Report on the STSM of Maike Buchin to Ross Purves (July 2011):

Analysing sparse trajectories in urban areas

(*formerly:* Semantically Enriching Road Networks using GPS-tracks and Geo-tagged photos)

Purpose of the STSM

The purpose of this STSM was to analyze movement data on road networks. Originally, we wanted to extract semantic information from GPS-tracks and geo-tagged photos and enrich the underlying road network with this information. During the STSM we shifted our research focus, as we explored the current state of the art, the widespread availability of data, and the possibilities for significant extensions to current work. We thus focused on analyzing sparse trajectories within urban areas. We were motivated by *photo-trajectories*, that is, trajectories consisting of space-time positions of photos taken by the same person. These trajectories differ from ideal trajectories in that they are very sparse and irregularly sampled. To analyze this data, we have to take a large amount of uncertainty into account. During the STSM we developed methods for similarity detection of sparse trajectories. We are planning to use these methods to test whether routes of short-term visitors and long-term visitors and residents differ.

Description of the work carried out during the STSM and of the main results obtained

Scenic routes and view places. First we discussed detecting scenic routes and view points on road networks based on GPS-tracks and geo-tagged photos. Scenic routes and view points may be characterized as routes or points, respectively, where many photos are taken. Based on this, we identified the following approach to detecting scenic routes and view points: Given a road network and positions of photos taken in the area of the network, associate photo positions to segments of the road network and find segments and points in the road network with a large number of associated photos. However, this question has been previously addressed, and we did not see new algorithmically challenging questions. Furthermore, the topic of scenic routes led us to research on photo-trajectories which we found more intriguing. We therefore slightly shifted the topic of our research to analyzing sparse trajectories in urban areas.

Photo trajectories. Trajectories of photos are becoming more common due to the growing popularity of photo-sharing sites, such as Flickr, where users upload geo-tagged photos with an (anonymised) userid. They are particularly interesting to analyze for understanding tourism and the use of urban spaces: What are typical tourist routes? How do routes differ for tourists of different origin and with different length of stay? An approach to answering these questions is grouping photo trajectories by similarity and comparing outcomes of the similarity grouping for different sets of trajectories. We are in particular interested in the question whether the movement of short-term tourists, long-term tourists and residents differ.

This approach crucially depends on the definition of similarity of photo-trajectories. Recent existing approaches to analyzing photo trajectories (Girardin et al. [1][2] , Andrienko et al. [3][4], Arase et al. [5]) have done the following: photo positions are clustered to detect popular places, and trajectories are abstracted to sequences of visitation of these places. This approach of trajectory similarity is very coarse. It does not allow distinguishing trajectories based on their behavior between cluster regions. Also, it fails if a cluster region was visited without taking pictures. Furthermore, it does not take into account the temporal component of trajectories.

For a finer analysis, we need to incorporate more information on trajectories and in particular consider the uncertainty introduced by sparse, irregularly sampled trajectories. Several measures of trajectory similarity have been developed. However, these typically assume a *linear motion model*, that is, in between measurement points the object moved with constant speed on a straight line. This model is suitable only for densely sampled trajectories.

A more suitable motion model for sparsely sampled trajectories is the concept of *space time prisms* (or *space time beads*). A space time prism assumes that a maximum speed of movement of the object is known. The space time prism between two known locations of an object is the set of all possible locations it could have visited in between given a known maximum speed. In 3D space-time dimensions (the *space-time cube*) this is the intersection of two cones. In 2D geographical space it projects to an ellipse. A sequence of space time prisms of a trajectory is called a *space time bead*. Space time prisms were developed in the context of time geography (see for instance Miller [6]). Surprisingly, measures of trajectory similarity based on space time prisms have not, to our knowledge, yet been considered.

Note that space time beads require a known (constant) maximum speed. If the mode of movement (e.g., walking, driving) is known or can be deduced, then this implies a maximum speed. This becomes more difficult when the mode of movement changes between fixes. However, in our setting of tourists or residents exploring a city centre, one can often assume that they are walking. Generally, space time prisms are a more flexible and realistic motion model for trajectories than the linear motion model. Linear motion can be emulated by a space time prism by choosing the constant speed of linear motion as maximum speed between consecutive points on the trajectory.

We defined the distance of two space time beads as the smallest possible distance between two paths in the two beads. That is, we define the distance of two beads as the infimum of distances of paths, taken over all paths in the two respective beads. As distance measure of the paths in the beads, arbitrary measures are possible. The inverse of distance gives a measure of similarity.

The temporal component of the trajectories is taken into account in the choice of distance measure of the paths in the beads. We identified several ways of dealing with time in the similarity analysis:

a. exactly equal times (independent of day)
b. equal times but allowing a shift in time
c. equal time proportions
d. equal times of day (e.g. morning, noon, afternoon, evening)
e. equal sequence but otherwise arbitrary matching of time

We can model all of these possibilities with the following two distance measures, if we also use shifting and scaling of trajectories.

1. Equal time distance: the maximum distance at corresponding times
2. Fréchet distance: the maximum distance at times according to a matching of times which respects temporal sequentiality.

1. directly corresponds to a., and 2. directly corresponds to e. Options b. and c. correspond to 1. after shifting and possibly scaling. Option d. corresponds to 2. with a bound on the matching.

The STSM was extremely valuable, in a number of ways. The first few days were spent exploring data, literature and identifying research questions together. Having decided that calculating similarity measures for sparse trajectories, using representations from time geography was a potentially interesting area for research, where our skills could be effectively combined, we then started work on real data. Initially, a framework was developed to select meaningful trajectories from Flickr data, and to represent these in a consistent manner. Having worked together on a data model, Ross Purves then developed methods to allow interactive visualization and exploration of trajectories, while Maike Buchin started work on the development of distance measures. Initial results are promising, in that visually similar trajectories exist of sufficient geographic and temporal length exist in the data, and provide us with a good basis for the continued development of our distance metrics.

Extensions. We would like to make our movement model more realistic by

- incorporating more knowledge about the underlying network
- allow for differing maximum speeds

Furthermore, we are considering pre-processing the trajectories, to take into account that typically several photos are taken at the same location. This adds complexity to the data, without adding much further information. To deal with this, we are considering to replace such clusters by geographic centroids tagged with a begin and end time (i.e., time of the first and the last photo taken in the corresponding cluster). We also considered a hierarchical analysis based on clusters of decreasing size.

Summary. In this research we developed new similarity measures for trajectories, which are particularly suitable for sparse trajectories. We are applying these techniques to photo-trajectories taken from Flickr to analyze whether long-term visitors, short-term visitors and residents take different routes. This research is still ongoing.

Future collaboration with host institution

The collaboration with the host institution is planned to be continued. First, we will continue and finish this research. Then we expect further collaboration, in particular spurred through further meetings at research visits and workshops.

Foreseen publications

We are planning to publish our research findings at a suitable conference and or journal, for instance GIScience or ACM GIS 2012.

References

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