Uncovering Patterns of Suspension of Movement

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1. Introduction

When analysing collective movement, one of the main research challenges is to detect movement patterns that are evidence of specific interactions between moving objects and their environment (Laube, 2009). We are particularly interested in the detection of patterns of movement suspension that take place when moving objects interact with any feature of the environment and as a result, they decrease their speed until a complete halt. Therefore, suspension patterns indicate the location of an element that represent either an attraction or an obstruction for the moving objects and can help us to improve our understanding of the movement behaviour of a set of moving objects. Very few approaches have been proposed to detect such kind of suspension patterns using positioning data, (Alvarez et al. 2007, Palma et al. 2008, Rinzivillo et al. 2008). A common characteristic for these approaches is that the movement of an object is represented as trajectories (i.e. spatio-temporal paths) and that the properties of each individual trajectory such as speed, distance, or spatial relationships are analysed in order to split the trajectories into stops and moves (Spaccapietra 2008). In any of these approaches, some kind of spatial and/or temporal threshold is necessary depending on the application requirements. Moreover, some a-priori knowledge about the collection of the data, the nature of human activities, and the characteristics of the geographical environment is also required to determine the candidate places where the stops might occur.

In this paper, we propose an exploratory statistical approach to detect patterns of movement suspension without the necessity of spatial or temporal thresholds nor detailed information about the moving entities and their spatial context. We assume that spatial heterogeneity and spatial dependence are present in the speed values of moving objects. In other words, the speed of an object is spatially dependent on the speed of other objects in the neighbourhood, and this dependence will decrease with the distance between observations, indicating the presence of a spatial feature affecting the speed of moving objects. This spatial dependence is computed using the Local Index of Spatial Association (LISA) (Anselin, 1995). We have evaluated the proposed approach within three experiments in order to detect patterns of movement suspension of different moving objects (i.e. elephants, vehicles and pedestrians).

2. Detecting Movement Suspension Patterns

In the proposed approach, the movement of one or many objects is represented by a set of movement vectors. A movement vector can be defined as a directed line segment of the Euclidean space from an origin point and represents the dimensions of the movement (i.e. speed, direction) that can be measured at one place at one time. The Local Indicator of Spatial Association (LISA) is computed for the speed value of each movement vector together with a significance score (Z) (Anselin 1995). When the speed and Z score for each vector are represented in a scatterplot diagram, they form a characteristic saddle-point shape that allows us to classify the vectors into five zones

taking into account the mean speed and a statistical confidence level (e.g. 95% = 1.96 SD) (Figure 1). The zones above and below the confidence levels represent positive and negative spatial correlation respectively, whereas the zone between the limits indicates no spatial correlation. Therefore, vectors in the upper left zone (highlighted in red in Figure 1) are low speed vectors forming spatial clusters with significant positive spatial correlation, which have been identified as movement suspension patterns.

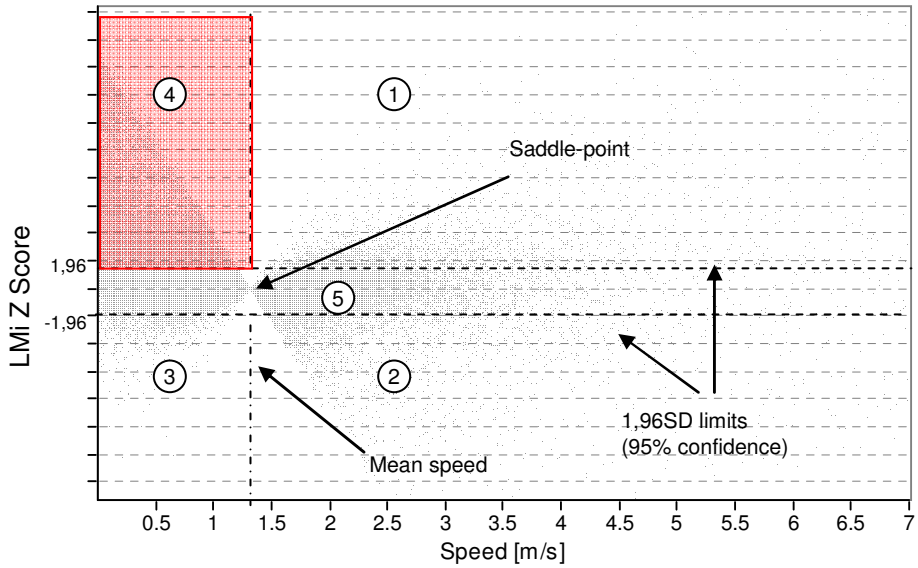

Figure 1. An example of a Local Moran scatterplot of the Z score against speed of different vectors. Vectors highlighted in red represent movement suspension.

3. The experiments

In order to explore the feasibility of the proposed approach, three applications have been used. They are: six elephants in a natural area in South Africa, fifty delivery trucks in Athens, and 419 children playing an urban mobile game in Amsterdam (Table 1).

Table 1: Overview of the moving data sets

	Moving Entities [n]	Movement Vectors [n]	Tracking time [days]	Avg travelling distance [km]	Temporal Resolution [sec]	Mean Speed [m/s]
Elephants	6	100377	1037	82.73	3600	0.09
Trucks	50	111419	40	26.52	30	5.9
Children	419	61782	10	1.248	10	0.83

3.1 Elephants in South Africa

During a research project in the Kruger National Park and adjacent private nature reserves in South Africa, the movement of six elephants (*Loxodonta africana*) was tracked with GPS collars recording the position of each individual over 34 months at 1 hour temporal resolution (De Knegt et al. in preparation). The elephants have moved around without following specific paths, and as a result, movement vectors are spread around all the area.

For this experiment, 6.76% (N=6789) of the vectors were classified into 85 clusters of movement suspension (Figure 2). Two large clusters were located the south part of the park (Figure 2b and f), an area characterized by the presence of several water bodies as well as ample and green vegetation. Another large cluster was located at the

boundaries of Klasserie Private Nature Reserve, an area with several dams, riverine vegetation and fenced in at three sites (W, S and E) (Figure 2a). These three clusters included more than 50% of the vectors classified as movement suspension. Many other clusters were associated to surface water, mainly rivers and riverine vegetation as well as artificial water points. Other clusters appeared not to be directly linked to areas with surface water, and there it is hypothesized that vegetation is an attractor for the elephants. For example, elephants are attracted to solitary large trees (e.g., marula trees, *Sclerocarya birrea*) or locations where the vegetation offers ample forage, e.g., areas where the vegetation is kept in a hedged state due to the frequent browsing (Fornara and DuToit 2007, De Knegt et al. 2008). This influence is currently being investigated in the study area.

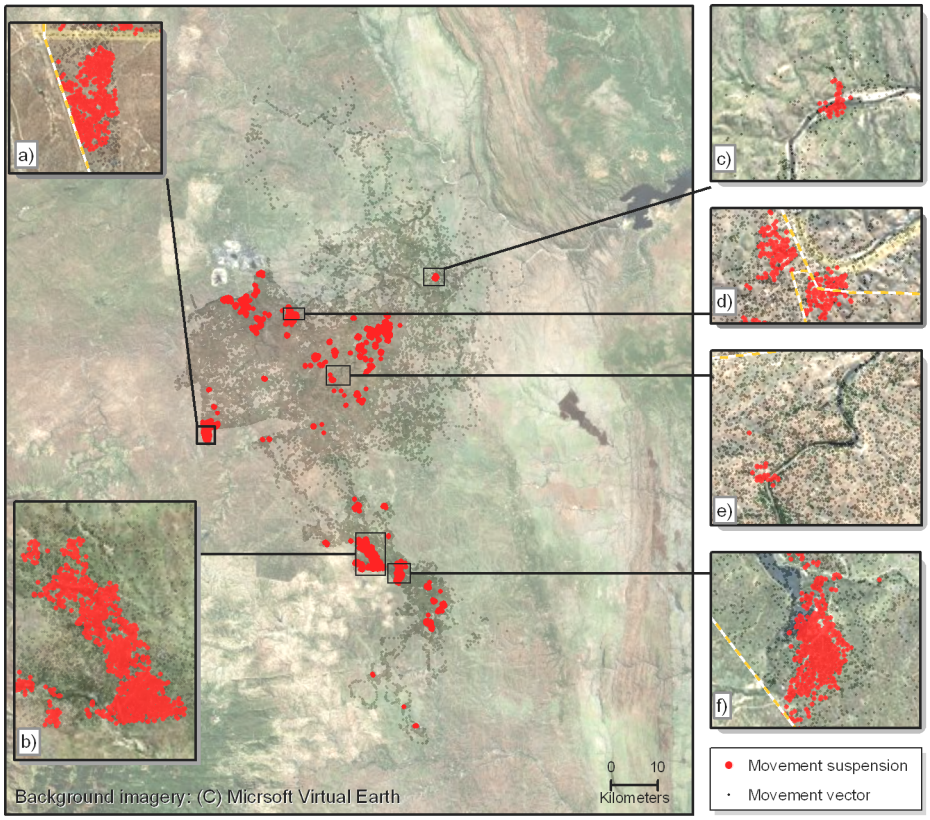

Figure 2. Suspension patterns (clusters of red dots) for six elephants in South Africa.

3.2 Trucks in Athens

A public available movement data set provided by Theodoridis (2003) contains the tracking data of 50 trucks transporting cement in the metropolitan area of Athens during 40 days (Frentzos et al. 2005). The typical movement of each vehicle consists of reaching a distribution point to get the cement and travel through the road network to some building project to deliver the material.

In this experiment, 31% (N=35535) of all movement vectors were classified into 252 clusters of movement suspension. The most noticeable fact is that the two largest clusters included 30% of the classified vectors and they were located at the two distribution points (Figure. 3d and 3g). The locations of other large clusters were associated with important building projects, such as the construction of the Olympic Village (Figure. 3a) and the Attiki Odos Avenue (Figure. 3b). Moreover, small clusters were associated with very specific locations, probably corresponding to minor building projects. Finally, some clusters were located in the middle of the roads and they could represent obstacles such as traffic jams or traffic lights (Figure. 3c and f).

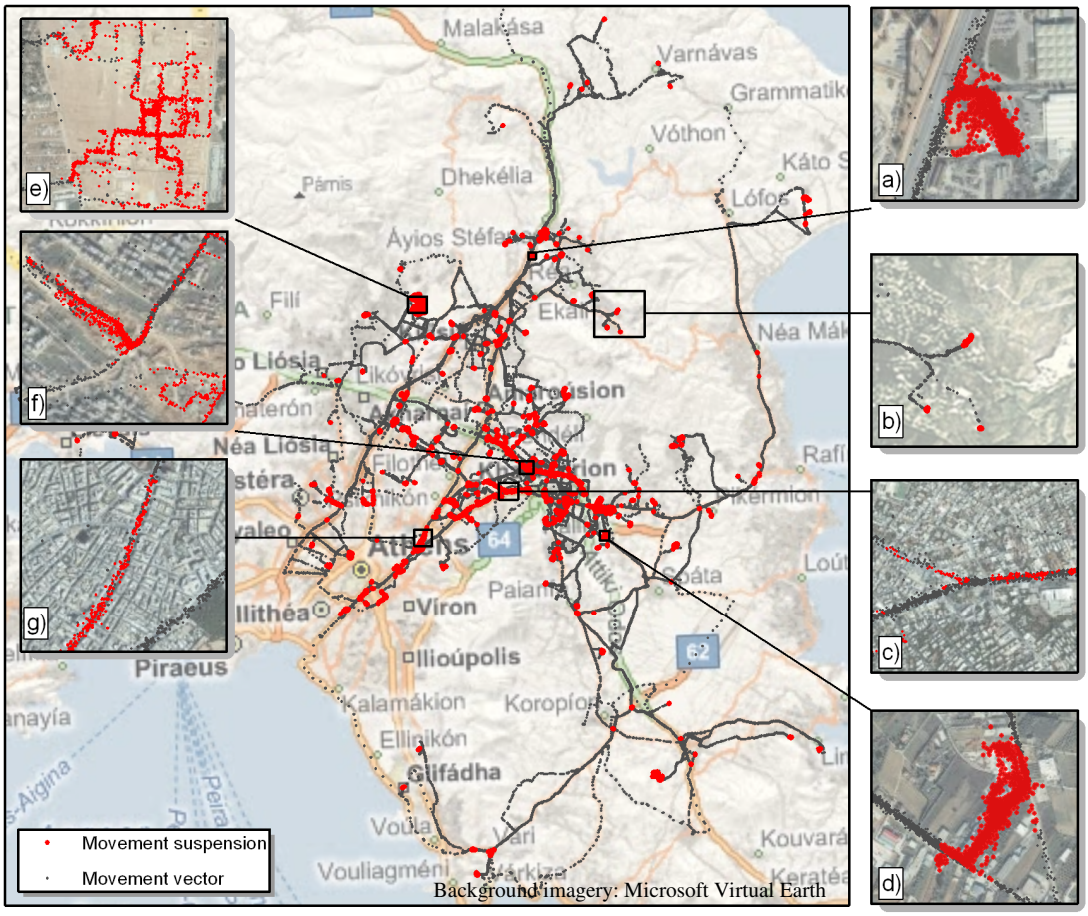

Figure 3. Suspension patterns (clusters of red dots) for 50 trucks delivering cement in Athens.

3.3 Children in Amsterdam

The movement of 419 children participating in an urban mobile game in Amsterdam was recorded using GPS-enabled mobile phones (Waag Society 2008). During the game, players walked in the city centre trying to discover some of the 18 checkpoints of the game; meanwhile they competed against other players by placing traps and confronting rivals.

Using the proposed approach, 17.78% (N=10861) of the movement vectors were classified into 55 clusters of movement suspension (Figure 4). 18 of these clusters were located at the 18 checkpoints of the game (Figure 4a, b, c) and 27 were located at places related to other events of the game such as confrontations and traps. Moreover, two small clusters were located at pedestrian crossings indicating some other pedestrian behaviour such as waiting for a traffic light (Figure 4e).

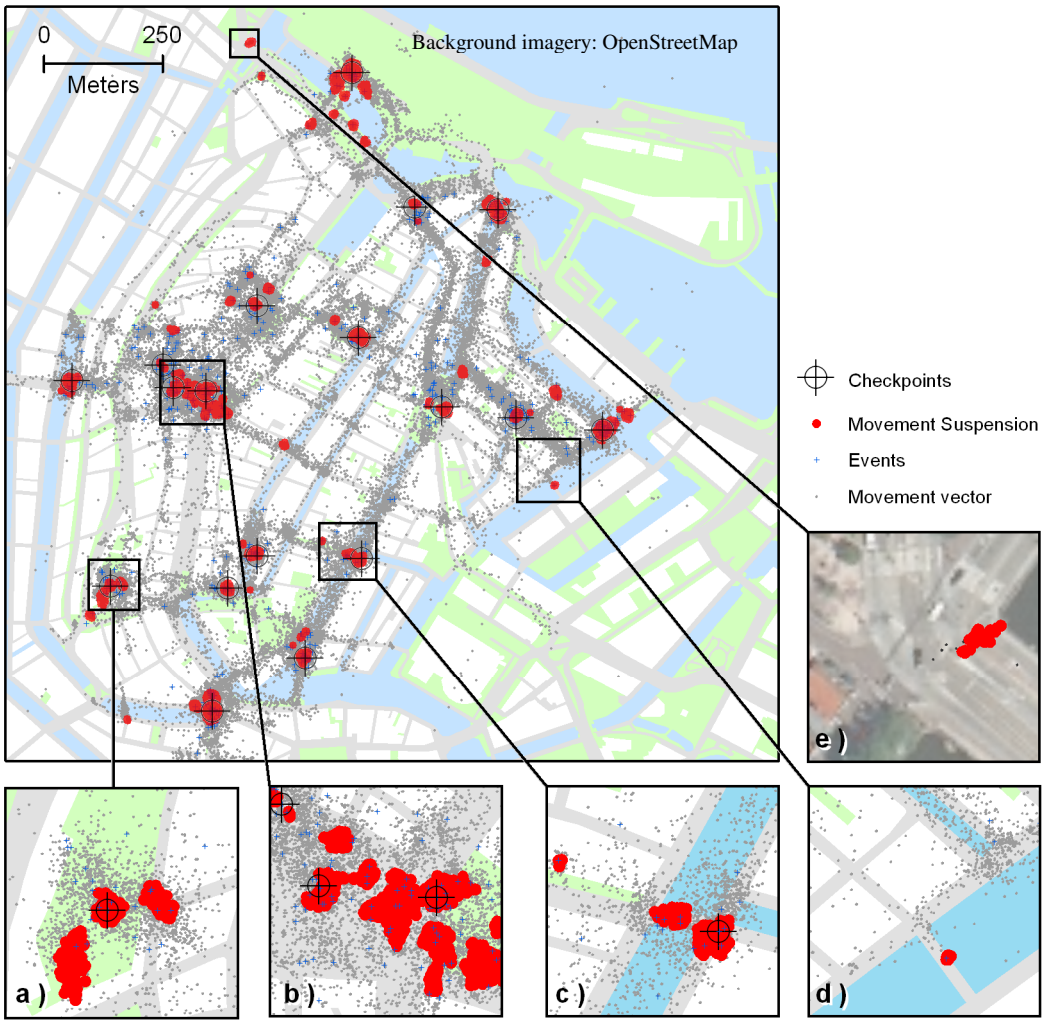

Figure 4. Suspension patterns (clusters of red dots) for 410 children in Amsterdam downtown.

4. Conclusions

Using the proposed approach, we were able to detect patterns of movement suspension for three different types of moving objects: elephants, trucks and children (Table 2). Each of these moving objects had a different kind of movement (i.e. unconstrained, constrained to a road network, and semi-constrained to public spaces) as well as different temporal resolutions (i.e. 10, 30 and 3600 seconds). These results suggest that LISA is a reliable index for assessing movement suspension and that the method is robust enough to detect patterns of suspension for different moving entities.

Table 2: Summary of the detected patterns for each experiment

	Movement vectors (#)	Vectors classified into Suspension Clusters (#)	Vectors classified into Suspension Clusters (%)	Suspension Clusters (#)
Elephants	100377	6789	6.76	85
Trucks	111419	35535	31.89	252
Children	61069	10861	17.78	55

Based on these results, we are interested on determining the interactions between the moving objects and their environment that cause movement suspension patterns in order to improve our understanding of movement behaviour. Currently the interactions are determined through the visual analysis of the places where the suspension patterns have occurred. Further research work will focus on developing an inference mechanism capable of improving our understanding about the interactions of collective movement behaviour.

Finally, we are also interested in explore the feasibility of LISA to analyse other movement properties such as direction and acceleration. Those properties has been studied before for discovering relative patterns of moving objects (Laube et al. 2005), however their spatial structure still needs to be explored to understand their relation with the geographical environment.

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