

DYNAMIC TIME TRANSFORMATIONS FOR VISUALIZING MULTIPLE TRAJECTORIES IN INTERACTIVE SPACE-TIME CUBE

ANDRIENKO G., ANDRIENKO N.

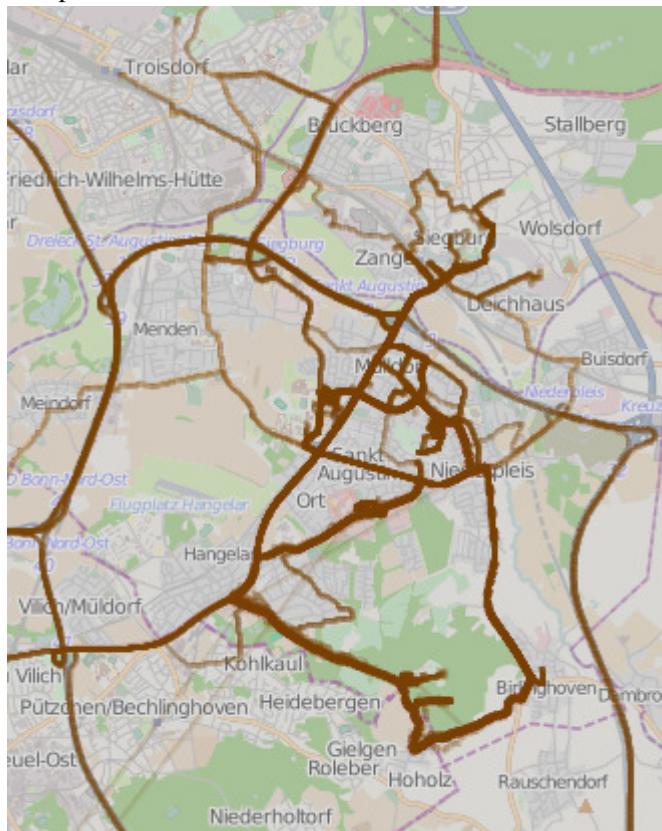
Fraunhofer IAIS, SANKT AUGUSTING, GERMANY

ABSTRACT

Space-time cube is a visualization technique representing (geographic) space and time by three display dimensions. This technique is used to visualize and explore trajectories of moving objects. However, it may be ineffective when the number of different trajectories is large and/or the time span of the data is long. We overcome the limitations in two complementary ways: first, clustering of trajectories by spatial similarity, and, second, transformation of the temporal references within the trajectories to facilitate comparisons within and between clusters. We demonstrate the work of the approach on a real data set about individual movement over one year.

INTRODUCTION

Interactive space-time cube (STC) has become a common technique for visualizing trajectories (Kraak 2003, Kapler and Wright 2005). STC can support comparison of spatial, temporal, and dynamic properties of several trajectories when they are close in time (dynamic properties include the speed profile over time and stops occurring on the way). However, exploration of a large number of trajectories distributed over a long time period is not effectively supported. One of the problems is visual clutter resulting from numerous intersections of lines representing spatially dissimilar trajectories. Another problem is that trajectories distant in time are hard to compare since the lines representing them are distant in the cube. The problems are illustrated below.



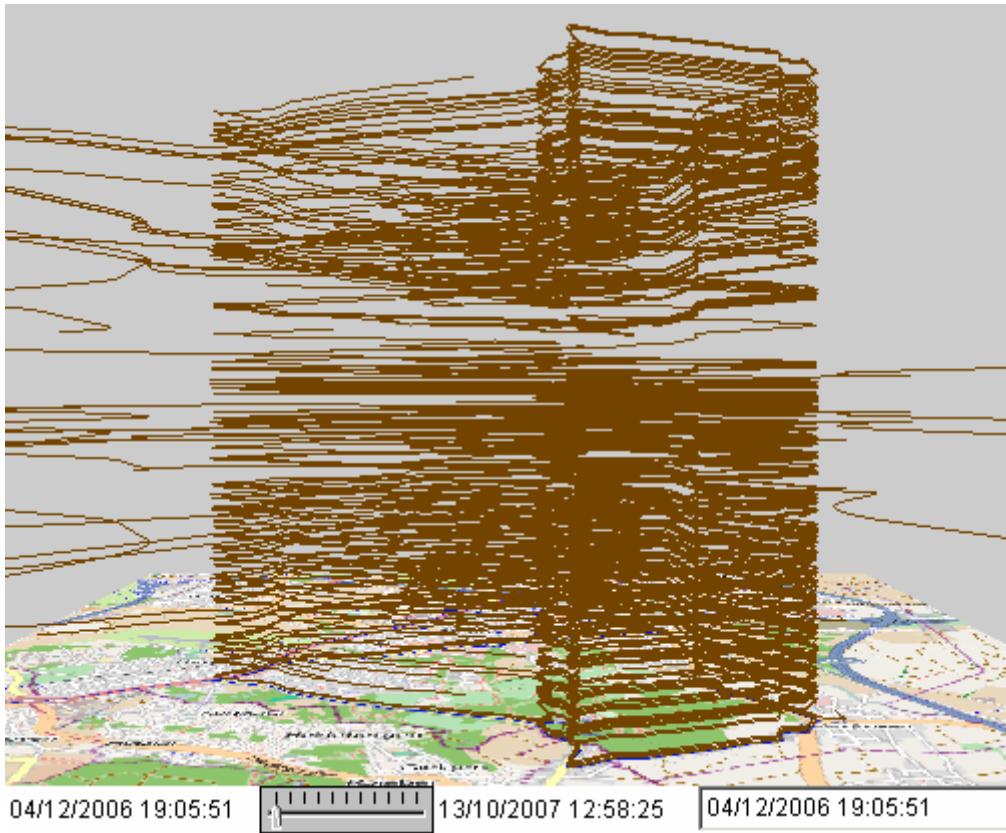
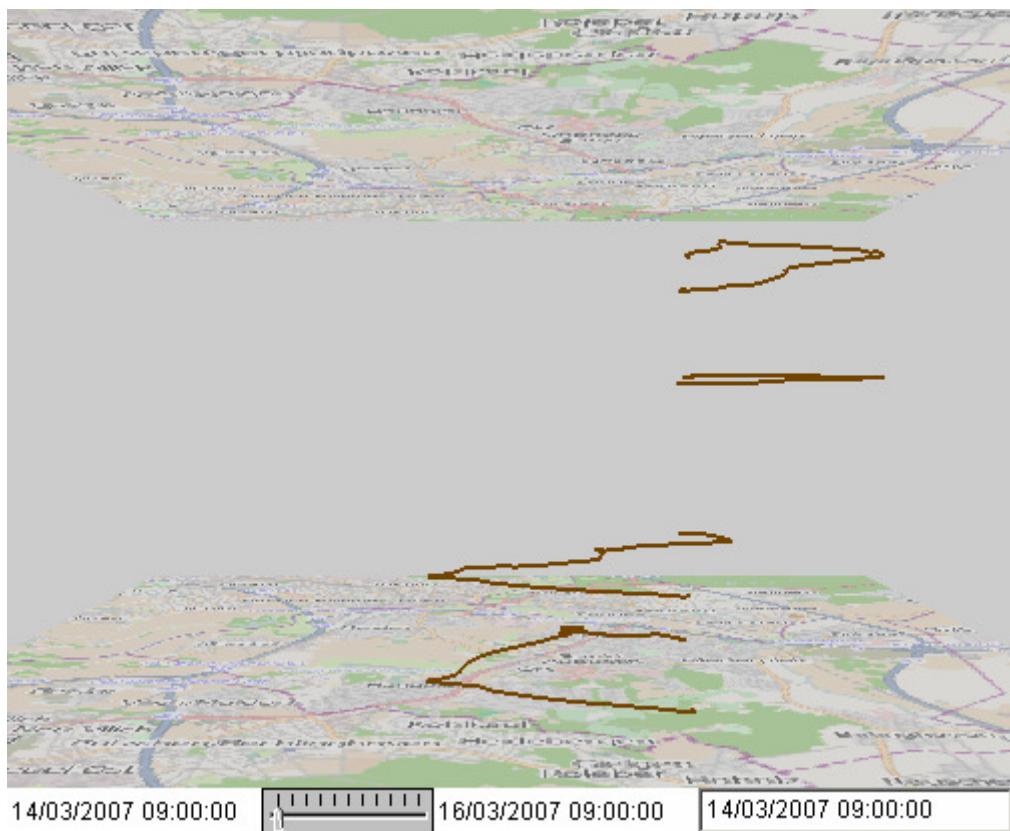


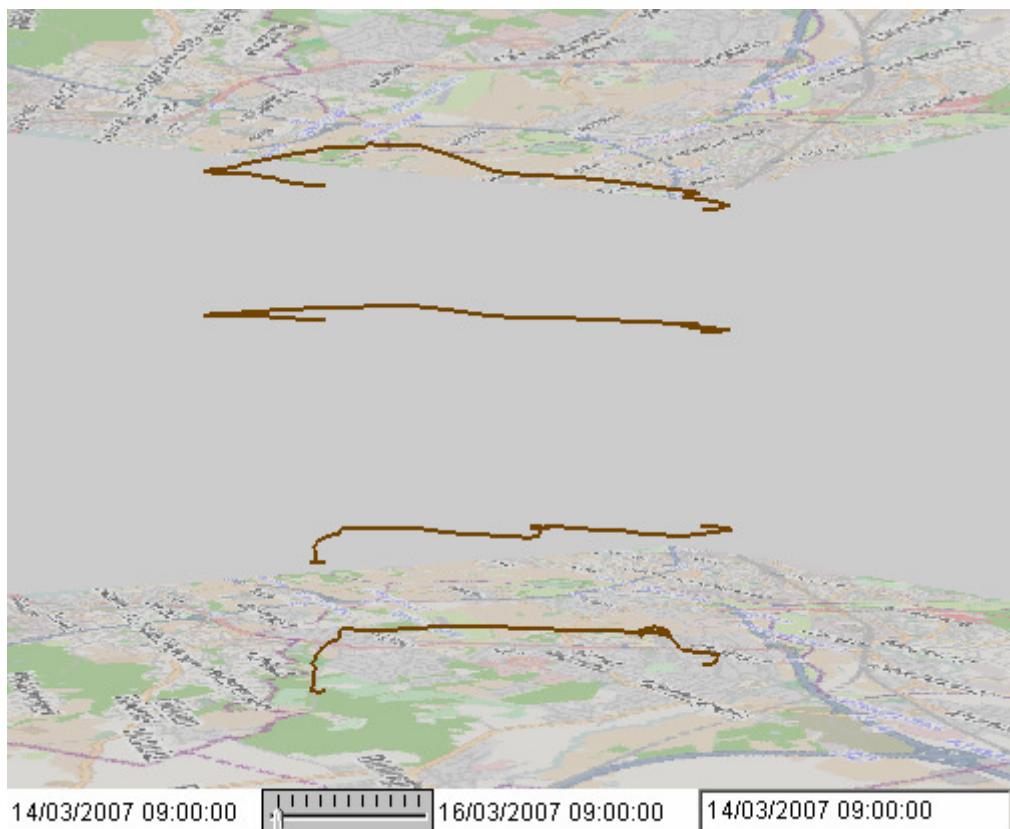
Figure 1: Left: a fragment of a map display representing 365 trajectories of a personal car made during a year. The trajectories are shown as brown-coloured lines drawn with 10% opacity. Right: the same trajectories represented in a space-time cube. The vertical dimension represents time; the time axis is oriented from bottom to top.

Figure 1 represents a set of about 365 car trajectories of one person recorded during about a year. Quite naturally, many of the trajectories correspond to regular trips of the person and therefore coincide fully or partly in space. This can be seen in the map on the left. The trajectories are represented by brown-coloured lines drawn with 10% opacity; hence, the saturation of the brown colour reflects the number of overlapping lines. On the right, the trajectories are represented in a STC as three-dimensional lines drawn according to the spatial and temporal positions of the trajectory points and segments. The horizontal plane of the cube represents the space, i.e., the geographic area in which the movements took place. The vertical dimension represents the temporal extent of the data; the time axis is oriented upwards. It can be seen that the STC display is illegible due to visual clutter.

The visual clutter can be substantially reduced by means of interactive temporal focusing and zooming: when the user reduces the time interval to be represented, the full vertical extent of the STC is used to represent the selected interval. For example, Figure 2 shows the result of selecting an interval of 48 hours length. This interval includes only four trajectories. The display is not cluttered any more; however, the visible trajectories cannot be compared to trajectories lying in time beyond the focus interval. Moreover, the visible trajectories are hard to compare even among themselves, despite the possibility to interactively rotate and translate the view in the STC (Figure 2 right). First, since even the limited length of the selected time interval is many times greater than the durations of the trajectories, each trajectory line has a very small vertical extent in the cube. Therefore, the speed of the movement and its variation along the route cannot be estimated. Second, the vertical distances between the lines representing different trajectories in the cube are very large. It should be borne in mind that these are three-dimensional lines viewed in a two-dimensional projection. The projection distorts the shapes of the lines differently depending on their vertical positions. Therefore, even spatially similar trajectories look quite differently. It is quite hard to find corresponding segments and detect real differences.



Show the map on top of the cube



Show the map on top of the cube

Figure 2: Left: interactive temporal focusing and zooming has been applied to the STC so that a selected time interval of 48 hours length is represented using the full vertical extent of the display. Right: the view has been interactively rotated so that the area and trajectories are viewed from the east.

We overcome these limitations of the STC display in two complementary ways: first, clustering of trajectories by spatial similarity, and, second, transformation of the temporal references within the trajectories. After a brief overview of the related works in the next section, we describe our approach and illustrate it by examples.

RELATED WORKS

The idea of representing paths of moving objects (particularly, people) in a space-time cube was introduced by Torsten Hägerstrand, the founder of time geography, in the 1960s (Hägerstrand 1970). Software implementations of this visualization method appeared relatively recently (Kraak 2003, Andrienko et al. 2003, Kapler and Wright 2005). These implementations include the following interactive features:

- change of the viewpoint;
- selection of spatio-temporal objects to be displayed;
- access to objects by pointing and dragging;
- zooming in the spatial and temporal dimensions;
- animation of the content of STC;
- moveable plane for additional temporal reference.

These interactive features are also available in our implementation of STC.

Clustering is a common approach to dealing with large number of objects. The idea is that an analyst groups objects by similarity of their properties and then considers the groups rather than individual objects. In the recent decade, numerous trajectory clustering methods were developed in the data mining (Li et al. 2004) and visual analytics (Andrienko et al. 2007, Rinzivillo et al. 2008, Schreck et al. 2008) communities. An example of transformation of temporal references in movement data can be seen in a cartographic poster designed by Drecki and Forer (2000). The poster deals with the tourism to New Zealand and contains a representation of the major movement flows of the tourists during the first 6 days of their holidays in New Zealand. To summarise individual data, the travel times of different tourists have been transformed from the absolute time scale, i.e. calendar dates, to a relative one starting from the day of tourist's arrival to New Zealand. So far we have not seen any publication telling about interactive tools for transforming time references in data; hence, we consider this as our novel contribution.

APPROACH

For the clustering, we use a density-based clustering algorithm OPTICS (Ankerst et al. 1999). The algorithm has been implemented in such a way that it can work in combination with any external method for measuring distances (degrees of dissimilarity) between the objects subject to clustering. Such a method is called "distance function". We have developed a library of diverse distance functions suitable for trajectories (Rinzivillo et al. 2008). In particular, the function "route similarity" measures the closeness of the spatial positions and similarity of the shapes of trajectories (Andrienko et al. 2007).

Applying the density-based clustering algorithm to a set of objects typically divides the set into several clusters and "noise", i.e., a subset of objects that have not been assigned to any cluster because of their insufficient similarity to others. Hence, clustering of trajectories with the "route similarity" distance function makes several groups of trajectories following repeatedly used routes and separates these from trajectories with unusual shapes. Our interactive tools allow the user to choose which groups of trajectories will be visible in the displays. The user may select one group to compare the trajectories within it or two or more groups for comparisons between them. The selection, particularly, hiding the "noise", substantially reduces line intersections and visual clutter.

Temporal transformations facilitate the comparison of temporal and dynamic properties of trajectories within the groups and between the groups using the STC. First, the transformations bring the trajectories closer in time and, hence, in the STC. Second, the transformations allow the user to explore the distribution of trajectories and their properties with respect to temporal cycles: daily, weekly, seasonal, etc. We suggest two classes of temporal transformations:

1. Transformations with respect to the individual lifelines of the trajectories, which include bringing the trajectories to a common start moment, a common end moment, or common start and end moments. In the first two cases, the lengths of the time intervals between the positions and, hence, the durations of the trajectories are preserved. In the third case, the lengths of the time intervals are proportionally modified so that the transformed trajectories have the same duration.
2. Transformations with respect to temporal cycles, which include bringing the times of the trajectories to the same year or season, the same month, week, day, or hour.

The transformations are chosen by means of the dialog shown in Figure 3. The possible options in the dialog depend on the properties of the temporal component of the data. The transformations in relation to the temporal cycles are included when the time references are calendar dates and times rather than abstract time counts. The temporal extent of the data determines which of these transformations are meaningful. The daily cycle is included in the dialog when the extent exceeds one day, and so on. In our example dataset, the time extent does not exceed one year. Therefore, the transformation according to the yearly or seasonal cycle has not been included as an option in the dialog shown in Figure 3.

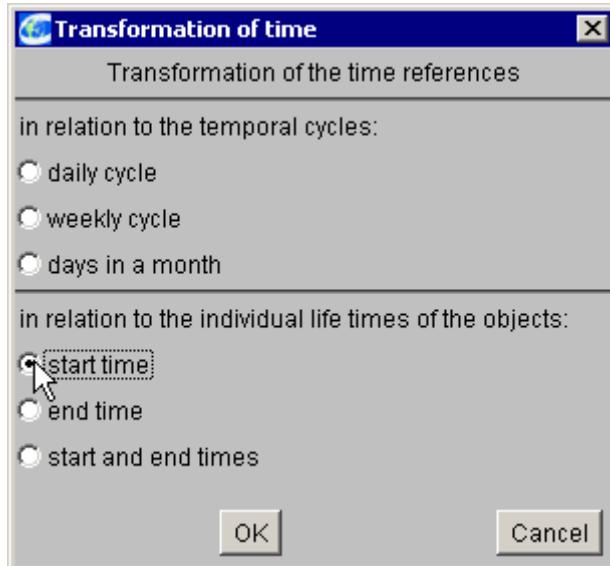


Figure 3: A dialog window for selecting temporal transformations.

The selected transformation is applied to all trajectories, irrespective of their current visibility. After each temporal transformation, the STC display needs to be rebuilt since all three-dimensional objects within it radically change their vertical positions and sizes. The rebuilding takes very short time and does not impede the process of interactive exploration of the data.

EXAMPLES

As an example, we use the earlier introduced dataset with the personal car trajectories. Using clustering methods, we obtained 9 major clusters of spatially similar trajectories; 121 trajectories were not included in clusters. Figure 4 illustrates how the clustering results are shown in the map. Each cluster gets its specific colour. The “noise” is shown in grey. The lower part of Figure 3 demonstrates how the user can control the visibility of the clusters by unselecting and selecting the respective checkboxes on the right of the map.

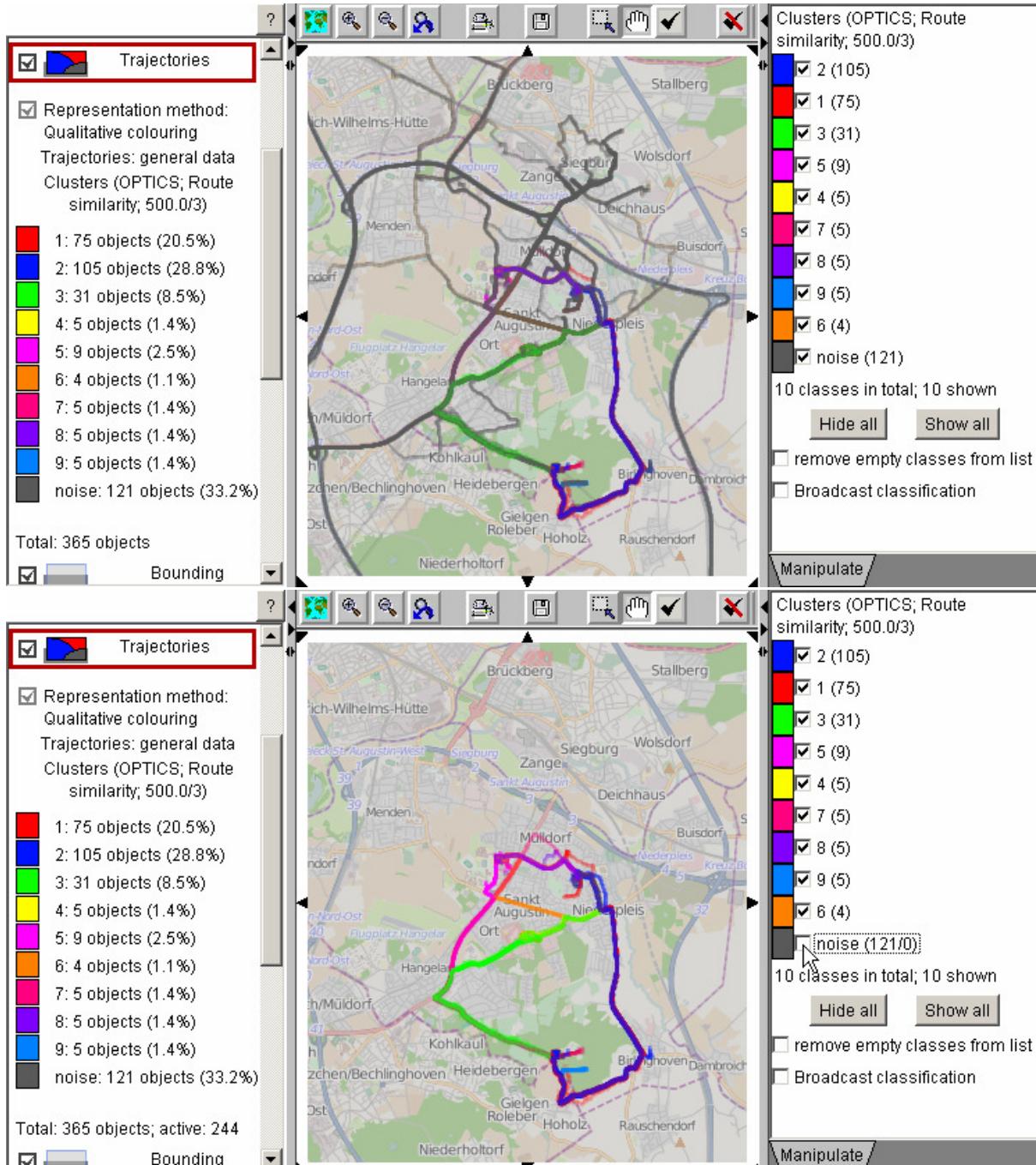


Figure 4: Top: the trajectories have been clustered by route similarity. The lines are coloured according to the clusters they belong to. Grey represents the “noise”, i.e., trajectories with unusual routes. Bottom: the user has interactively switched off the visibility of the “noise”.

Now we shall apply various temporal transformations to compare the trajectories within and between the clusters. To compare the dynamic properties of the trajectories within the clusters, it is useful to bring the start times or end times of the trajectories to a common time moment. In Figure 5, shifting to a common start time has been applied. The user has selected one cluster (cluster 1) for a detailed inspection. One can easily discern trajectories with stops and note differences in the speeds, which are reflected in different slopes of the lines. By applying temporal focusing and zooming, the user can examine the similarities and differences in more detail.

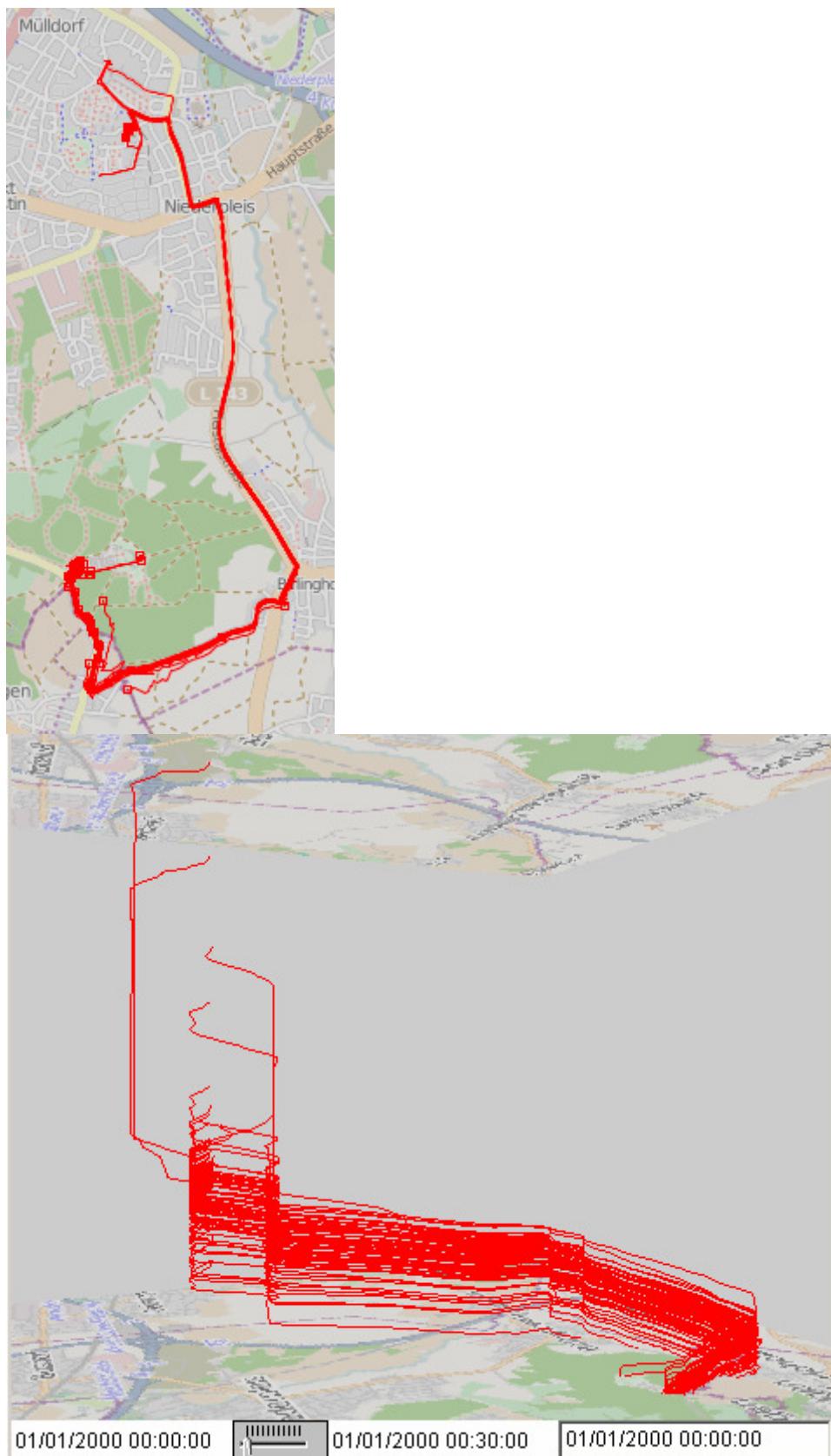


Figure 5: Left: a cluster of spatially similar trajectories in a map display. Right: a space-time cube with these trajectories shifted to a common start time. The display has been rotated so that the trajectories are viewed from the west.

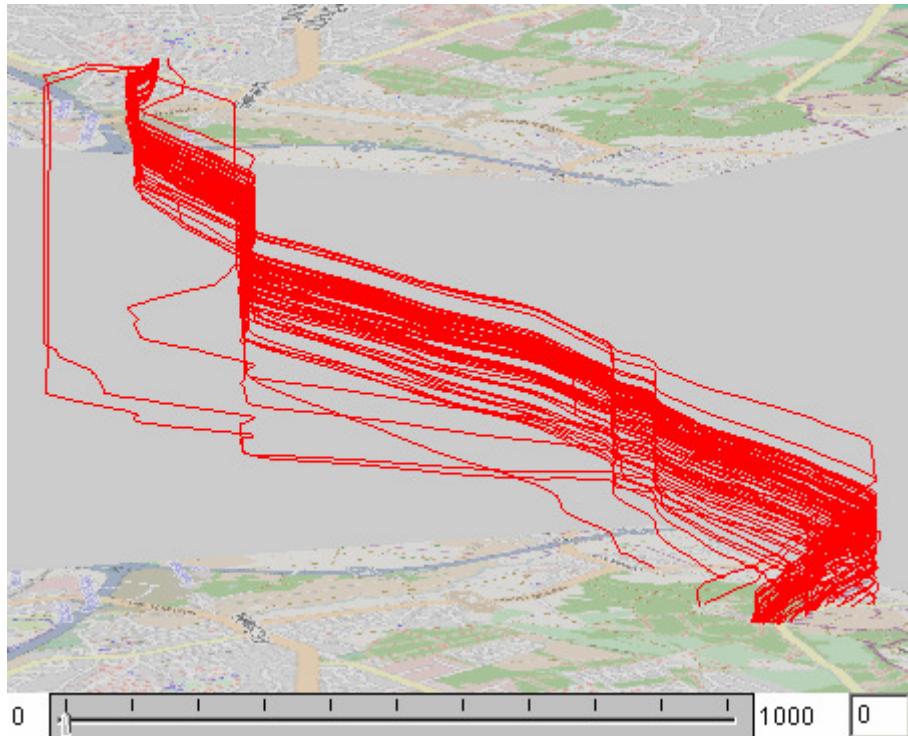
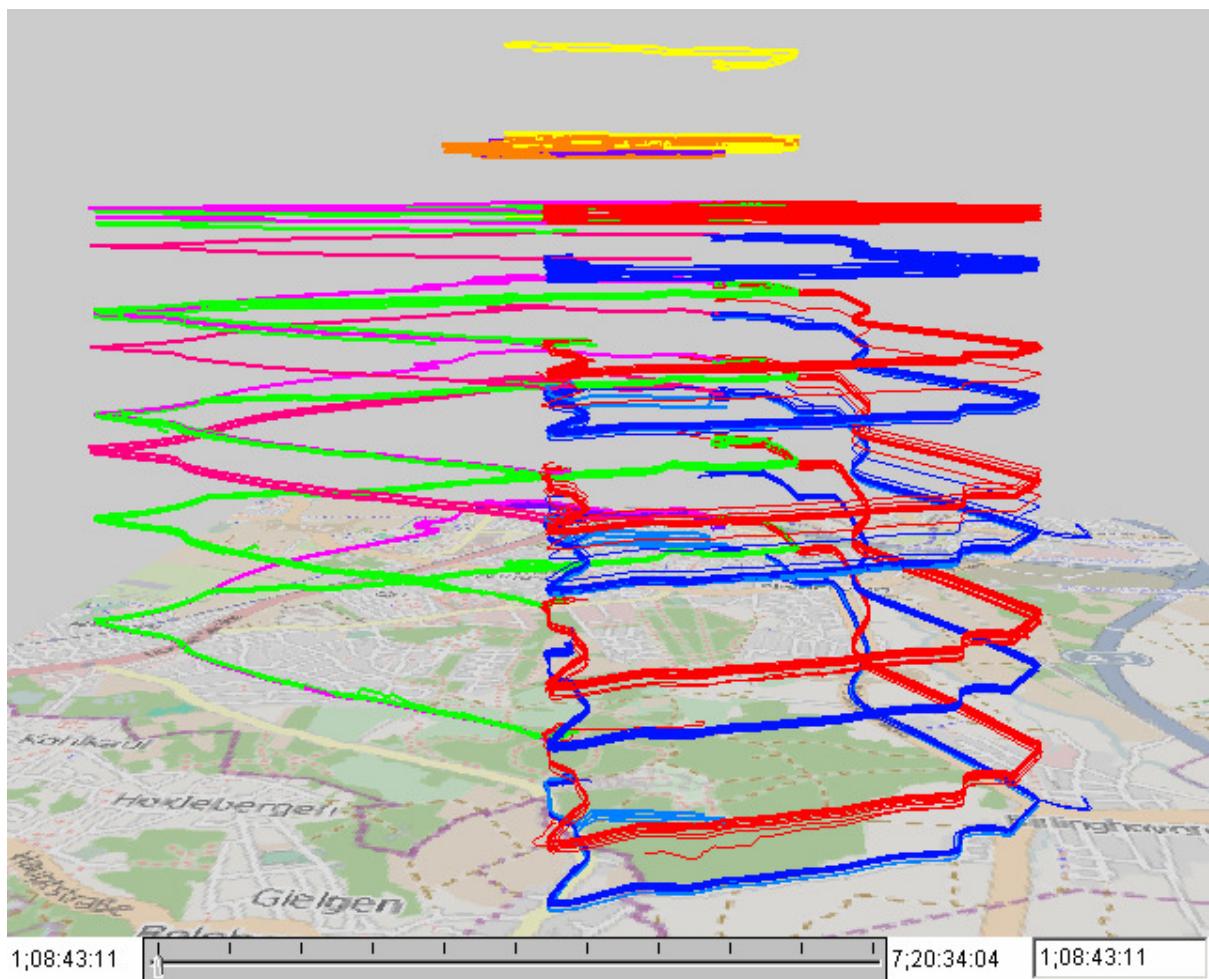


Figure 6: The same cluster of trajectories as in Figure 5 after the transformation of the time references relative to the start and end times of the trajectories.

Figure 6 shows the same cluster after the trajectories have been brought to common start and end times. In this case, the temporal references are transformed to abstract time counts from 1 to 1000 representing to the start and end times of the trajectories, respectively. A few trajectories differing in their dynamic characteristics from the bulk of the cluster are immediately detectable. The same applies to trajectories deviating from the majority by their spatial characteristics. The display also allows us to estimate the relative durations of the stops and movement times.



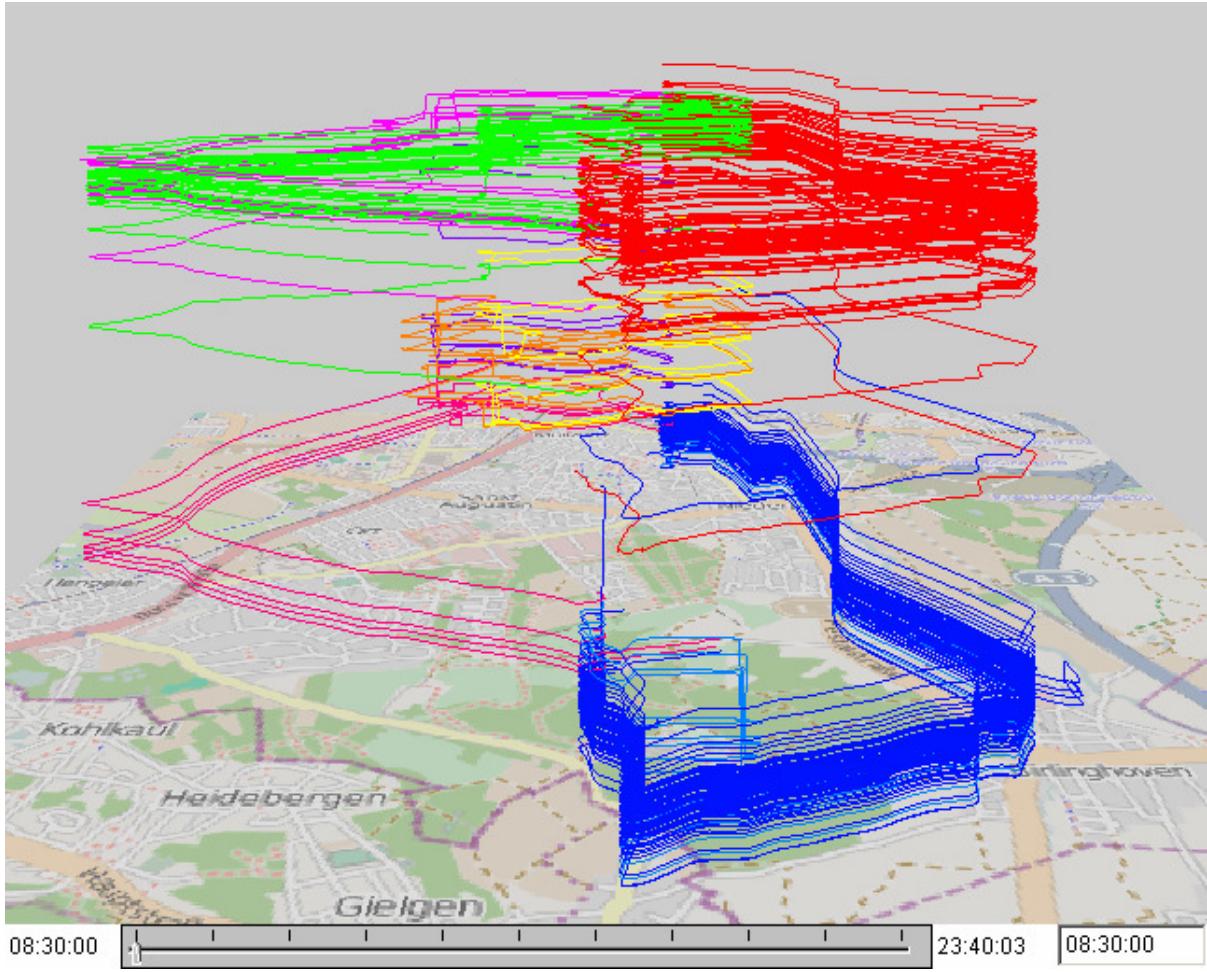


Figure 7: Left: The clusters of trajectories (see Figure 4) with the time references transformed relative to the weekly cycle. Right: The time references have been transformed relative to the daily cycle.

The transformations of the time references relative to the temporal cycles are useful for comparisons of the temporal characteristics of trajectories both within and between clusters. In Figure 7 left, the STC shows all nine clusters of car trajectories with the time references transformed according to the weekly cycle. This means that trajectories that occurred on the same day of the week are shifted to one and the same day. The vertical dimension of the display represents seven days of the week from Monday (bottom) to Sunday (top). It can be seen that the trajectories from the yellow, orange, and violet clusters (labelled 4, 6, and 8, respectively, in Figure 4) occurred only on Saturday and Sunday while the trajectories from the other clusters occurred only on the working days from Monday to Friday. In Figure 7 right, the trajectories have been shifted in time to one day so that the times of the day have been preserved. The time in the display is from the morning (bottom) to the evening (top). It can be easily seen that the trajectories from the blue, cyan, and pink clusters (2, 9, and 7) occurred mostly in the morning, yellow, orange, and violet (4, 6, and 8) around the middle of the day, and red, green, and purple (1, 3, and 5) in the evening.

Figure 8 demonstrates the use of the transformation to the daily cycle for the comparison of trajectories within a cluster. The STC shows the red cluster (cluster 2). The display has been rotated so that the trajectories are viewed from the west. On the left, temporal focusing and zooming limit the view to the interval from 14:05 to 21:00; it includes all 75 trajectories of the cluster. On the right, the view has been further focused to the interval from 17:20 to 21:00, which includes 73 trajectories. The display allows us to compare the times of the day in which the trajectories were made and note the interval of the highest density, i.e., the most usual time of driving along this route. By moving an horizontal plane within the cube, as suggested by Kraak (2003), we can find the approximate start and end times of this interval: from 18:15 to 19:20.

These examples demonstrate that clustering of trajectories by spatial similarity and interactive transformations of time references allows us to effectively use the STC to visualize and explore large sets of trajectories extended in time. These techniques also proved to be useful for other real datasets such as seasonal migration of birds, movement of thousands of car in a big city, trajectories of ships, and others.

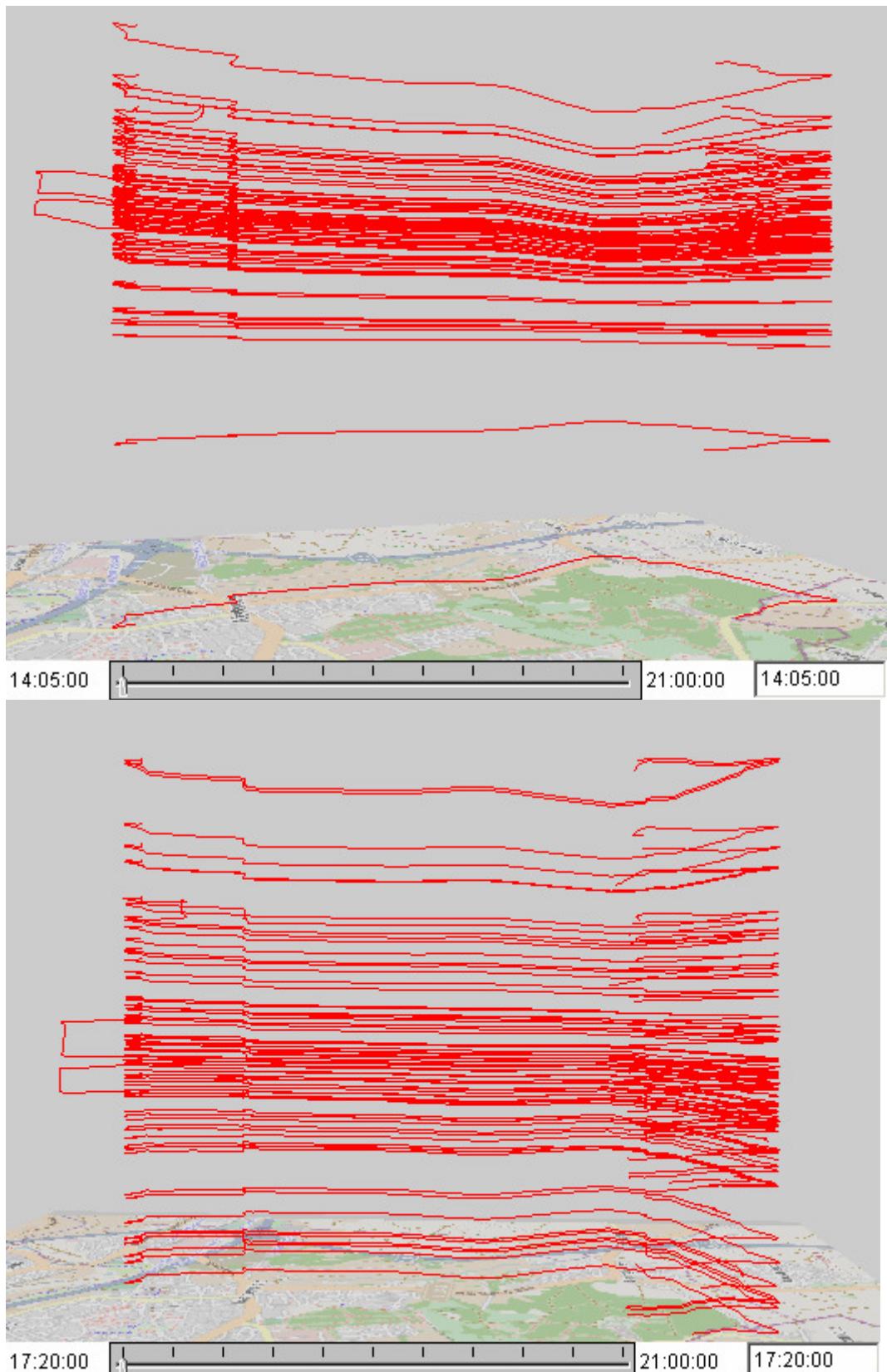


Figure 8: A single cluster of trajectories with the time referenced transformed relative to the daily cycle. Left: The STC shows the time interval from 14:05 to 21:00 including all 75 trajectories of the cluster. Right: The STC shows the interval from 17:20 to 21:00 including 73 out of the 75 trajectories.

CONCLUSION

We have suggested an approach to support interactive visual exploration of large sets of trajectories with a space-time cube. The approach combines clustering of trajectories by spatial similarity and temporal

transformations of the trajectories, i.e. replacing absolute time references by relative positions within temporal cycles or in respect to the starting and/or ending times of the trajectories. Clustering and subsequent interactive filtering reduce display clutter. Time transformations bring trajectories closer in time and facilitate comparisons within and between clusters. Another benefit is the possibility to investigate the distribution of the trips over times of the day, days of the week, or within a season. We have demonstrated the effectiveness of the approach on a real data set about individual movement over one year.

ACKNOWLEDGEMENT

This work is supported by DFG within the priority research program on visual analytics (SPP 1335).

REFERENCES

- Andrienko, N., Andrienko, G., and Gatalsky, P. (2003). Visual Data Exploration using Space-Time Cube. In Proceedings of the 21st International Cartographic Conference, Durban, 10 - 16 August 2003. International Cartographic Association, pp. 1981-1983.
- Andrienko, G., Andrienko, N., & Wrobel, S. (2007). Visual Analytics Tools for Analysis of Movement Data. ACM SIGKDD Explorations , 9(2), December 2007, 38-46.
- Ankerst, M., Breunig, M., Kriegel, H.-P., & Sander, J. (1999). OPTICS: Ordering Points to Identify the Clustering Structure. Proceedings of ACM SIGMOD International Conference on Management of Data (SIGMOD'99). Philadelphia: ACM, 49-60
- Drecki, I., and Forer, P. (2000): Tourism in New Zealand - International Visitors on the Move (A1 Cartographic Plate); Tourism, Recreation Research and Education Centre (TRREC): Lincoln University, Lincoln.
- Hägerstrand, T. What about people in regional science? Papers of the Regional Science Association, 24, 7-21. 1970
- Kapler, T. and Wright, W. (2005). GeoTime information visualization, Information Visualization, 4(2), 136-146
- Kraak, M.-J. (2003). The space-time cube revisited from a geovisualization perspective. In Proceedings of the 21st International Cartographic Conference, Durban, 10 - 16 August 2003. International Cartographic Association, pp. 1988-1995
- Rinzivillo, S., Pedreschi, D., Nanni, M., Giannotti, F., Andrienko, N., and Andrienko, G. (2008). Visually–driven analysis of movement data by progressive clustering. Information Visualization, 7(3/4), 2008, 225-239.
- Schreck, T., Bernard, J., Tekusova, T., and Kohlhammer, J. (2008). Visual cluster analysis in trajectory data using editable Kohonen maps. In Proceedings IEEE Symposium on Visual Analytics Science and Technology (VAST 2008), IEEE, pp. 3-10