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An algorithm to identify avoidance behavior in moving object trajectories

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Abstract The research on trajectory behavior has increased significantly in the last few years. The focus has been on the search for patterns considering the movement of the mobile object in space and time, essentially looking for similar geometric properties and dense regions. This paper proposes an algorithm to detect a new kind of behavior pattern that identifies when a mobile object is avoiding specific spatial regions, as for instance, security cameras. This behavior was called avoidance pattern. The algorithm was evaluated with real trajectory data and achieved very good results.

Keywords trajectory behavior · spatio-temporal pattern · mobile objects · trajectory data mining · avoidance behavior

1 Introduction

The use of location aware devices as GPS and mobile phones has significantly increased in the last few years. This kind of devices can generate sequences of space-time points capturing the trajectories of the object that carries the device. This kind of data - trajectory data - acquired for operational level use, are being generated in an incredible rate and can be analyzed to obtain new knowledge, a higher level knowledge for decision making processes.

There are several situations in the real world that consider spatio-temporal fenomena that are target of analysis and research, as the pattern of humans buying items in a supermarket or a shopping center, animal migration behavior monitoring, human behavior in parks and cities, vehicle traffic, boats movement, etc. The study of trajectory behavior of these mobile objects intends to transform these enormous quantity of raw data in useful information to the decision making process, knowledge discovery and reality interpretation. It can contribute to problem solving (for instance identifying fishing areas [21]), to identify standards and tendencies, or to discover outliers, for instance. Trajectory data are obtained as a sequence of points (id, x, y, t), where (x, y) represent the geographic coordinates of the object id in the time instant t. We call this data as raw trajectories.

Many works have been developed in the last years considering the study of trajectory behavior. These works are being developed according to two main research optics: a geometric one [12, 10, 6, 9, 3] and a semantic one [2, 20, 5, 4, 19].

Some works analyze one trajectory at a time while others evaluate sets of trajectories, using, for instance, clustering techniques. Several works search for some kind of similarity between trajectories: spatial format, time interval, velocity, stops at the same points, and so on.

Those works dsicover different types of patterns as: flocks, convergence, leadership, encounter, co-location episodes, and so on.

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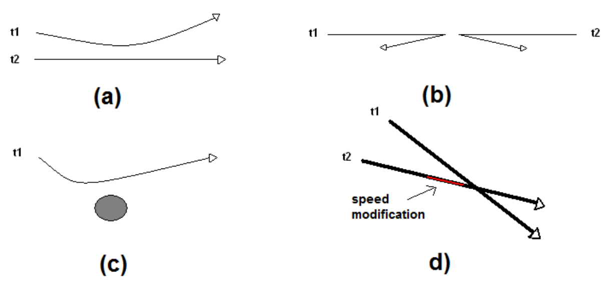

Fig. 1 Examples of the avoidance behavior

However, as far as we know, there are no works that identify, in trajectory data, the behavior of mobile objects that avoid some regions or that avoid other trajectories. For instance, people avoiding to collide with other people during a walk in a park, vehicles that change their route in situations of low speed traffic, or individuals that move in a suspicious manner avoiding vigilance cameras or security points.

An avoidance behavior can occur, for instance, when a trajectory avoids a specific spatial region, when one or more trajectories change their direction to avoid intersecting each other, or when one or more trajectories change their speed to avoid other mobile objects, as can be seen in Figure 1. In Figure 1 (a) and (b) the avoidance is between two trajectories and by direction changing. Figure 1 (d) presents an example of avoidance between two trajectories by speed changing, while (c) presents another kind of avoidance where a mobile object avoids a static region.

This work presents a new algorithm able to identify an avoidance behavior where a mobile object avoids a specific spatial region, as in the example show in Figure 1 (c).

The remainder of this paper is organized as follows: Section 2 shows the main related works, Section 3 presents the heuristics used to identify an avoidance, Section 4 presents the developed algorithm to recognize an avoidance pattern, Section 5 shows some experiments, and Section 6 concludes the paper.

2 Related Work

Detecting patterns of movement has been of interest since 1970, when Hagenstrand posed the bases of Time-Geography [11], where he first proposed the idea of "spatio-temporal prism" to represent the human movement. From that time, a number of approaches tried either to represent the human movement or to detect patterns from datasets of movement traces. The paper from Dodge et al. ([8]) presents a taxonomy of movement patterns. The interesting part of this work is that they first propose a systematic vision of the movement patterns distinguishing between Generic and Behavioral patterns, and the Generic pattern is divided in Compound and Primitive. For example, a moving cluster is classified as a Primitive pattern whereas a flock is a Behavioral pattern. Despite the fact that this proposal is interesting as a tentative to classify the many movement patterns proposed in the last decade, we believe that some important patterns are not included, as, for example, the avoidance pattern.

Several recent works define trajectory patterns basically considering the geometric part of trajectories. Laube in 2005 introduced the mobile group pattern, which is a set of trajectories close to each other, with distance less than a given threshold, for a minimal amount of time (minTime) [13]. In this approach the direction is not considered and frequent groups are computed with the algorithm Apriori [1]. Laube also [12] proposed five types of *geometric* trajectory patterns based on movement, direction, and location: convergence, encounter, flock, leadership, and recurrence. A Flock pattern has at least m subtrajectories within a region of radius r that move in the same direction during a certain time interval. The Leadership pattern must have at least m subtrajectories within a circular region of radius r, that move in the same direction, and at least one of the entities is heading in that direction for at least a certain time. Encounter is the pattern characterized by at least m subtrajectories that are concurrently inside the same circular region of radius r, assuming they move with the same speed and direction. Reccurence patterns occur when at least m entities visit a circular region at least k times.

Later in 2006, [10] extended the flock algorithm to compute the longest duration flock patterns, where the longest pattern has the longest duration and has at least a minimal number of trajetctories. In [6] Co-location episoids in spatio-temporal data are computed, where groups of trajectories are spatially close in a time window and move together.

Lee [14] proposed an algorithm to find outliers between a set of trajectories.

Another approach is the T-pattern [9]. It is a sequential trajectory pattern mining algorithm that first generates regions of interest considering dense regions in space, and than computes sequences of regions visited, taking into account transition time from one region to another and minimum support.

In trajectory data analysis there are no works that define avoidance patterns. The few works about avoidance concerns collision-avoidance. The idea is to develop real-time systems, called "collision-avoidance systems" that proactively detect the risk of collision between vehicles, and are intended to be used by pilots or automatically during their travels to avoid the collisions with other vehicles. The focus has been on avoidance of different types of collisions as cars[7], ships [16], and air traffic [22]. Also in transportation systems collision-avoidance is studied [18], for pedestrians.

Some works in Robotics [23,15,24] use the idea of avoidance in trajectories, but instead of analyzing a trajectory to identify an avoidance, as proposed in our work, they use the concept of collision-avoidance for planning the future trajectories of a robot.

On the contrary, our proposal aims at analyzing historical GPS traces (trajectories) in order to find if there is the presence of avoidance patterns. This method is not intended to be used for real time systems collision avoidance, but to detect a specific avoidance behavior in past trajectories. To the best of our knowledge, there are no similar approaches in the literature.

This paper is a extended version of the work presented in Portuguese at [17].

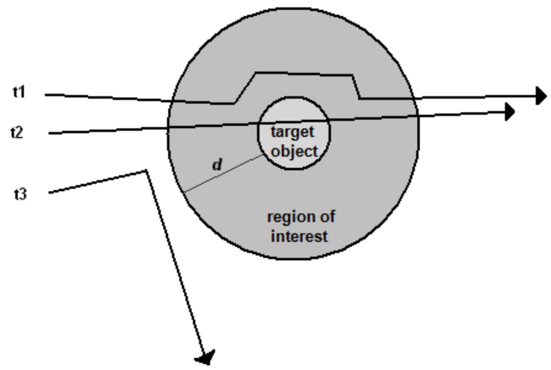

Fig. 2 Example of target object, region of interest and trajectories behavior

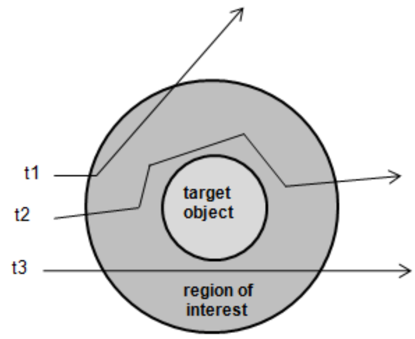

Fig. 3 Examples of trajectory behaviors

3 Heuristics to identify an avoidance behavior

The avoidance behavior pattern occurs when a mobile object is moving toward an object of interest or target object (as a surveillance or security camera for example), shifts to avoid passing the object of interest, and after that goes back to its original path. The problem is to differentiate what is really a shift to avoid the object of interest from a natural path change caused by another reason.

Some aspects that have to be considered:

The mobile object should not cross (intersect) the object of interest called *target object* (the region covered by the security camera, for instance), because if the mobile object changes its direction but yet crosses the target object, it did not keep away from object, what therefore does not characterize an avoidance.

The mobile object should be going in direction to the target object (the object to be avoided) and to deviate from the target object relatively close to it to be considered an avoidance. A counter-example is a person walking and one or more kilometers away he/she deviates from a security camera; this person is probably changing his/her direction by any other reason and not for escaping from the security camera, and therefore not characterizing an avoidance behavior. To materialize this idea we created the concepts of *target object* and *region of interest*. *target object* is a convex spatial location that a trajectory could avoid. The *region of interest* is defined by a distance d from the target object. Any behavior outside of the region of interest is not considered because it is too far from the target object. Then, a mobile object must intercept the region of interest in order to characterize an avoidance.

Figure 2 shows these intuitions. Trajectory $t1$ was moving in direction to the target object, deviated to avoid it, and after a while continued more or less its original path, characterizing a case of avoidance. Trajectory $t2$ moves in direction to the target object and intersects it, without avoiding it, and therefore not characterizing a case of avoidance. Finally, trajectory $t3$ was moving in direction to the target object but changed its direction far away from the target, and the deviation occurred outside the region of interest, and therefore not characterizing an avoidance behavior.

Even with the definition of region of interest, we observed that some trajectories, although intersecting the region of interest and not crossing the target object, do not presented a clear behavior of moving toward the target object before changing direction. In these cases, it is not possible to give to these trajectories a suspicious behavior, considering the example of security cameras. Figure 3 shows some examples. The trajectory t_2 clearly presents an avoidance behavior, but for the trajectories t_1 and t_3 this is not so obvious.

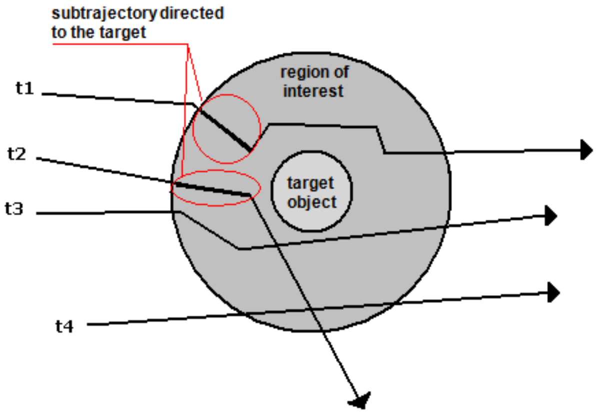

Fig. 4 Example of subtrajectory directed to the target

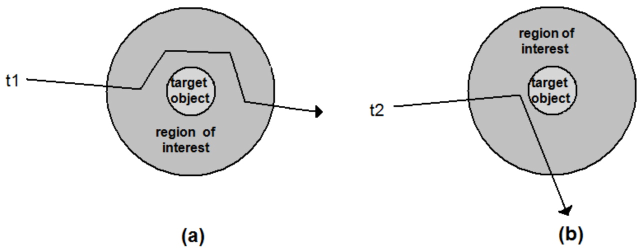

Fig. 5 Two different examples of avoidance

In order to make more robust the identification of an avoidance behavior, we introduce the notion of subtrajectory directed to the target. The *subtrajectory directed to the target* is the greatest subtrajectory that is moving in direction to the target object, inside the region of interest, with length greater or equal to a minimum length l. Then, a new condition to characterize an avoidance is: the trajectory should have a *subtrajectory directed to the target*. Figure 4 presents some examples of this concept. The trajectories t_1 and t_2 have a subtrajectory directed to the target but the trajectories t_3 and t_4 do not.

After these considerations, we can define the heuristics to characterize an avoidance: a *trajectory* t has an avoidance in relation to a *target object* o if it has a *subtrajectory directed to the target* o and does not intersect the target object o.

However, if we observe the avoidance behavior of the trajectories in Figure 5, intuitively we can say that the avoidance of trajectory t_1 is stronger than the avoidance of trajectory t_2, because t_1 returns to its original path after deviating the target object (the security camera), with a clear intent of avoiding the target. In the case of trajectory t_2, this is not so obvious, because the trajectory deviated the camera and follows this new direction without returning to its original path.

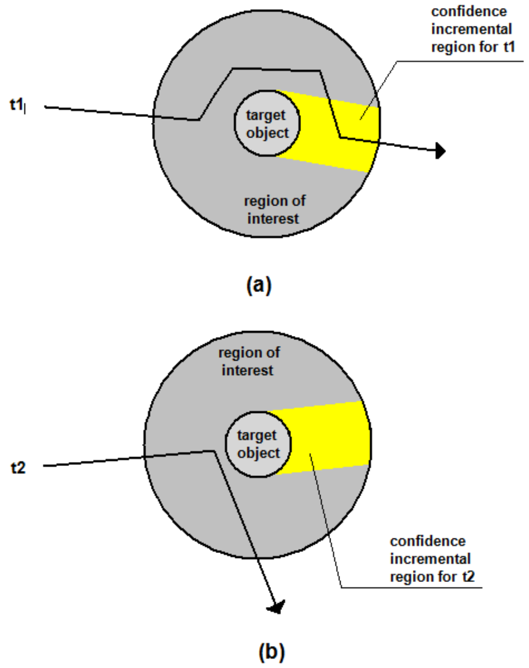

Fig. 6 Examples of confidence incremental regions

To know if a trajectory returns to its original path or not after deviating the target, we create the notion of *confidence incremental region*, denoted by a region inside the region of interest, that does not contain the target object and is situated between the target object and the edge of the region of interest, on the opposite side to the subtrajectory directed to the target, with width equal the diameter of the target object. An example is shown in Figure 6. This region is unique for each trajectory considering a target object.

Intuitively, trajectory t_1, in Figure 6 (a) presents an avoidance with greater degree of certainty than trajectory t_2 in Figure 6 (b), because t_1 intersects the confidence incremental region. Using this intuition we create two levels of avoidance of one trajectory in relation to a target object: *strong* - when the trajectory intersects the confidence incremental region, and *weak* - when a trajectory moves in direction to a target, has a subtrajectory directed to the target, but neither intersects the target nor the confidence incremental region. This idea is mapped to a value, called local avoidance confidence (in relation to a specific target object): 0.0 for no avoidance, 0.5 for weak avoidance and 1.0 for strong avoidance.

A last heuristic is that if there is a region with several security cameras we can analyze the behavior of the whole trajectory in relation to the whole set of target objects. To do this, if a trajectory crosses the region of interest of several target objects, we can have a *global avoidance value* for the whole trajectory, considering

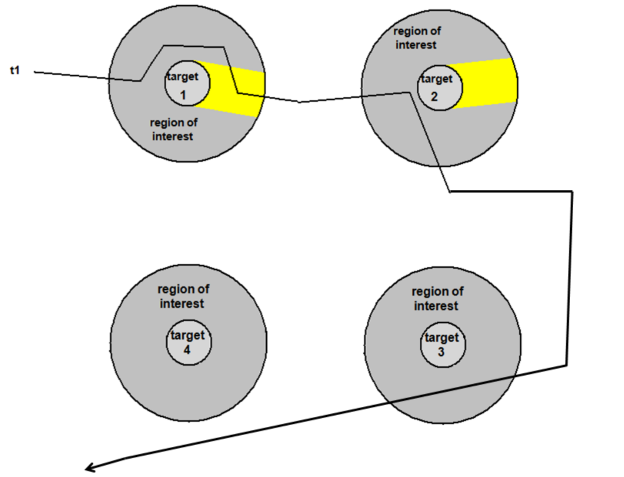

Fig. 7 Example of a trajectory in a region with four target objects

each *local avoidance value*. As a first approximation, we define the equation

$$Avt_i = \frac{\sum_{k=1}^{n} Av_{i_k}}{n} \tag{1}$$

where Avt_i stands for the avoidance confidence for the whole trajectory i. Av_{i_k} is the value of local avoidance for trajectory i in relation to the target object k, and n is the number of regions of interest intersected by trajectory i.

Figure 7 shows an example of avoidance confidence for a whole trajectory. Trajectory t_1 has a strong avoidance considering the target object 1, a weak avoidance in relation to target object 2 and has no avoidance for targets 3 and 4. Therefore, its global avoidance confidence is (1+0.5+0)/3=0.5. The target object 4 is not counted in the denominator because its region of interest is not intersected by the trajectory.

4 An algorithm for avoidance detection

Based on the heuristics presented in Section 3, we propose an algorithm to detect avoidance patterns, in the pseudo-code shown in Listing 1.

Initially, the algorithm tests the intersection of the trajectory points with the regions of interest of each target object (line 12). Only the trajectory points that intersect any region of interest are considered in the rest of the algorithm, what significantly decreases the processing time. If the trajectory intersects the region of interest then it is not an avoidance (lines 14– 15). The function SubtrajDT() (line 17) returns the longest subtrajectory that goes to the target inside the region of interest. The pseudocode is presented in Listing 2 and is detailed later in this section. The fuction ConfIncrR() (line 18 of Listing 1) determines the confidence incremental region, and is detailed later in Listing 3. If the trajectory intersects the increasing confidence region in a time period posterior to the time period of the subtrajectory directed to the target, then the avoidance is strong (lines 19– 20); otherwise the avoidance is weak (lines 21– 22). The global confidence of the avoidance of a whole trajectory i is computed in line 29, using equation (1).

Listing 1 Pseudo-code of the proposed avoidance algorithm

```
1  INPUT: T //set of trajectories
2         O //set of target objects
3         d //size of the buffer for the region of
4           //interest around the target object
5         subt //minimal size of the subtrajectory
6              //directed to the target
7
8  OUTPUT: Avt //set of degrees of avoidance
9
10
11 METHOD:
12 FOR each t_i ∈ T | intersects(t_i,buffer(O,d)) DO
13   FOR each o_k ∈ O DO
14     IF intersects(t_i,o_k)
15       av_ik = none
16     ELSE
17       IF SubtrajDT(t_i,o_k,d) >= subt
18         CIR=ConfIncrR(t_i,o_k,d)
19         IF intersects(t_i,CIR)
20           av_ik = strong
21         ELSE
22            av_ik = weak
23         ENDIF
24       ELSE
25         av_ik = none
26       ENDIF
27     ENDIF
28   ENDFOR
29   calculate Avt_i
30 ENDFOR
31 return Avt
```

The function SubtrajectoryDT() shown in Listing 2, considers the first trajectory point inside the region of interest and takes the next points, one by one, while the direction of the line segment from the initial point to the last considered point intersects the target object. This procedure is repeated for the next points to determine the longest subtrajectory directed to the target object inside the region of interest.

As shown in Listing 2, the procedure starts with the two first trajectory points that intersect the region of interest of the target object being considered (lines 11– 12) and a loop is performed for all points in P (lines 14– 29). Inside the loop, the first step is to calculate the azimuth between the two points to determine the direction of the trajectory and to extend this line segment until a possible intersection with the target object occurs (lines 15– 17). If the line segment intersects the target object, then the mobile object is moving in direction to the target (line 18). The next step is to calculate the euclidean distance between the points and save the longest subtrajectory directed to the target (lines 20–

21). While the line segment is moving in direction to the target, the initial point is kept and the next point is taken. If the line segment is not moving in direction to the target (line 24), the initial point becomes the next after that one that was the initial (lines 25– 27). This procedure continues until all points of P have been evaluated.

Listing 2 Pseudo-code of the SubtrajDT function

```
1  INPUT: P //set of trajectory points that
2           //intersect the interest region
3         o //target object being analyzed
4         d //size of the buffer for the region of
5           //interest around the target object
6
7  OUTPUT: dist //greater euclidean distance in the
8               //direction of the target object
9
10 METHOD:
11  i = P.firstPoint()
12  next = P.nextPoint()
13  dist,auxdist = 0
14  REPEAT
15    ap = azimuth(p_i, p_next)
16    p_aux.x = sen(ap)*2*d+(p_i.x
17    p_aux.y = cos(ap)*2*d+(p_i.y
18    IF intersects(makeline(p_i, p_aux), o)
19      auxdist = calcDistance(p_i, p_next)
20      IF auxdist >dist
21        dist = auxdist
22      ENDIF
23      next = P.nextPoint()
24    ELSE
25      P.point = i
26      i = P.nextPoint()
27      next = P.nextPoint()
28    ENDIF
29  UNTIL the end of P
30  return dist
```

Figure 8 exemplifies the calculus of the subtrajectory directed to the target. Figure 8 (a), (b), and (c) show the same trajectory t_1 and the line segment calculated to test the intersection with the target at each cycle of the repeated loop. In Figure 8 (a), the line segment is created between the two first points inside the region of interest, p_2 and p_3. As it intersects the target object, the point p_2 is kept and the procedure continues with the points p_2 and p_4, as show in Figure 8 (b), where the line segment intersect the target. In Figure 8 (c), the line segment is between the points p_2 and p_5, where the expanded line does not intersects the target. The procedure continues between the points p_3 and p_4 and after between p_3 and p_5, and so on. The subtrajectory directed to the target will be the distance between p_2 and p_4.

The function ConfIncrR() (line 18 of Listing 1) calculates the confidence incremental region. Its pseudocode is presented in Listing 3. The function initially computes the azimuth between the first point of the trajectory inside the region of interest and the centroid of the target object. In the sequence, two line segments are computed, tangent to the target and with the azimuth calculated, from the target object to the exterior limit of the interest region (lines 13– 14). Finally, the

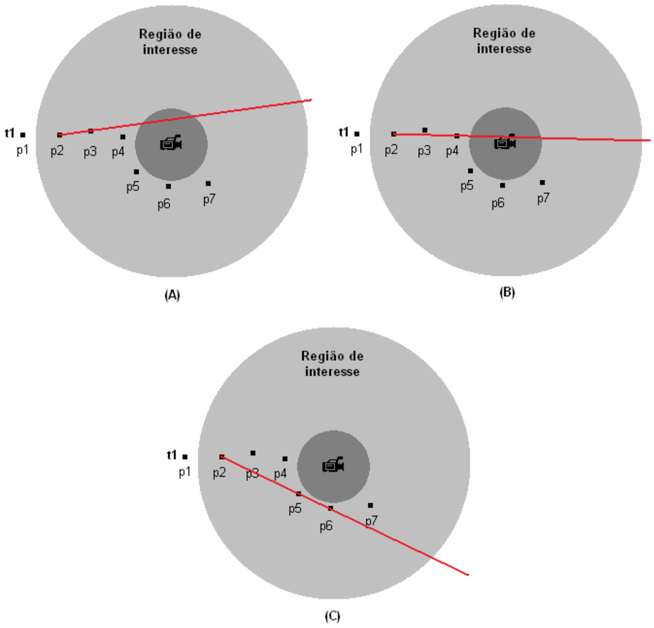

Fig. 8 Example of subtrajetory directed to the target calculus

geometry of the confidence incremental region is computed (line 15).

Although all the examples of target objects are circular, this function works for any convex target object.

Listing 3 Pseudo-code of the ConfIncrR function

```
1  INPUT: P //set of trajectory points that
2           //intersect the interest region
3         o //target object being analyzed
4         d //size of the buffer for the region of
5           //interest around the target object
6
7  OUTPUT: reg // confidence incremental region
8
9  METHOD:
10  i = P.firstPoint()
11  O_c = centroid(o)
12  az = azimuth(i, O_c)
13  lim1 = makeLine1(az, o, exteriorRing(buffer(o, d)))
14  lim2 = makeLine2(az, o, exteriorRing(buffer(o, d)))
15  reg = computeRegion(lim1, exteriorRing(o), lim2,
16        exteriorRing(buffer(o, d)))
17  return reg
```

5 Experiments

In order to evaluate the results of the proposed algorithm, two different experiments where performed with real GPS data collected at the rate of one point each second. One dataset was collected by cars and the other one by pedestrians.

5.1 Experiment I - Car Trajectories

The car trajectories were collected in the city of Porto Alegre, with and without restrictions, i.e., avoiding or

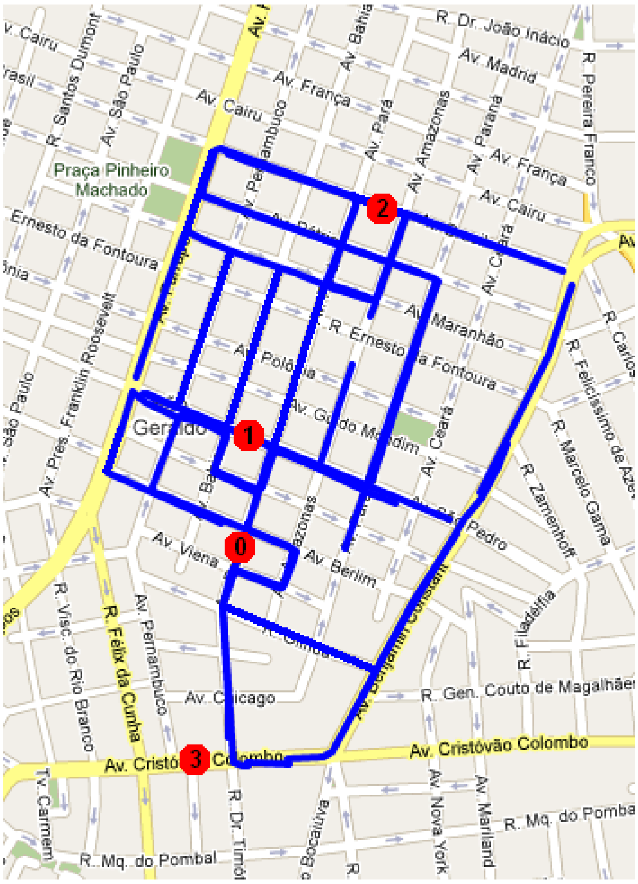

Fig. 9 Car trajectories in Porto Alegre

Table 1 Result of the first experiment considering 20 meters as the diameter of the target object, 80 meters for the buffer of the region of interest around the target object and 8 meters as minimum length for the subtrajectory directed to the target

Tid	Global Confidence
t7	1
t13	1
t18	0.875
t21	0.5
t15	0.333
t11	0.25

not specific regions mapped as the target objects. The target object may be any convex geometry, but in our experiments we considered this object as a circle with a radius of 20 meters and 80 meters around the target as the region of interest. As the minimal length for the subtrajectory directed to the target we defined 8 meters. The 8 meters represents 10% of the size of the buffer around the region of interest. Figure 9 shows these trajectories.

Table 1 shows the result of the first experiment that found avoidance patterns in 6 of 21 trajectories with the respective global confidence.

Figure 10 shows the avoidance patterns for trajectories in Table 1. Figure 10 (a) shows trajectory t7 that intersects only the region of interest of target object 2, and Figure 10 (b) shows trajectory $t13$ that intersect only the region of interest of target 1. Both are cases of *strong* avoidance because they crossed the respective confidence incremental region. Figure 10 (c) shows trajectory t18, which intersects all 4 regions of interest. For target objects 0, 1 and 2 it also intersects the confidence incremental region, therefore, getting a local confidence as *strong*. Because this trajectory does not intersect the confidence incremental region at target object 3, it has a *weak* local avoidance at this point, and therefore the global avoidance confidence is (1+1+1+0.5)/4=0.875.

Figure 10 (d) shows trajectory t21, which intersects 3 regions of interest, all with *weak* local confidence, since there was no valid intersection of any confidence incremental region. This trajectory intersects the region of interest of target 1 twice. The first time, it does not have any subtrajectory directed to the target. The second intersection of trajectory $t21$ with the region of interest of target 1 had a subtrajectory directed to the target that was long enough, but after that the trajectory did not intersect the confidence incremental region.

Trajectory t15, shown in Figure 10 (e), presents one *strong* local avoidance considering the target 0. In relation to the target 1 the local avoidance is *none*, since the trajectory intersects the target object. In relation to the target 3, the local avoidance is also *none*, i.e., there is no avoidance since the trajectory intersects the region of interest but it has no subtrajectory moving in direction to the target with a valid length. Therefore, the global confidence for this trajectory is 1/3 (0,333), having one strong avoidance and intersections with three regions of interest.

Finally, trajectory t11, shown in Figure 10 (f), intersects the region of interest of target objects 0 and 1, and has one *weak* local avoidance in relation to target object 1 and no avoidance in relation to target 0 because the subtrajectory moving to the target was less than 8m when the trajectory finished.

For this dataset, a total of 11 avoidance patterns were computed for all trajectories.

5.2 Experiment II - Pedestrian Trajectories

The second dataset is a set of 17 pedestrian trajectories collected at the Germania park in the city of Porto Alegre, considering four monitoring regions located on the crossing paths of the main routes in the park. Differently from the car trajectories that follow a road network, pedestrians may follow any directions, anywhere.

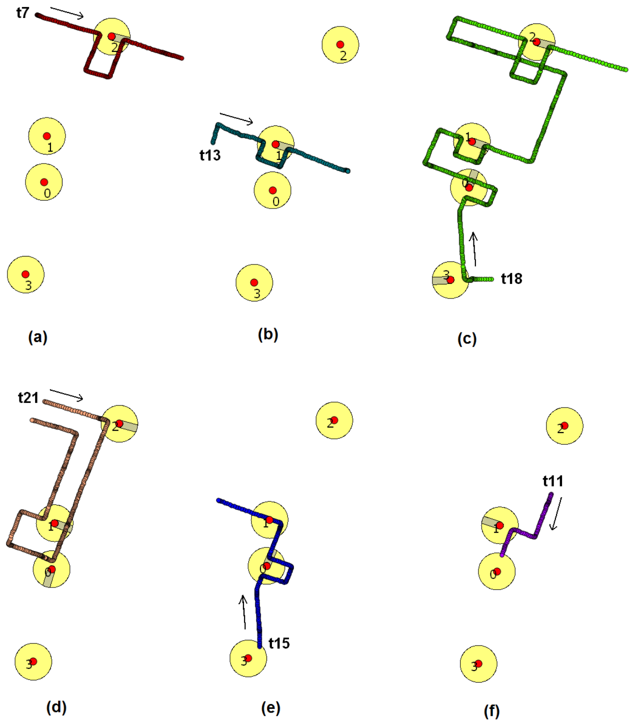

Fig. 10 Avoidance patterns for trajectories in Table 1

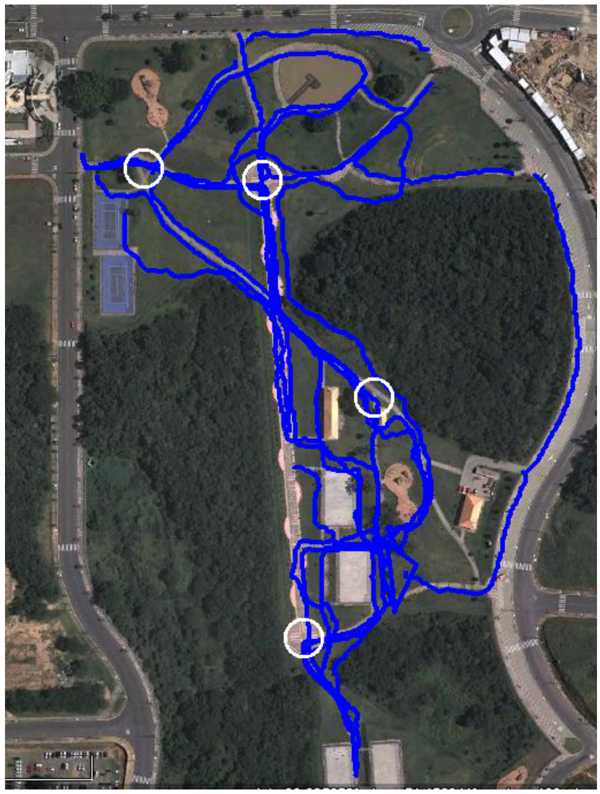

Fig. 11 Pedestrian trajectories in a park

Although there are a few main routes, the objects move in aleatory ways in the park, therefore these trajectories present characteristics very different from car trajectories. Indeed, the speed as a pedestrian moves may affect the density of the points, since the path followed by a pedestrian during 15 minutes, for instance, will be much shorter and more dense than a car traveling in a highway during the same time period. As the GPS for the pedestrians was configured as for the car trajectories, i.e., the collection of a point every one second, this trajectory dataset is much more dense than the previous one, and this behavior difference motivates this experiment.

In this experiment we considered 10 meters as the radius of the target object and 40 meters as the buffer of the region of interest, simulating a reasonable distance for a pedestrian to identify a camera and then to choose a change on her/his path. We used 4 meters as the minimal length for the subtrajectory directed to the target.

Figure 11 shows the visualization of these trajectories in Google Earth. The circles represent the monitoring regions defined as the target objects. After running the algorithm, five avoidance patterns were found. Table 2 shows the result of the avoidance patterns of these trajectories, with its respective global confidence.

Among the trajectories with avoidance patterns, trajectory t7 had the highest global confidence. As can be seen in Figure 12 (a), this trajectory avoided the target objects 1 and 2 with *strong* local confidence. The global confidence was reduced by the intersection of this trajectory with the region of interest of the target object 0, where there was no subtrajectory directed to the target with a valid length. Additional experiments have demonstrated that when we use 2 meters for the minimal subtrajectory length directed to the target, the global confidence for this trajectory becomes maximal.

Table 2 Result of the pedestrians experiment considering 10 meters as the diameter of the target object, 50 meters for the buffer of the region of interest around the target object and 4 meters as minimum length for the subtrajectory directed to the target

Tid	Global Confidence
t7	0.667
t6	0.5
t8	0.5
t4	0.167

In trajectory t6 (Figure 12 (b)) we identify one case of *weak* local avoidance, in relation to the target object 3, and one *strong* local avoidance in relation to the target object 2. This trajectory intersected the region of interest of target object 0, but has no subtrajectory directed to the target with 4m length to characterize an avoidance. Then, no avoidance was identified

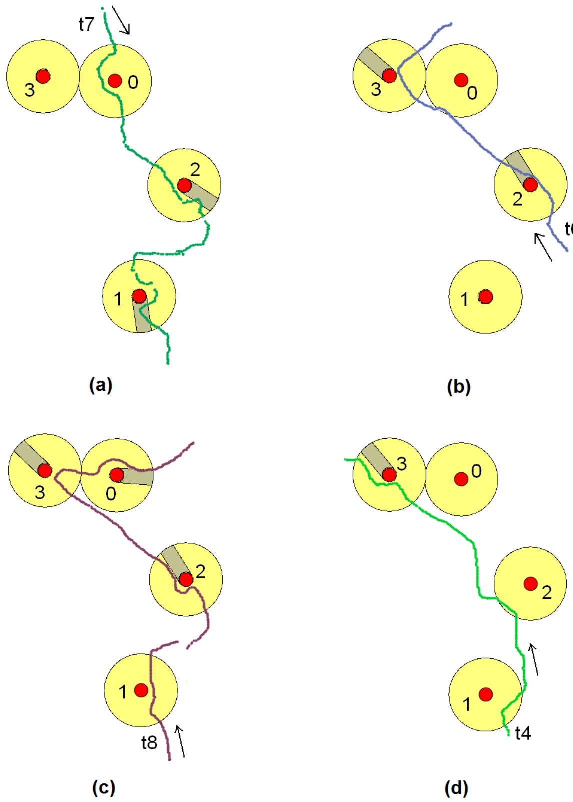

Fig. 12 Some pedestrian trajectories

in relation to this target. This trajectory does not intersected the region of interest of target 1. Therefore, the avoidance level for the whole trajectory resulted in (1+0.5+0)/3=0.5.

Trajectory 8, shown in Figure 12 (c),intersects the four regions of interest but in relation to the target object 1 there is no valid subtrajectory directed to the target. Considering the targets 2 and 3, the trajectory does not intersect the confidence incremental region, receiving the value weak (0.5) as local avoidance. In relation to the target object 0, a strong avoidance has been identified because the trajectory satisfies all avoidance conditions.

In Figure 12 (d), trajectory 4 intersects three regions of interest, but in relation to the target objects 1 and 2 there is no subtrajectory directed to the target with the minimal length of 4m, and hence has no avoidance with these targets. A weak avoidance exists with respect to the target object 3. The avoidance for the whole trajectory is then (0+0+0.5)/3=0.167.

Although in this paper we presented only two small datasets to evaluate the proposed algorithm, we have performed more experiments and the results show that the algorithm found correctly the existing avoidance patterns. Of course, the parameters - the length of the buffer around the target object to define the region of interest, and the minimal length of the trajectory directed to the target - are very important and should be defined according to the specific application in hand.

6 Conclusion and Future Works

Trajectory data are becoming more and more common in daily life. Several works have been developed to extract interesting information and knowledge from these data, as well as trying to infer the behavior of the moving object. Most works focus on the common behavior of groups of trajectories of different mobile objects.

In this paper we contribute to move the literature in trajectory data analysis one step forward proposing a novel work to identify avoidance behavior in trajectories. Our work identifies avoidance behavior of individual objects in relation to existing static targets,that could be, for instance, security cameras, police offices or police controllers, and so on.

The method proposed in this work may be useful in several application domains like the monitoring of prisoners in semi-open (pre-release) level, traffic management, hurricane analysis, and so on.

As we use raw trajectory data, without considering semantic information, the proposed heuristics can not know if a trajectory deviated the target with the unique intention to avoided it, or if it is the normal path of the mobile object. As future works are investigating new measures to ensure if an avoidance was intentional or forced by an event, like a blocked street, for instance.

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