Inferring Drivers Behavior through Trajectory Analysis

Eduardo M. Carboni[1] and Vania Bogorny[1]

[1]Universidade Federal de Santa Catarina (INE/UFSC) – Brazil

{eduardo, vania}@inf.ufsc.br

Abstract. Several works have been proposed for both collective and individual trajectory behavior discovery, as flocks, outliers, avoidance, chasing, etc. In this paper we are especially interested in abnormal behaviors of individual trajectories of drivers, and present an algorithm for finding anomalous movements and categorizing levels of driving behavior. Experiments with real trajectory data show that the method correctly finds driving anomalies.

Keywords: trajectory data mining, abnormal trajectories, trajectory behavior, driver classification, abrupt movements

1 Introduction

Everyday thousands of people are victims of traffic accidents that are directly related to the behavior of drivers. According to the *World Health Organization*, the total number of road traffic deaths worldwide is around 1.24 million per year [14]. The top causes of accidents are related to excess of speed, drunk drivers, unsafe lane changes, improper turns, street racing and others [15]. Driver behaviors can affect not only traffic, but pedestrians crossing a street, passengers in a bus or taxi, and the transportation of delicate products like fruits and vegetables. According to the Brazilian food supply company (ANVISA), it is stated that around 30% of fruits and vegetables are damaged during transportation, because of driving behavior.

Several works have been proposed for driver behavior analysis in simulation systems [2, 3, 4, 5, 6, 7, 8], [13]. In [2], [4], [8], for instance, sensors and simulators are used to recognize the movements of drivers as pass over, change lane, acceleration. In [3], [5], [7] drivers are classified in levels of danger considering characteristics of a vehicle in relation to the distance and speed of vehicles in the neighborhood. A more recent work classifies drivers based on simulation data using excess of speed, car out of lane, abrupt swings on the wheel and abrupt changes in throttle and brake pedals [13].

With the popularity of mobiles devices such as GPS and cell phones, large amounts of real traces are available to analyze the behavior of drivers. Only a few works in the literature consider trajectories of moving objects, i.e., real trajectories of drivers. Existing works that consider trajectories basically look for general patterns or trajectory outliers, and do neither analyze driving behavior nor classify drivers in levels of danger [9, 10]. In [9] the aim is to find reckless taxi drivers based on the speed of the taxi and the region where the taxi is passing. In [10] the focus is on abnormal trajectories of taxis that deviate the standard route from origin and destination, where the standard route represents the path followed by the majority of taxis.

The discovery of anomalous driving in advance can help companies to advise drivers about their behavior or to keep them out of such jobs. Indeed, it may help to prevent accidents and to reduce waste in food supply. In this paper we focus on real trajectories of drivers, and propose an algorithm (that is an evolution of a previous short work [11]) to identify anomalous behavior based on abrupt movements of individual trajectories, and classify drivers in levels of danger. In summary, we make the following contributions in relation to existing works: (i) find abrupt movements based on abrupt accelerations, decelerations and direction changes in the driver real trajectory; (ii) discover events close to subtrajectories with anomalous movements; (iii) analyze repetitive (frequent) anomalous movements in individual trajectories of the same object; (iv) analyze common abrupt movements between different trajectories, i.e., if the anomalies happened at the same spatial location; (v) compare anomalous movement subtrajectories with road network characteristics, such as maximal speed limit; and (vi) classify drivers in levels of danger.

The rest of the paper is organized as follows: Section 2 presents the related work, Section 3 presents the main definitions and the proposed algorithm, Section 4 presents experiments with real data and Section 5 concludes the paper.

2 Related Work

Several works have focused on driver behavior analysis in simulation systems, considering sensors and simulators. Pentland et al. [2], for instance, proposed a model for human driving behavior analysis in order to predict sequences of behaviors in a few seconds. In a computer graphic simulation, using a car with sensors, the driving control of steering angle and steering velocity, speed, and acceleration are analyzed. The main objective is to recognize, in advance, the future actions of a driver, but not to detect anomalies in movements. Gindele et al. [8] developed a model that estimates the behavior of vehicles using sensors on wheels. In relation to other vehicles in the neighborhood, the following behaviors are estimated: free_ride (when there is no vehicle in front), following (when there is a vehicle ahead on the same lane), acceleration_phase (the vehicle accelerates to become fast enough to pass the vehicle in front), sheer_out (the vehicle keeps accelerating and changes lane for overtaking), overtake (the vehicle changes lane until it is far enough from the other vehicle to sheer back in) and sheer_in (the vehicle moves back to the original lane and changes to back to free_ride or following). The focus of this work is on analyzing driving movements in relation to other vehicles, and not in discovering abrupt movements or classifying drivers in levels of danger. Sathyanarayana et al. [4] analyses speed, steering wheel angle and brake/acceleration pedal counts to find different maneuvers. With the detected sequence of movements the proposed method discovers three different maneuvers (left turn, right turn and lane change). In this work the only objective is to find different maneuvers.

In the set of works that analyze driving behavior using simulators and sensors instead of real trajectories, some of them classify the behavior of drivers. Imamura et al.

[5] classifies drivers in *normal* and *abnormal*, using a correlation between steering wheel operation and vehicle velocity in a driver simulator system. Inata et al. [6] proposed a method to find anomalous behavior of drivers based on speed, distance from neighbor vehicles, and acceleration and deceleration measured by sensors on the pedals. Rigolli et al. [3] classifies drivers as *aggressive*, *safe* and *cautious*. The analysis is performed for each vehicle in relation to the vehicles in the neighborhood, considering the speed of a vehicle in relation to the speed and the distance of the objects in the neighborhood. The normal speed of a vehicle should be similar to the speed of the vehicles in the neighborhood. So if the vehicles in the neighborhood have speed around 100km/h and one vehicle is at speed 150km/h, the faster is classified as *aggressive*. In summary, Rigolli defines the behavior of drivers in relation to other drivers considering distance and speed, while we look for abrupt movements in individual trajectories of each driver.

Among the works developed in simulation systems, the work of Quintero et al. [7] is the closest to our approach. The objective is to discover driving faults as excess of speed, movement out of lane, abrupt swings on the wheel, and abrupt changes in throttle and brake pedals, generating a percentage of errors. This work is extended in Quintero et al. [13], where the percentage of faults is used to classify the drivers in levels of danger: *moderate* and *aggressive*.

The previous works have been developed for driving behavior analysis in simulation systems using different types of sensors. So far, only a few works were developed for driving behavior analysis in GPS trajectories. Verroios et al. [12], for instance, analyzes cars with dangerous behavior in order to send alerting messages to vehicles in the neighborhood. A dangerous behavior can be, for instance, a car entering a main road with high speed. The focus is not in discovering types of dangerous behaviors but in the communication protocols, the format of the messages and their content, and which cars send and receive messages. The message is automatically send by the car with anomalous behavior to all cars that may collide.

Liao et al. [9] and Zhang et al. [10] look for anomalies in taxi trajectories. Liao et al. detects reckless behaviors of taxi drivers considering speed, time, position and passenger loading information. If the speed of a taxi is either higher or lower than the normal speed of the region (extracted from other taxi trajectories that pass at the same region) at the same period (morning, morning_rush_hour, noon, afternoon, afternoon_rush_hour, night, late_night) the taxi driver is considered *abnormal*. In [14], the space is split into a grid. The trajectories that have the same origin and destination should move through the same cells. The majority of the trajectories that move along the same cells are considered a normal behavior, while the outliers are considered anomalous.

Although the previously detailed works analyze several characteristics of driving, most of them have not been developed for real trajectories. Apart from these existing approaches, there are commercial tools as [16] which evaluate the behavior of drivers. These tools, in general, evaluate the driver based on individual movements, and do not compare a behavior to other trajectories or external events, as proposed in this paper.

In this work we propose to find abrupt movements without considering pedal sensors and without considering the behavior of objects in the neighborhood, but simply analyzing the trace of the moving object. In summary, we analyze the following properties of individual trajectories to classify the driver in levels of danger: abrupt movements including acceleration, deceleration and curves, the reason of the abrupt movements (e.g. external events that can affect the movement as a traffic jam or a radar), repetitive abrupt movements, and the speed at the abrupt movement in relation to the speed of the road network.

3 Finding Anomalous Driving Behavior

In this section we first present some basic definitions (Section 3.1) and a two-step algorithm for discovering anomalous driving (Section 3.2).

3.1 Main Definitions

We start with the basic definitions for trajectories that are well known: point, trajectory and subtrajectory.

Definition 1. Point**.** A point p is a triple (x,y,t), where x and y are the latitude and longitude that represent space and t is the timestamp in which the point has been collected.

Definition 2. Trajectory. A trajectory T is an ordered list of points $\langle p_1, p_2, p_3, ..., p_n \rangle$, where $p_j = (x_j, y_j, t_j)$ and $t_1 < t_2 < t_3 < ... < t_n$.

In general, a trajectory does not present the same behavior during the complete trajectory. Therefore, we analyze trajectory parts, i.e., the subtrajectories.

Definition 3. Subtrajectory. A subtrajectory s of T is a list of points $<p_k, p_{k+1}, . . . , p_l>$, where $p_k \subset T$ and $k \geq 1$ and $l \leq n$.

The first analysis for characterizing driving behavior is to look for subtrajectories with abrupt movement. Here we consider as abrupt movement any subtrajectory with abrupt acceleration, abrupt deceleration or abrupt direction change. *Acceleration* in Physics is defined as the variation of speed divided by the variation of time. We define as *abrupt* the acceleration where the variation of speed divided by the variation of time is higher than a given threshold called minimal acceleration *minA*.

Definition 4. Abrupt Acceleration. The acceleration from a point p_i to a point p_j of a trajectory, where $t_j > t_i$, is considered *abrupt* if $\frac{v_{pj} - v_{pi}}{t_j - t_i} > minA$, and $minA > 0$.

Similarly, we define as *abrupt* a negative acceleration which is higher than a minimal deceleration threshold, called *minD*.

Definition 5. Abrupt Deceleration. A deceleration from a point p_i to a point p_j of a trajectory, where $t_j > t_i$, is abrupt if $\frac{v_{pj} - v_{pi}}{t_j - t_i} *(-1) > minD$, and $minD > 0$.

The third analysis is related to abrupt direction change. We consider a direction change as abrupt when it makes the object feel uncomfortable. While in Carboni and

Bogorny et al. [11] we considered as abrupt direction change a turn in high speed, here we make use of the centripetal force, which is well defined in physics. Centripetal force is a force that keeps a body moving with a uniform speed along a circular path and is directed along the radius towards the center [1]. In this work we define abrupt direction change when the centripetal acceleration is higher than a given threshold, called *minC*.

Definition 6. Abrupt direction change. Given v_p as the speed of the moving object at point p and r as the radius of the curve, a direction change is abrupt if and only if the centripetal acceleration $\frac{{v_p}^2}{r} > minC$.

With the previous definitions we are able to find subtrajectories with *abrupt movement.*

Definition 7. Abrupt movement. A trajectory has abrupt movements when it has at least one subtrajectory with abrupt acceleration, abrupt deceleration or abrupt direction change.

Having defined *abrupt movement* we start a deeper analysis on these movements, looking for some characteristics that may justify such behavior. In this analysis we consider three main features:

F1: the existence of previously known *episodes/events* in the same area of the *abrupt movement,* which could be the reason for the anomaly.

In this paper we consider as event or episode a place that is previously known as the possible cause of an anomaly, like a traffic light, a police office, a blitz of even a pedestrian cross, etc.

F2: the *speed* of the moving object when the abrupt movement starts in relation to the speed of the road network, i.e., if the speed is similar to the road speed or if it is above the maximum limit.

F3: if the *abrupt movement* in different trajectories occurs at the same spatial area, i.e., different trajectories share an abrupt movement.

Based on the previous features we define four categories of drivers:

Level 1 (Careful driver): a trajectory is of a careful driver when it does not present abrupt behavior. Although someone may complain that it makes no sense to discover careful drivers, we claim that it is very interesting for applications where the company may want to give a reward or compliment to the good drivers.

Level 2 (Distracted driver): A distracted driver has subtrajectories with anomalous behavior, but only at places with events (F1) OR at places where other trajectories present similar behavior (F3).

Level 3 (Dangerous driver): a driver is considered dangerous when he/she has subtrajectories with anomalous movement in places *without events* OR when he/she has more than one subtrajectory with abrupt movements which do not overlap anomalous movements of other trajectories.

Level 4 (Very dangerous driver): a driver is considered *very dangerous* when it has subtrajectories with speed above the street maximum speed limit (F2) and when he/she has subtrajectories with one of the following behaviors: (i) several subtrajectories with anomalous behavior, (ii) anomalous subtrajectories which do not intersect abrupt subtrajectories of other objects, (iii) anomalous subtrajectories in places *without* events.

3.2 The Proposed Algorithm

In this paper we propose a two-step algorithm for discovering anomalous driving behaviors: first it identifies *abrupt movements* (abnormal subtrajectories) based on abrupt acceleration, deceleration and direction change; second, it analyzes the area where abrupt movements happened, the speed of the trajectory and the maximal speed of the road in order to classify the drivers.

As the analyzed movements are very *short*, the subtrajectories with anomalous behavior are normally only a few points. By considering abrupt movements between every two points only, noise can be introduced. By considering too many points (as four or more) the abrupt movement may not be captured. So after some analysis and experiments on real trajectory data, we consider in our algorithm that at least three consecutive points should have abrupt change of behavior for a subtrajectory to be characterized with abnormal movement. Another important issue is that abrupt movements can be captured well for trajectories with frequently sampled points, like 1 or 2 seconds. A dataset with sampling rate as 30 seconds, for instance, would not reveal anomalous movements, unless the data were previously interpolated.

The pseudo code of the algorithm is split in two main steps: *findAbrupt*, which is shown in Part 1 and *driverClassifier* in Part 2.

```
Part 1: findAbrupt
Input:
(01) T       // set of trajectories
(02) minA    //minimal acceleration
(03) minD    //minimal  deceleration
(04) minC    //minimal direction change (centripetal acceleration)
Method:
(05) for(i=0;i<= count(T.tid);i++){          // for each trajectory
(06)  for(p=0,p< trajectory.size - 2,p++){   // for each point
(07)    if(((v_{p+2}-v_{p+1})/(t_{p+2}-t_{p+1}))>minA
           AND((v_{p+1}-v_p)/(t_{p+1}-t_p))>minA)
(08)      abruptList.add((p),(p+1));
(09)    if(((v_{p+2}-v_{p+1})/(t_{p+2}-t_{p+1})*-1)>minD
           AND ((v_{p+1}-v_p)/(t_{p+1}-t_p)*(-1))>minD)
(10)      abruptList.add((p),(p+1));
(11)    r= getRadius(p, p+1, p+2);
(12)    if((v_p^2/r)>minC AND (v_{p+1}^2/r)>minC AND(v_{p+2}^2/r)>minC)
(13)      abruptList.add((p),(p+1));
(14) }}return abruptList();
```

Part 1 of the algorithm has as input the set of trajectories T (line 1) and the thresholds for acceleration, deceleration and direction change (lines 2, 3 and 4). For each trajectory (line 5) the algorithm analyses the points (line 6) in order to find anomalies.

If there is a subtrajectory of at least three points with abrupt acceleration (line 7), it is stored in an abrupt movement behavior list (line 8). The same test is performed to find subtrajectories with abrupt deceleration (lines 9 and 10). The next step (line 11) is to find the radius of the trajectory turns to analyze abrupt curves (line 12).

Figure 1 shows how the radius is computed. We consider 3 sequential points p_1, p_2 and p_3. From these points the line segments $\overrightarrow{p_1p_2}$ and $\overrightarrow{p_2p_3}$ are created. Two perpendicular lines $\overrightarrow{l_1}$ and $\overrightarrow{l_2}$ are created crossing the centroid of $\overrightarrow{p_1p_2}$ and $\overrightarrow{p_2p_3}$. The point where $\overrightarrow{l_1}$ and $\overrightarrow{l_2}$ intersect each other is the center of the curve. The distance from the intersection point to p_2 is the radius of the curve. Having computed the radius the algorithm computes the centripetal acceleration of the movement to discover the subtrajectories with abrupt direction change and adds these subtrajectories to the list of anomalous movements (line 13). It finishes returning the list of abrupt movements.

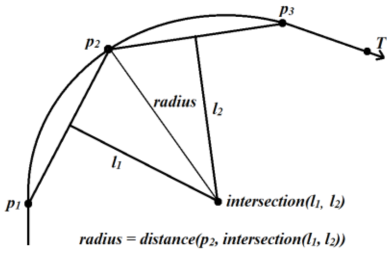

Fig. 1. Radius of the curve

The second part of the algorithm (part 2) receives as input the set of abrupt subtrajectories, the set of streets *R* and the set of events *E*. We make a buffer (line 04) around the abrupt movements in order to increase the area of the anomalies. As the abrupt movements are very few trajectory points, a buffer is needed to capture the intersections with other anomalies at the same place and with the roads and events. After some experiments we found 10 meters as a good measure to overlap anomalies.

The algorithm starts comparing each anomalous subtrajectory (line 5) with all other anomalous subtrajectories (line 7). If a trajectory has several subtrajectories with anomalous behavior (line 10) it is added to a repetitive anomalies list (line 11). If a trajectory has subtrajectories with abrupt movements where no other trajectory presents similar anomaly (line 12), this trajectory is added to the list of trajectories with individual anomalies (line 13). The next step is to verify if the anomalous subtrajectories intersect events (line 14). If this is not the case, the trajectory is added to a nonevent anomalous list (line 15). If the anomalous subtrajectory has speed higher than the maximum speed limit of the street where the object is moving (line 16), then this subtrajectory is added to a speed abrupt list (line 17). It is important to notice that so far we compare the speed of the trajectory of the moving object in relation to the speed of the road only when an abrupt movement happens. The intent is to discover if an abrupt movement of deceleration or direction change was made to suddenly move according to the maximum speed of the road network.

Having analyzed the anomalous subtrajectories, the algorithm starts classifying the trajectories. A trajectory is classified as *Level 4* (Very Dangerous Driver) at lines 18 and 19, as trajectory of *Level 3* (Dangerous Driver) at lines 20 and 21, as trajectory *Level 2* (Distracted driver) at lines 22 and 23 or as a trajectory *Level 1* (Careful driver) at lines 24 and 25.

```
Part 2: driverClassifier
Input:
(01)  abruptList;   // subtrajectories with abrupt movements
(02)  R;                    // set of streets
(03)  E;                  // set of events
Method:
(04)buffer (abruptList.the_geom, 10);
(05)for each anomaly i ∊ abruptList{//for each abrupt subtrajectory
(06)   IND = TRUE; // individual anomalies
(07) for each anomaly j ∊ abruptList {
(08)  if(intersects(i.the_geom, j.the_geom)
          AND i.tid<>j.tid)
(09)   IND = FALSE;    // anomalies with other trajectories
(10)  if(not intersects(i.the_geom, j.the_geom)
          AND i.tid = j.tid)
(11)   repeatList.add(i.tid);        }
(12) if (IND = TRUE) // has no shared anomalies
(13)   trajectoryList.add(i.tid);
(14) if(not intersects(i.the_geom, E.the_geom)//check events
(15)   nonEventList.add(i.tid);
(16) if(intersects(i.the_geom,R.the_geom)
        AND i.speed > R.speed) // check speed
(17)   speedList.add(i.tid);
(18) if(i.tid in(speedList.tid) AND i.tid in (
     nonEventList.tid,repeatList.tid,trajectoryList.tid))
(19)   level.add(i.tid,'LEVEL4');   // Very Dangerous Driver
(20) elseif(i.tid in(nonEventList.tid, repeatList.tid))
(21)   level.add(i.tid,'LEVEL3');     // Dangerous Driver
(22) elseif(i.tid not in (nonEventList.tid
            AND i.tid not in (trajectoryList.tid))
(23)   level.add(i.tid,'LEVEL2');   // Distracted Driver
(24) else
(25)   level.add(i.tid,'LEVEL1');   // Careful Driver
(26)}return level();
```

4 Experimental Results

In this section we present experimental results with real trajectories of cars collected in the city of Florianopolis, Brazil. The dataset consists of 33 trajectories with points collected at intervals of 1 second. For this experiment we have the set of streets of the city and a set of events as traffic lights, schools, crosswalks, speed bumps. We considered five different values for the thresholds *minA*, *minD*, and *minC*, as shown in

Table 1. These thresholds were defined starting with small values (Exp1) and increasing until almost no anomalies were found (Exp5). Acceleration starts with 3 m/s^2 up to 7 m/s^2 and deceleration and direction changes increase twice as much (double of acceleration). Deceleration is a movement that is more abrupt than acceleration, since suddenly braking a car when it is at high speed is more abrupt than to accelerate. After some tests we came to the conclusion that both direction change (centripetal acceleration) and deceleration can be two times greater than acceleration to find abrupt movements. This can help to automatically define these two parameters.

Table 1. Experimental results for 5 sets of parameter values

Thresholds	Exp1	Exp2	Exp3	Exp4	Exp5
minA	$3_{m/s^2} \Leftrightarrow 10.8_{Km/h}$	$4_{m/s^2} \Leftrightarrow 14.4_{Km/h}$	$5_{m/s^2} \Leftrightarrow 18.0_{Km/h}$	$6_{m/s^2} \Leftrightarrow 21.6_{Km/h}$	$7_{m/s^2} \Leftrightarrow 25.2_{Km/h}$
minD	$6_{m/s^2} \Leftrightarrow 21.6_{Km/h}$	$8_{m/s^2} \Leftrightarrow 28.8_{Km/h}$	$10_{m/s^2} \Leftrightarrow 36.0_{Km/h}$	$12_{m/s^2} \Leftrightarrow 42.2_{Km/h}$	$14_{m/s^2} \Leftrightarrow 50.4_{Km/h}$
minC	$6_{m/s^2} \Leftrightarrow 21.6_{Km/h}$	$8_{m/s^2} \Leftrightarrow 28.8_{Km/h}$	$10_{m/s^2} \Leftrightarrow 36.0_{Km/h^2}$	$12_{m/s^2} \Leftrightarrow 42.2_{Km/h}$	$14_{m/s^2} \Leftrightarrow 50.4_{Km/h}$
Results					
Anomalous Trajectories	21	16	8	7	2
Number of Anomalies	103	42	19	11	3
CAREFUL	12	17	25	26	31
DISTRACTED	2	2	0	0	0
DANGEROUS	3	6	5	6	2
VERY DANGEROUS	16	8	3	1	0

For each set of parameters (each column in Table 1), we show the number of *trajectories with anomalies*, the total *number of anomalies* in all trajectories, and the driver *classification levels*. One can notice that for the lower parameter values (Exp1), 21 anomalous trajectories were found with a total of 103 anomalous movements. For this experiment, 12 drivers were classified as careful, 2 as distracted, 3 as dangerous and 16 as very dangerous. The number of anomalies decreases as the thresholds for abrupt movements increase. In Exp5, for instance, only 2 trajectories presented anomalous behavior with a total of 3 anomalies. Most drivers (31) were classified as careful (without anomalies) and only two as dangerous.

Notice that as the values of the parameters to measure abrupt movements increase (from Exp1 to Exp5), the number of *anomalous trajectories* reduces (from 21 to 2), as well as the number of *very dangerous* drivers (from 16 to 0). As a consequence, the number of *careful drivers* increases (from 12 to 31). However, it is worth mentioning that the higher the parameter values, the lower is the number of anomalous movements; but the movements that are still discovered with higher thresholds, are much more abrupt. For instance, the 2 dangerous drivers in Exp 5 make abrupt movements two times greater than the 3 dangerous drivers in Exp1, because in Exp5 the parameter values are minA=7m/s, minD=14m/s and minC=14m/s, while in Exp1, minA=3m/s and minD=6m/s and minC=6m/s.

Figure 2 shows part of the trajectory dataset where most anomalies happened. Figure 2 (left) shows a satellite image of the area where the trajectories were collected and *A*, *B*, and *C* are places where the anomalous movements were known a priori. *A* is a place with an event (traffic light), *B* is a strong curve followed by an event (traffic light) and *C* is a strong curve. The algorithm correctly found the previously known abrupt movements for the three first experiments in Table 1 (Exp1, Exp2 and Exp3), with acceleration varying from 3m/s to 5m/s and deceleration and direction change varying from 6m/s to 10m/s.

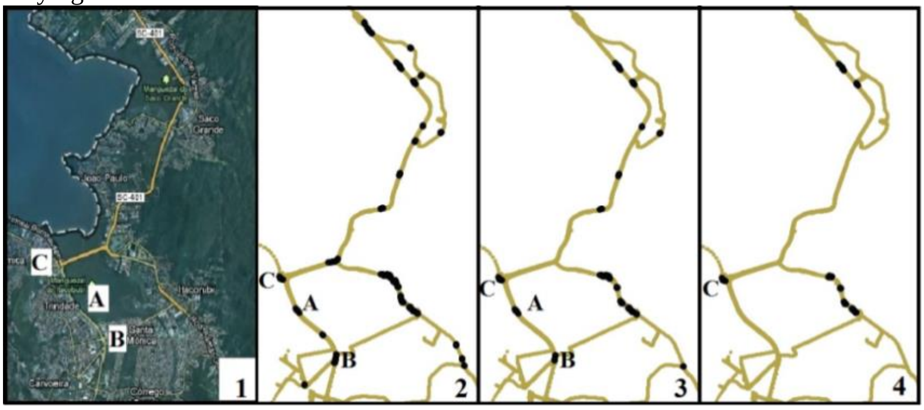

Fig. 2. Results for three different sets of parameter values

Figure 2 (2) shows the result for Exp2, where the lighter color (yellow) represents the trajectories with anomalous subtrajectories and the black colors represent the abrupt movements (anomalous subtrajectories). Figure 2 (3) shows the result for parameter values of Exp3, where one can notice that the anomalies *A*, *B* and *C* were still found. The fourth set of parameter values in Table 1 (Exp4) was too high to detect the anomalies *A* and *B*, so only the abrupt curve *C* was detected.

In order to illustrate some anomalous trajectories in detail, we show a dangerous and very dangerous trajectory. Figure 3 (left) shows the area of the trajectory on a map, Figure 3 (center) shows a very dangerous driver (tid 14) and Figure 3(right) a dangerous driver (tid 18) from the set of Exp3. In yellow are all trajectories and in light gray the two anomalous trajectories. In Figure 3(center) e_1 is a subtrajectory with abrupt deceleration intersecting a traffic light (event); s_1 is an abrupt deceleration starting with excess of speed. The speed at that point was 78 km/h on a road where the limit is 60 km/h. The other anomaly at u_1 is an anomaly without event. So the two last anomalies characterize a *very dangerous* driver.

Fig. 3. Very Dangerous and Dangerous trajectories

In Figure 3(right) the anomalous subtrajectories are highlighted in black (u_2 and u_3) and were at places without events and not above speed limit, therefore characterizing a *dangerous* driver.

5 Conclusions and Future Works

Trajectory behavior analysis is becoming very useful in several application domains. In this paper we presented a two-step algorithm to measure the behavior of drivers. First, the algorithm finds abrupt movements considering abrupt accelerations, decelerations, and abrupt changes of direction. Second, according to different characteristics related to the abrupt movements as repetitive anomalies, events/episodes, and speed above street speed limit the driver is classified in levels of danger. Initial experiments were performed with real data of car trajectories, where part of the anomalous movements was previously known. The algorithm correctly found the anomalous movements.

As future works we intent do perform more experiments with real data, to evaluate other characteristics of movement, evaluate the picks with higher speed in the complete trajectory, and define other features for detecting driving anomalous behavior.

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