Uncovering Interactions between Moving Objects

Natalia Andrienko[1], Gennady Andrienko[1],
Monica Wachowicz[2], Daniel Orellana[2]

[1]Fraunhofer Institute Intelligent Analysis and Information Systems, Germany
{natalia,gennady}.andrienko@iais.fraunhofer.de

[2]Technical University of Madrid, Spain
m.wachowicz@topografia.upm.es, d.orellana@topografia.upm.es

INTRODUCTION

Movement data resulting from tracking positions of various moving objects (people, animals, goods, etc.) have recently got close attention of researchers. Methods for analysis of movement data have been developed in the areas of geographic information science (Buliung and Kanaroglou 2004), geovisualization (Dykes and Mountain 2003), information visualization (Kapler and Wright 2005), data mining (Giannotti and Pedreschi 2007), and visual analytics (Andrienko et al. 2007). The methods intended for analysis of large datasets include computational techniques, which either aggregate and summarize the data (Dykes and Mountain 2003, Buliung and Kanaroglou 2004, Nanni and Pedreschi 2006, Andrienko et al. 2007) or extract specific features, e.g. occurrences of certain types of relationships between moving objects (Laube et al. 2005).

Our recent research on analyzing movement data has lead towards the need to uncover the interactions between objects in the process of their movement. Movement data usually consist of time-stamped position records and do not contain any explicit information about interactions; hence, it is only possible to detect *indications* of possible interactions. One indication is *spatial proximity* between two or more objects at some time moment or during a time interval. The notion of spatial proximity depends of a number of factors; some of them are listed in Tab.1. Hence, the spatial proximity might be defined using a specific threshold of distances in each case of analysis. Furthermore, it may be insufficient to use only a distance threshold for identifying possible interactions. For example, it may be important to account for the duration of the spatial proximity between objects, or to look whether the objects stopped or continued their movement.

Tab. 1: Factors influencing the notion of spatial proximity

Factor	**Examples**
Type of movement	walking, cycling, driving, …
Type of relation in focus (analysis task)	possibility to observe, possibility to talk, possibility to touch, …
Place	city center, shopping mall, nature park, highway, …
Time	early morning, rush hours, late evening, night, …

The main research challenge relies on the definition of a theoretical and methodological framework for the detection and analysis of possible interactions between moving objects and between objects and the environment in which they move. This research challenge has two main foci: (1) the development of a theoretical foundation, including a formal definition of interaction and its indications, an inventory of factors influencing these interaction indications, and a typology of interactions; (2) the support of a methodology for visual exploration and analysis of possible interactions in large sets of movement data. This paper describes our first attempt towards uncovering interactions between moving objects by combining visual and filtering techniques.

EXTRACTING INTERACTIONS FROM MOVEMENT DATA

In case of a large dataset, possible interactions need to be extracted from the data by means of computational techniques. Then, a human analyst can explore the extracted interactions using visual and interactive tools. Developing efficient computational algorithms is beyond the scope of our research interests. However, in order to have material for the visualization and empirical basis for the theoretical framework, we have developed a simple and fast computational method for extracting possible interactions from movement data.

The user is expected to specify threshold values for the spatial and temporal distances between positions of two objects. The method first searches for pairwise interactions. For each pair of objects, it tries to find respective positions in their trajectories such that the spatial and temporal distances between them are within the given thresholds. In case of detecting such positions, the following positions of the trajectories are checked. For a better efficiency, we apply spatial and temporal indexing of trajectory fragments, which allows us to avoid scanning of all positions. After extracting pairwise interactions, the method combines interactions sharing a fragment of a trajectory into interactions with more members.

In fact, this simple approach can work sufficiently well only in case of fine time spacing between the position records in the data. If this is not the case, it is more appropriate to use the approach based on computing spatial and temporal relations between space-time prisms (Hägerstrand 1970). Yu and Shaw (2007) describe a prototype implementation of such a method; however, it is not clear how it scales to large datasets with trajectories of hundreds or thousands of moving objects.

VISUAL EXPLORATION OF ELEMENTARY INTERACTIONS

After the possible interactions have been extracted, they need to be visualized for enabling a human analyst to explore and interpret them. Currently we are developing techniques and tools to support the *elementary level* of analysis (Bertin 1983), when the analyst considers particular instances of interaction between individual objects. We shall henceforth call such instances *elementary interactions*. An elementary interaction can be represented on a map, for example, as is shown in Fig.1A.

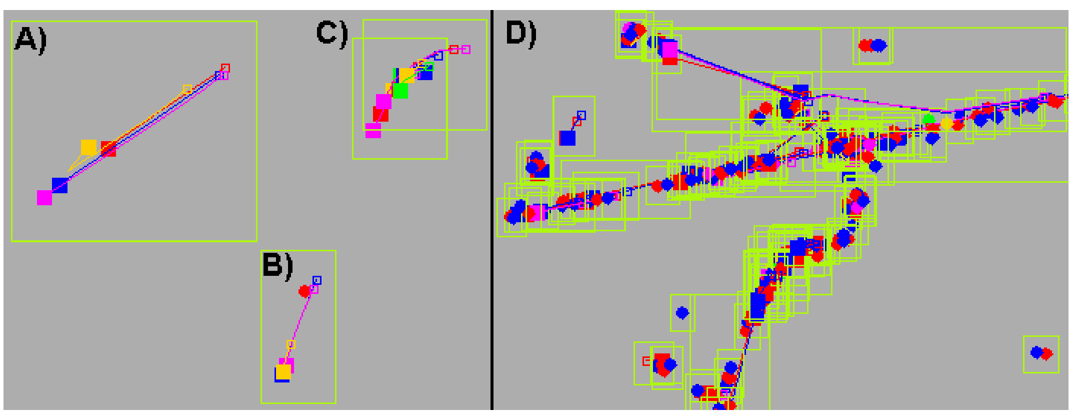

Fig. 1: Representation of extracted interactions on a map

The representation includes the “footprints” of the moving objects (i.e. the fragments of their trajectories made during the interaction) and a bounding rectangle around them for better visibility. The smaller hollow squares mark the beginnings of the trajectory fragments and the bigger filled squares mark their ends. In the interaction shown in Fig.1B, one of the objects is represented by a small circle. This means that only one point of its trajectory was within the given spatial and temporal distance thresholds from the positions of the other objects.

Fig. 2: A popup window with information about a selected interaction

Details about any elementary interaction can be accessed by selecting it on a map with the mouse. A special popup window (Fig.2) will inform the user about the time interval of the elementary interaction, the identifiers and names (if available) of the objects, and the earliest and the latest times of their participation in the interaction. Additionally, any attributes of the trajectories can be chosen for viewing. In Fig.2, one can see the start and end times of the trajectories. Fig.2 corresponds to the interaction shown in Fig.1A.

The number of possible elementary interactions extracted from a big dataset may be very large. In our experiments, we obtained from 750 to 1100 interactions from a set with 303 trajectories representing the walking movement of pedestrians and about 2000 interactions from 6187 trajectories representing the driving movement of cars (the number of extracted interactions depends on the selected values of the spatial and temporal thresholds). Several interactions might occur at the same place, as shown in Fig.1C. Extracting a large number of interactions might result in severe visual cluttering of the map display, as shown on a small map fragment in Fig.1D.
To be able to consider selected elementary interactions, an analyst needs flexible and convenient tools for interactive filtering. Our visual analytics toolkit supports the following types of filtering:

- Temporal filter: the user selects a time interval; all displays show only the elementary interactions that occurred within this interval.

- Spatial window: the user specifies a rectangular region on a map; all displays show only the elementary interactions which are located within this region.
- Attribute filter: the user can specify constraints on values of one or more attributes of the elementary interactions, for example, duration and/or number of objects. Only the interactions satisfying these constraints will be visible.
- Direct selection of interactions for viewing.
- Specially designed "aggregate filter" (Fig.3), which allows the user to find interactions involving specific objects.

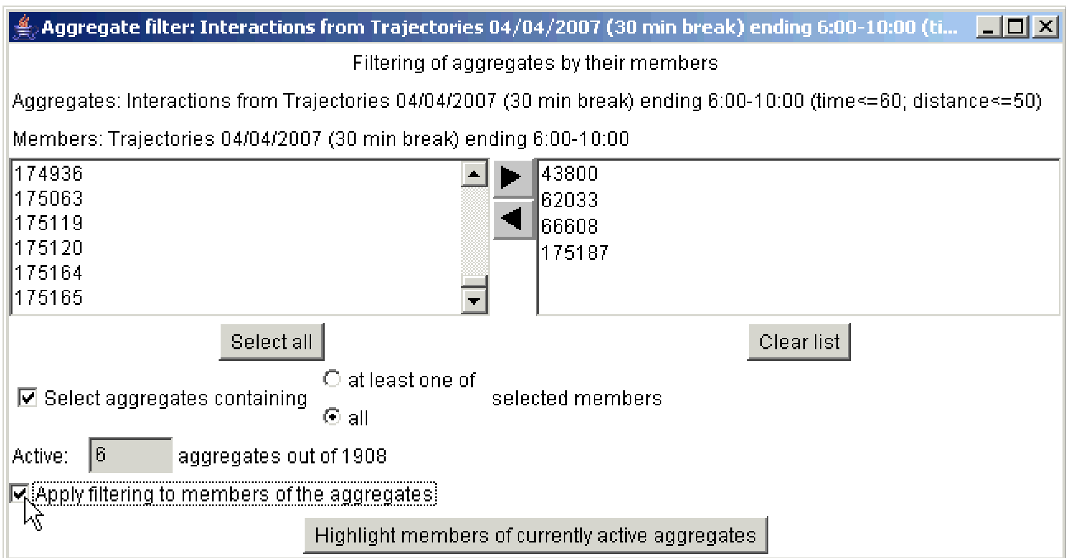

Fig. 3: The user interface of the "aggregate filter", which is used for selecting interactions involving particular trajectories.

Fig.4 shows the four trajectories participating in the interaction 1749, which is represented in Figs.1A and 2, together with all interactions involving at least one of these trajectories (there are 36 such interactions). Fig. 5 shows a fragment of the map; the background image has been switched off. Fig.6 shows the same four trajectories as Fig.4 and the interactions involving all these trajectories (there are 6 such interactions). In both cases, the filtering has been done with the use of the aggregate filter.

The analyst can simultaneously use several filters. Their results are combined through intersection. Any kind of filtering is applied to all displays the analyst uses for viewing the data. Thus, the space-time cube in Fig.7 represents the same four trajectories as in Figs.4-6 (the time filter is additionally used). Currently we are designing a method for explicit marking of interactions in a space-time cube display.

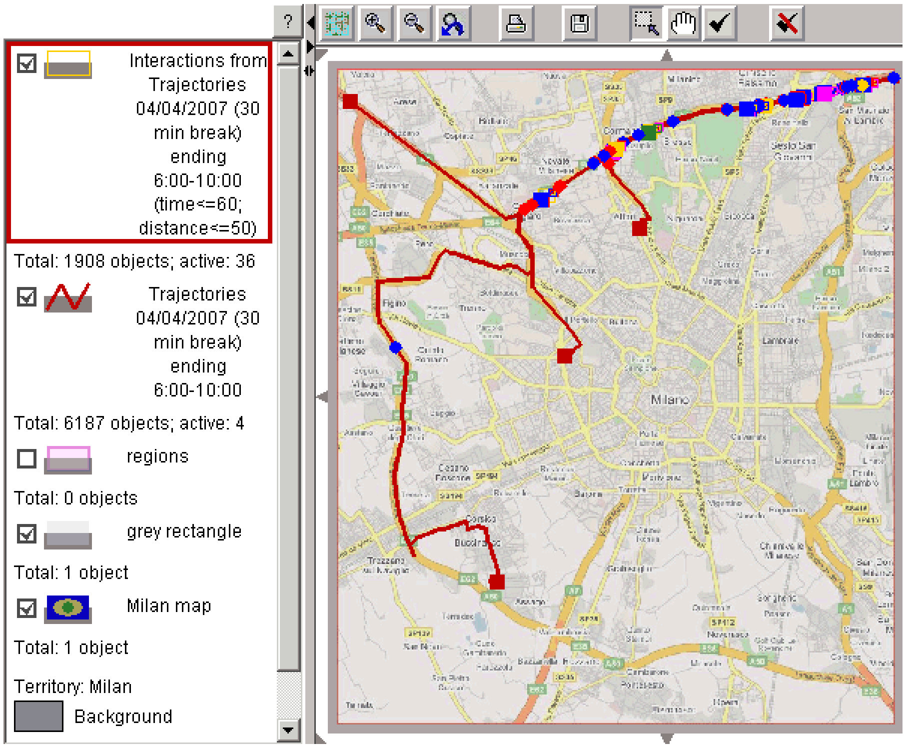

Fig. 4: Four selected trajectories and all interactions involving at least one of the trajectories.

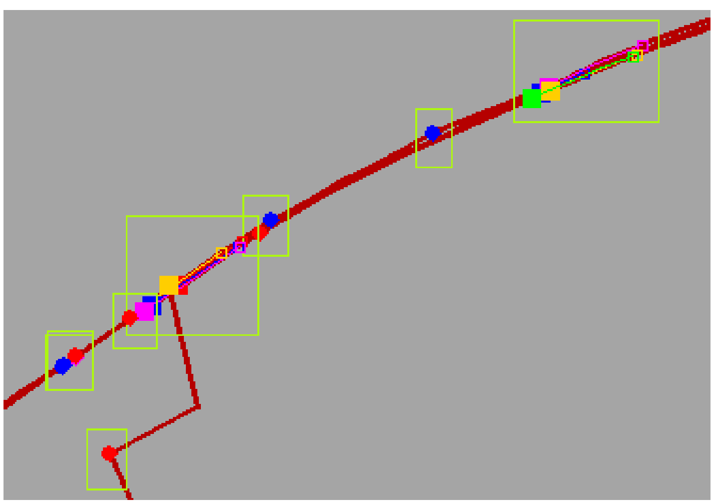

Fig. 5: A fragment of the map from Fig.4, without the background image.

Fig. 6: The same trajectories as in Fig.4 and the interactions involving all these trajectories.

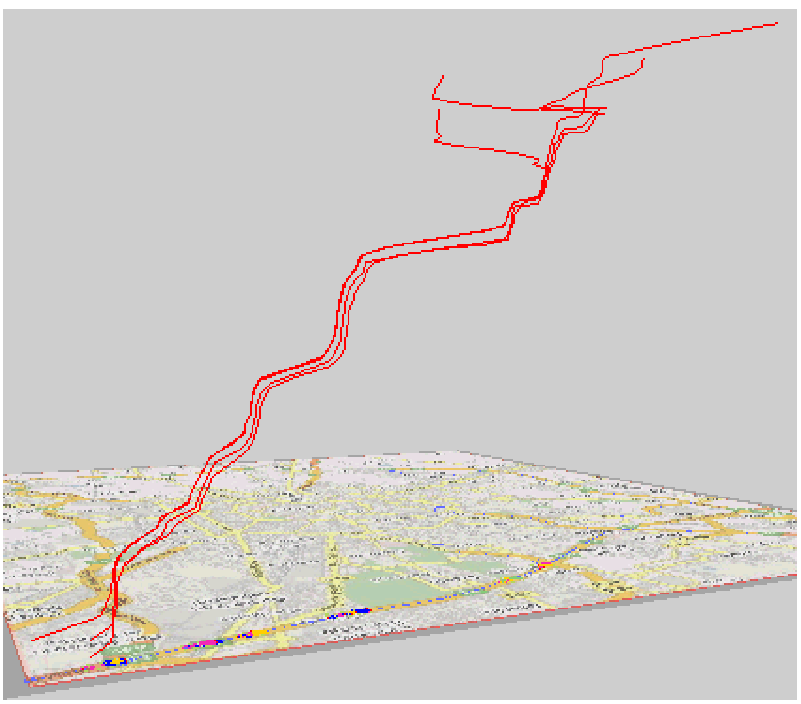

Fig. 7: The four selected trajectories in a space-time cube.

The analyst can simultaneously use several filters. Their results are combined through intersection. Any kind of filtering is applied to all displays the analyst uses for viewing the data. Thus, the space-time cube in

Fig.7 represents the same four trajectories as in Figs.4-6 (the time filter is additionally used). Currently we are designing a method for explicit marking of interactions in a space-time cube display.

To view the times when the interactions occur, the analyst may use the timeline display, which is demonstrated in Figs. 8 to 12. The horizontal dimension represents the time. The dark grey lines represent the trajectories; the lines are positioned according to life times of the trajectories. The yellow line segments represent the interactions. For each interaction, there are segments in the lines of all trajectories involved in it. As a result of data filtering, Fig.8 shows the same four trajectories as in the previous figures and the interactions involving all these trajectories. Fig.9 shows these four trajectories (they are highlighted in black) and all trajectories interacting with at least one of these four trajectories. The yellow line segments represent, as in Fig. 8, the interactions involving all four selected trajectories. It may be seen that three other trajectories are involved in some of these interactions. In Fig.10, the interactions involving at least one of the four trajectories are visible. Pointing with the mouse cursor on a line segment representing an interaction allows the user to see details about this interaction (Fig.11). Clicking on a segment highlights all segments representing the corresponding interaction; they are shown in red (Fig.12).

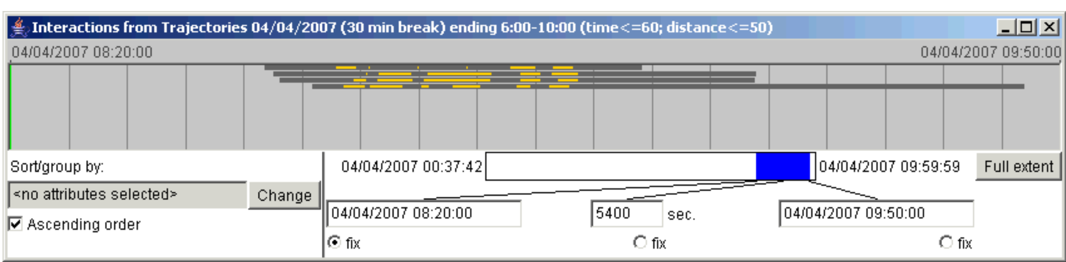

Fig. 8: The four selected trajectories and their interactions in a timeline display.

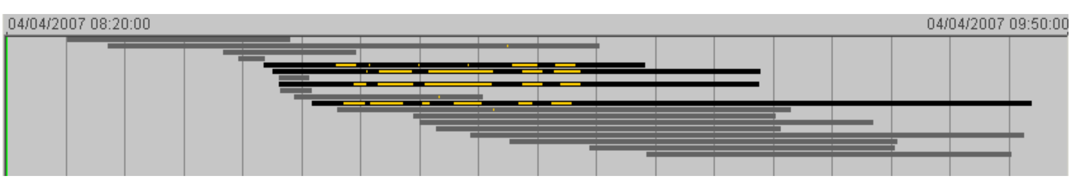

Fig. 9: The four selected trajectories are highlighted in black; all trajectories with which these trajectories interact are shown in gray.

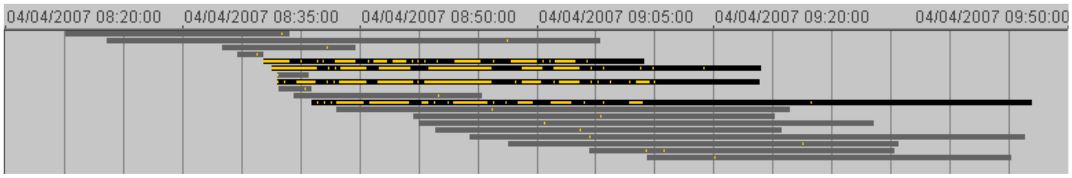

Fig. 10: All interactions involving at least one of the four selected trajectories.

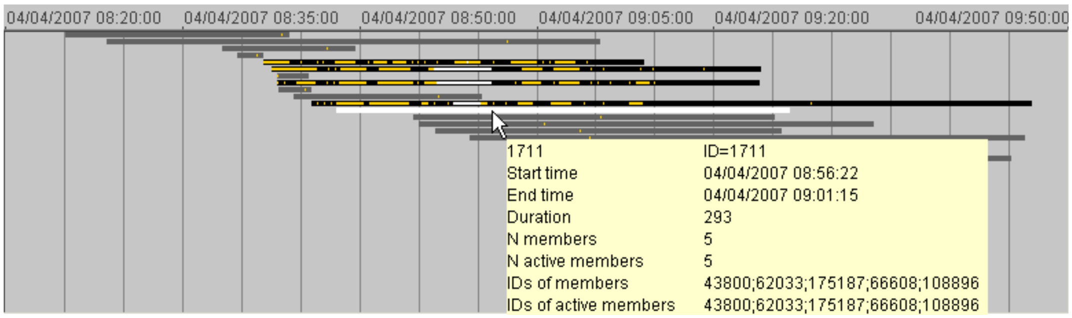

Fig. 11: Obtaining information about an interaction by mouse pointing.

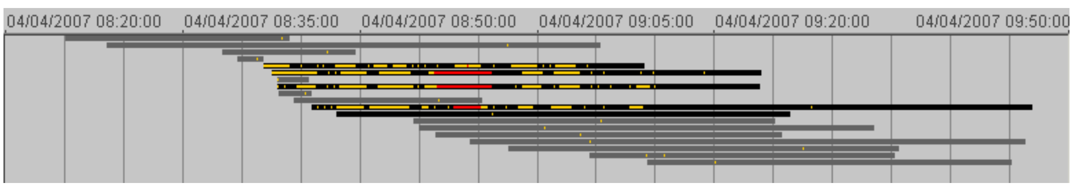

Fig. 12: One interaction, which has been selected by mouse clicking, is highlighted in red.

OPEN ISSUES AND FURTHER RESEARCH DIRECTIONS

With the use of the filtering techniques, an analyst can select a small subset of trajectories and interactions for a detailed examination by means of various visual displays. However, the whole set of extracted interactions may be too large for analyzing in this way. Hence, besides the current tools for examining elementary interactions, it is necessary to develop methods and tools supporting the exploration of large sets of interactions. In these methods, aggregation and summarization of the interactions need to be used. The question is how such non-trivial constructs can be aggregated and summarized for supporting various analyses. The most obvious ways are spatial aggregation (by areas in space), temporal aggregation (by time intervals), and aggregation by values of attributes such as duration or number of objects involved. For the aggregates so obtained, various statistics may be computed, such as the count of the members, minimum, maximum, and average values of numeric attributes.

However, these ways of aggregation and summarization do not seem sufficient. The analyst may be interested not only in the places, times, and durations of the interactions but also (perhaps, even primarily) in the behaviors of the interacting objects. For example, did the objects stop for a while, or just pass each other, or move together for some time, or follow one another? Did the speeds and/or directions of their movement change after the interaction as compared to those before the interaction and during the interaction? Such questions are easy to answer for one or a few elementary interactions but not for multiple interactions. It is therefore necessary to continue the theoretical and practical research where the main tasks are:

- Identify the relevant characteristics of interactions;
- Define appropriate classes of interactions;
- Find ways to automatically characterize and classify interactions and, on this basis, aggregate and summarize them;
- Design suitable techniques for visual analysis of aggregated and summarized interactions.

REFERENCES

Andrienko, G., N.Andrienko and S.Wrobel (2007). "Visual Analytics Tools for Analysis of Movement Data". ACM SIGKDD Explorations, 9(2): 38-46.

Bertin, J. (1983). "Semiology of Graphics. Diagrams, Networks, Maps". University of Wisconsin Press, Madison.

Buliung, R.N., and P.S. Kanaroglou (2004). "An Exploratory Data Analysis (ESDA) toolkit for the analysis of activity/travel data". Proceedings of ICCSA 2004, LNCS 3044, Springer, Berlin, 1016-1025.

Dykes, J. A., and D. M. Mountain (2003). "Seeking structure in records of spatio-temporal behaviour: visualization issues, efforts and applications". Computational Statistics and Data Analysis, 43: 581-603.

Giannotti, F., and D. Pedreschi, eds. (2007). "Mobility, Data Mining and Privacy - Geographic Knowledge discovery". Springer, Berlin

Hägerstrand, T. (1970). "What about people in regional science?". Papers of the Regional Science Association, 24: 7-21.

Kapler, T., and W. Wright (2005). "GeoTime information visualization". Information Visualization, 4(2): 136-146

Laube, P., Imfeld, S., and R.Weibel (2005). “Discovering relative motion patterns in groups of moving point objects”. International Journal of Geographical Information Science, Vol. 19(6): 639–668

Nanni, M., and D. Pedreschi (2006). “Time-focused clustering of trjectories of moving objects”. Journal Intelligent Information Systems, 27: 267-289.

Yu, H. and S-L. Shaw (2007). “Exploring potential human activities in physical and virtual spaces: a spatio-temporal GIS approach”. International Journal of Geographical Information Science, 22(4): 409-430