiments: a running example and a real trajectory dataset where the encounters are known.

4.1. MORE applied on a Running Example

For a better understanding of the relationship inference we apply the $MORE$ algorithm over the example shown in Figure 1. The output is illustrated on Table 1, which is sorted in descending order by R, forming a relationship degree rank. Table 1 shows frequency, duration, and number of different encounter areas between Marie, Louis, John and Susan.

Table 1. Relationship Measures for the running example

O	$frequency$	$duration$	$area$	R_f	R_d	R_a	R
{Marie, Louis}	3	12	3	1	1	1	1
{Marie, Louis, John}	3	4	3	1	0.333	1	0.778
{Marie, Louis, Susan}	3	3	3	1	0.25	1	0.75

According to Figure 1, Marie and Louis stayed together from 9h to 13h on each one of the three days, therefore the frequency of this group is equal to 3 and the duration is 12h. Marie, Louis and Susan, stayed together for one hour on 5th of May (from 12h to 13h), one hour on 12th of May and another hour on 19th of May, hence the total duration is 3 hours. Assuming that, in this example, the objects met at three different places, each group has 3 different encounter areas.

Observing the example in Figure 1, the group with the highest relationship during the period between 5th of May to 19th of May was Marie and Louis. Notice that the relationship degree between the objects Marie, Louis and John is a bit higher than between the objects Marie, Louis and Susan. This is because there was one encounter (Figure 1) at 12th of May between objects Marie, Louis, John with duration of 2 hours (from 9h to 11h), while all others had the same one hour of duration.

4.2. UFSC dataset

On August 13th, 2015, a group of eleven volunteers walked around the UFSC campus to simulate encounters, generating a dataset with 29329 points. The seven simulated encounters are represented by rectangles in different colors in Table 2 and are visually represented in Figure 3. The participants received a smartphone, a map, and the instructions to visit three different places during the time described in Table 2 (from 17:40 to 18:20). The visits, with around 10 minutes of duration each, happened at different places as shown in Table 2. For instance objects 1, 2, and 3 have only one encounter alone, at $Place_1$ and in the path to $Place_7$, where they met object 4, generating a new encounter with four objects. Objects 7 and 8, for instance, have two different encounters at $Place_3$ (from 17:40 to 17:50 and 18:10 to 18:20). The detected encounters are illustrated in Figure 3. All simulated encounters were correctly detected by the algorithm considering Δ_t = 10 s, Δ_d = 15 m, $minTime$ = 5 min.

Table 2. Encounters at UFSC

oid	**1st place** [17:40, 17:50]	⇒	**2nd place** [17:55, 18:05]	⇒	**3rd place** [18:10, 18:20]
1	$Place_1$	⇒	$Place_7$	⇒	$Place_9$
2	$Place_1$	⇒	$Place_7$	⇒	$Place_9$
3	$Place_1$	⇒	$Place_7$	⇒	$Place_9$
4	$Place_6$	⇒	$Place_7$	⇒	$Place_9$
5	$Place_2$	⇒	$Place_4$	⇒	$Place_9$
6	$Place_2$	⇒	$Place_4$	⇒	$Place_9$
7	$Place_3$	⇒	$Place_8$	⇒	$Place_3$
8	$Place_3$	⇒	$Place_6$	⇒	$Place_3$
9	$Place_4$	⇒	$Place_9$	⇒	$Place_6$
10	$Place_4$	⇒	$Place_9$	⇒	$Place_5$
11	$Place_5$	⇒	$Place_3$	⇒	$Place_4$

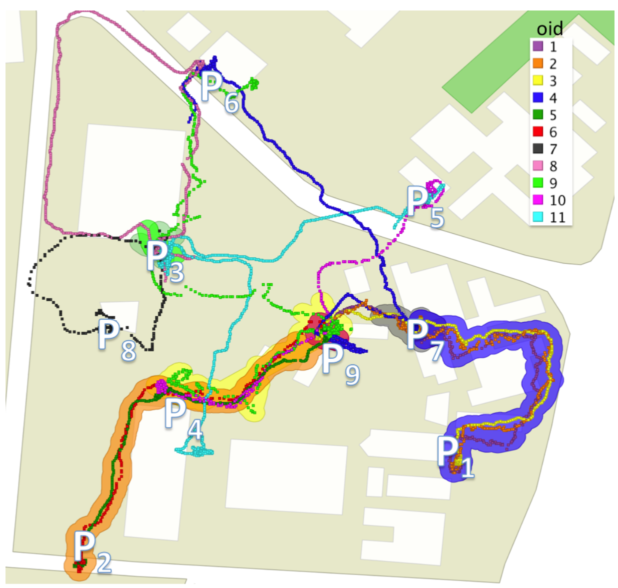

Figure 3. Trajectories and Encounters at UFSC

Table 3. Relationship Degrees between objects at UFSC

O	$frequency$	$duration$	$area$	R_f	R_d	R_a	R
{1,2,3}	1	35.1	3	0.5	0.992	1	0.831
{5,6}	1	35.4	2	0.5	1	0.667	0.722
{7,8}	2	24.3	1	1	0.687	0.333	0.673
{1,2,3,4}	1	19.9	2	0.5	0.562	0.667	0.576
{10,9}	1	27.5	1	0.5	0.779	0.333	0.537
{1,2,3,4,5,6}	1	8.4	1	0.5	0.238	0.333	0.357

Table 3 shows the relationship degree for each group of objects, and is sorted in descending order of R. As can be seen in Table 3, objects 1, 2 and 3 have the highest relationship degree (0.831). Those objects stayed together during all the experiment and their encounters happened at three different areas. Objects 5 and 6 also stayed together during all the experiment. However, they are the second in the rank because their encounters happened at only two different areas. As can be seen in Table 2, while objects 5 and 6 visited $Place_2$ and $Place_4$ they stayed together alone, generating only one encounter in this case.

Although objects 7 and 8 have the highest frequency of the experiment, they are only the third group of the rank. This happens because although they had two encounters, they were at the same place ($Place_3$), so having only one encounter area.

The group of objects 1, 2, 3, 4, 5, and 6 had the lowest relationship degree (0.357), because this group had only one encounter, and this encounter had the lowest duration of the experiment. Object 11 (see Table 2) did not have any encounter during the experiment, so it has no relationship.

This experiment showed one of the key advantages of the $MORE$ algorithm over related work: the inference of a relationship degree between moving objects. Independently of the size of the group, if they had an encounter, their relationship degree will be calculated. Even in a small dataset it is possible to understand the relevance of this information. The knowledge of relationship allows the understanding of which objects are the most related inside larger groups.

Further experiments, with larger datasets and comparing the $MORE$ algorithm with related work will be conducted in an extended version of this paper.

5. Conclusion and Future Work

In the last two decades, there was a popularization of different GPS-enabled devices, that allow recording the moving objects location. Consequently, there was an increase in the amount of mobility data generated from these devices. To best of our knowledge, none of existing works in the literature proposed the inference of relationship degree between multiple objects based on their encounter patterns extracted from trajectories.

In this work we proposed $MORE$, a new algorithm to compute the relationship degree of a level-wise moving objects. This algorithm is based on the new proposed definitions of encounter and encounter area. The algorithm considers the encounter duration, the frequency of encounters, and the different encounter areas. $MORE$ presents conceptual advantages over related work, such as the possibility to infer the relationship degree between multiple objects. We evaluated the proposed method with a running example and performed an experimental study with real trajectory data in a simulated scenario, where the encounters were known. The results of the experiment showed that our method was able to identify relationships between pairs and groups of objects.

In the proposed approach we use raw trajectory data without considering semantic information. However, as future ongoing work, we are investigating new measures to ensure the value of a relationship degree among a group of objects.

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