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Detecting avoidance behaviors between moving object trajectories

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ABSTRACT

Several algorithms have been proposed in the last few years for mining different mobility patterns from trajectories, such as flocks, chasing, meeting, and convergence. An interesting behavior that has not been much explored in trajectory pattern mining is *avoidance*. In this paper we define the avoidance behavior between moving object trajectories, providing a set of theoretical definitions to precisely describe various kinds of avoidance, and propose an effective algorithm for detecting avoidances. The proposed method is quantitatively evaluated on a real-world dataset, and correctly detects with high precision the quasi totality of the trajectory pairs that exhibit avoidance behaviors (F-measure up to 95%).

1. Introduction

Current advances in mobile technology such as GPS and smartphones have increased the interest in mobility data analysis in several application domains such as security, smart cities, transportation systems, urban planning, and biological studies. As a consequence, several algorithms have been proposed for discovering various types of behaviors in trajectory data such as T-patterns [1], flocks [2, 3], meet [4], periodic movements [5, 6], anomalous traffic patterns [7] and chasing [8]. In [9] a taxonomy with different types of trajectory behaviors is proposed, while a summary of the most well known trajectory behaviors (also called patterns) is presented in [10].

In this paper we focus on *avoidance detection* for trajectories, whose goal is to detect situations in which a moving object avoids a static object (area), as shown in Fig. 1 (a), or a moving object, as shown in Fig. 1 (b, c, and d).

Avoidance detection can be interesting for discovering suspicious behaviors such as objects avoiding static objects, like surveillance cameras, police patrols, or speed controllers, or moving entities like criminals or terrorists that avoid policemen. In marine surveillance, ships with illicit products or illegal immigrants may avoid Coast Guard boats. In computer games, pin-pointing avoidance behaviors can be useful to detect, for instance, the avoided enemies, while in soccer games it may be useful to analyze players avoiding markers. In zoological studies, avoidance detection may reveal how preys avoid predators (e.g., at which distance, by changing direction or changing speed).

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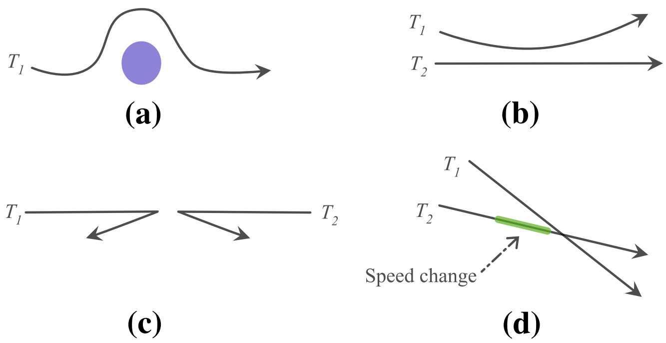

Fig. 1. Different kinds of avoidance behaviors: avoidance with respect to a static object (a), and avoidance between moving objects: *individual* (b), *mutual* (c), and *individual* induced by a change in speed (d).

The problem of avoidance detection has not received much attention in the literature. In [11] the authors introduce notions of attraction and avoidance degree between trajectories. Roughly, the attraction degree between two trajectories is higher when the corresponding objects meet (get close) more frequently than they would by moving randomly along the same points. Avoidance degree is defined as the dual relation. This approach thus takes a global view on the trajectories, highlighting the frequent behaviors and hiding the occasional episodes. For example, consider a boat that generally passes close to a Coast Guard boat and changes just once its route for a specific part of its trip to avoid the encounter. The approach in [11] would reveal a relevant degree of attraction between the trajectories of the boat and the Coast Guard due to their most frequent behavior, despite the occasional avoidance of the Coast Guard, which is essentially ignored.

The technique we propose in this paper, instead, is aimed at detecting all specific instances of avoidance between trajectories, including occasional episodes as those described above. A first treatment of this problem in [12] is limited to the simpler case of avoidance of static objects. Here we aim at treating avoidance in the general case in which both objects are moving. The discovery of this type of avoidance is clearly challenging. Some natural new questions that arise are: what are the main features that characterize an avoidance between two trajectories? Who is avoiding who? At what distance two objects initiate an avoidance?

As a first step we introduce a notion of *avoidance behavior*. An avoidance between two trajectories occurs when both objects are moving towards the same area at the same time, but either one or both change their behavior when they come close enough to be aware of each other. Avoidance is thus characterized in terms of a change of behavior which prevents the two objects to meet, i.e., a discordance between a forecast of the movement of the two objects and their actual behavior. Fig. 1 shows three examples of avoidance behavior of interest: Fig. 1 (b) illustrates an example of trajectory avoidance where T_1 avoids trajectory T_2 by changing its direction. In Fig. 1 (c) both T_1 and T_2 avoid each other by changing their direction whereas in Fig. 1 (d), although the trajectories have a spatial intersection relationship, T_2 avoids T_1 by slowing down the speed in order to not spatio-temporally intersect T_1.

We also introduce a classification of avoidance based on the evidence of changes in the behavior of the trajectories. Avoidance is called *mutual* when both trajectories alter significantly their movement in order to cause a missed meet, as shown in Fig. 1 (c). On the other hand, we classify an avoidance as *individual* when only one trajectory presents a relevant change while the other one behaves as expected. Fig. 1 (b) and (d) provides examples of this kind of avoidance. Finally, in some cases an avoidance is determined by minor changes in the movements of one or both trajectories: this is referred as a *weak* avoidance.

In order to detect avoidances we propose an algorithm that returns, for each pair of trajectories, all the occurrences of avoidance labeled by the corresponding type. The algorithm requires some parameters, like the spatial threshold for considering two trajectories in a *meet* relationship and the temporal look-ahead used for forecasting the future behavior of trajectories, and is able to process real-world trajectories collected at different sampling rates. The algorithm is also used to define two different kinds of detectors: the *single* detector consists of a single run of the algorithm with fixed input parameters, while the *fused* detector considers multiple runs of the algorithm with different parameters, lastly fusing the results in a unique output to improve the quality of results.

The proposed methods are evaluated under different points of view. First, we quantitatively test the *effectiveness* of the methods by analyzing the ability to correctly detect expected avoidance behaviors. To this end we use an ad-hoc annotated dataset, our ground truth, created for the purposes of this work. Second, we assess the ability of the algorithm to highlight interesting and previously unknown patterns emerging from avoidance behaviors when using datasets for which no prior knowledge related to avoidance behaviors is available.

In summary, we make the following contributions in this paper: (i) we propose a framework which defines the avoidance between pairs of trajectories considering changes of behavior and a criteria to classify any avoidance as *weak*, *mutual* or *individual*; (ii) we present an algorithm which is able to automatically detect every avoidance between two trajectories; (iii) we define a detector for analyzing the avoidance with different sets of parameters; finally, (iv) we show the effectiveness of our methods when considering real-world datasets.

The rest of the paper is organized as follows: Section 2 presents the related work. Section 3 introduces some basic definitions. Section 4 illustrates the new definitions for avoidance detection while Section 5 proposes an algorithm to detect