

# Interaction and Collective Movement Processing

Edited by

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## Abstract

This report documents the program and the outcomes of Dagstuhl Seminar 14132 “Interaction and Collective Movement Processing”. This seminar brought together a group of 30 scientists with varied backgrounds, but with a shared interest in computations involved in the processing of moving entity data, like humans or animals. The seminar focused on characterizing and modelling interaction between moving entities, and featured four invited talks in four main research fields: ecology, computational geometry, GIScience, and collective motion. The remainder of the program consisted of short presentations, open problem sessions, break-out groups to work on open problems, and reporting sessions based on research done in the break-out groups.

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**Edited in cooperation with** Frank Staals


## 1 Executive Summary

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The Dagstuhl Seminar on Interaction and Collective Movement Processing brought together a group of 30 scientists with varied backgrounds, but with a shared interest in computations involved in the processing of moving entity data, like humans or animals. There are different reasons for such computations: they are needed for the initial processing (cleaning, recognition), for the analysis (derived properties, patterns), and for more advanced features like characterizing and modelling interaction between entities. This seminar focused on the latter, the hardest of these tasks. The majority of the participants had a background in ecology, behavioral sciences, or geometric algorithms, but there were also participants from statistical physics, GIScience, and computer vision.



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The seminar featured four invited talks in four main research fields: ecology (Greg Stephens), computational geometry (Jack Snoeyink), GIScience (Patrick Laube), and collective motion (Andrea Perna). The remainder of the program consisted of short presentations, open problem sessions, break-out groups to work on open problems, and reporting sessions based on research done in the break-out groups.

While the original intention was to tackle the challenging problems of interaction and collective motion, part of the research was done on other closely related topics in movement analysis, like quality issues in movement analysis. The problems that were investigated—also described in this report—have led to the start of new research, which was exactly the purpose of the seminar.

The participants enjoyed both the seminar setting and the interdisciplinarity of the seminar, which gave a new impulse to the research of many. A number of collaborations have started up, and we hope that these not only lead to publications but also to longer lasting collaborations. While all participants would be happy to return to such a seminar later, it was agreed that the focus will shift to keep the dynamics and cross-fertilization of different research fields.

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### 3 Invited Talks

#### 3.1 Sampling the movement phenospace: from posture to behavior in the free-wiggling of *C. elegans*

*Greg Stephens (VU University – Amsterdam, NL)*

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We apply a low-dimensional yet complete representation of body shape (eigenworms) to construct a principled parameterization of the 2D movement behavior of the nematode *C. elegans*. Despite its simplicity, we show that a linear dynamical model of the eigenworm projections captures long-range temporal correlations and reveals two periodic dynamics, the primary body wave and an oscillation between the head and body curvature which underlies arcs in the centroid trajectory. We parameterize the movement phenospace by constructing dynamical systems locally in time and show that variation within this space is remarkably restrained; with increasing window size, a single behavioral mode dominates the variance and represents the coupled control of speed and turning. The distribution of this primary mode is bimodal, suggesting a correspondence to roaming and dwelling states. Finally, we apply our behavioral parameterization to show that the worm's response to a strong impulsive heat shock includes a Hopf-like bifurcation corresponding to an early-time growth of the amplitude of the crawling wave.

#### 3.2 Models for moving data in Computational Geometry

*Jack Snoeyink (University of North Carolina – Chapel Hill, US)*

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The wide variety of sensors for and applications of data on motion creates a large problem space; the theory of computer science tries to classify problems to understand how solutions can generalize. In particular, computational geometry is a branch of the theory of computer science that studies the design and analysis of algorithms and data structures for problems best stated in geometric form. Because of these origins, it assumes that inputs are moving geometric objects (often points) in low dimensions, and that the desired output is a dynamic geometric graph or structure, such as the convex hull or nearest-neighbor graph, on these objects. Blunck et al. [2] observed that many types of input can be unified by assuming each object provides trajectory, which is a continuous function of its position over time—algorithms can be built on primitives that query objects at specific times or calculating the next time a pair of objects change their interaction. This decouples computation of output structure from interpolation to obtain a trajectory from sensor measurements of an object. (For the implementer: since the interpolation often even depends on object state, the interaction primitives must handle double-dispatch.) Since the algorithms on moving data need not stop, the usual efficiency measure, asymptotic worst-case running time, does not apply. Basch et al. [1] originated the analysis of kinetic data structures, which compares the worst-case number of internal changes to data structures to the worst-case number of external output changes; this analysis framework has inspired many novel data structures.

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## 3.3 Computational Movement Analysis

*Patrick Laube (ZHAW – Wädenswil, CH)*

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In the last decade, advances in tracking technologies resulted in geographic information representing the movement of individuals at previously unseen spatial and temporal granularities. This new, inherently spatiotemporal, kind of geographic information offers new insights into dynamic geographic processes but also challenges the traditionally rather static spatial analysis toolbox. This talk first makes the case for Computational Movement Analysis (CMA), as an interdisciplinary umbrella for contributions from a wide range of fields aiming for a better understanding of movement processes, including GIS, spatiotemporal databases and data mining. Then the talk will discuss three aspects of CMA: (1) Characteristics of spatio-temporal movement data, especially implicit relationships, uncertainty, and scale, (2) conceptual modeling of movement and movement spaces, (3) a range of analysis methods that GISciences contributes to movement analysis. The talk will conclude with some reflection on the grand challenges in movement analysis, including (i) bridging the semantic gap, (ii) privacy issues related to movement data involving people, (iii) the arrival of big and open data in movement analysis, and (iv) opportunities for decentralized CMA arising from the internet of things.

## 3.4 Collective Motion

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Collective animal behaviour is the study of how interactions between individuals produce group level patterns, and why these interactions have evolved. This study has proved itself uniquely interdisciplinary, involving physicists, mathematicians, computer scientists, engineers and biologists. Almost all experimental work in this area is related directly or indirectly to mathematical models, with regular movement back and forth between models, experimental data and statistical fitting. In this presentation, I describe how the modelling cycle works in the study of collective animal behaviour. Studies can be classified as addressing questions at different levels or linking different levels, i.e. as local, local to global, global to local or global. In addition, three distinct approaches are typically used – theory-driven, data-driven and model selection – to answer these questions. I will show with different examples how we move between these different levels of description and how these various approaches can be applied to link levels together.

## 4 Participant Talks

### 4.1 Mining Candidate Causal Relationships

*Matt Duckham (The University of Melbourne, AU)*

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**Joint work of** Bleisch, Susanne ; Duckham, Matt ; Galton, Antony ; Laube, Patrick ; Lyon, Jarod

**Main reference** S. Bleisch, M. Duckham, A. Galton, P. Laube, J. Lyon, “Mining candidate causal relationships in movement patterns,” *International Journal of Geographical Information Science*, 28(2):363–382, 2014.

**URL** <http://dx.doi.org/10.1080/13658816.2013.841167>

The environmental context for, and drivers of movement patterns are arguably just as important as the patterns themselves. This research explores techniques for mining dense spatiotemporal data about the relationships between observed movement of objects and related environmental changes. The aim is to assist domain experts in identifying and testing hypotheses about possible causal relations between movement events and environmental events. The approach is based on a foundational model of the ontology of causation [1]. The raw environmental and movement data is categorized into sequences of atomic events experienced by each moving object over time. These events might include movement of an object from one place to another, or the start of an environmental event (e.g., the start of a high temperature even in the vicinity of a moving object). The output of the mining is an exhaustive set of frequent event sequences (candidate causal relationships), which can be ranked by support (the number of identified sequence as a proportion of all sequences). The analysis has been applied to real data about fish movement in the Murray River in Australia, helping to identify a number of expected and unexpected candidate causal relationships.

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### 4.2 A computation model of human navigation

*Roland Geraerts (Utrecht University, NL)*

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**Joint work of** Geraerts, Roland; van Toll, Wouter; Jaklin, Norman;

**Main reference** N. Jaklin, W. van Toll, R. Geraerts, “Way to go – A framework for multi-level planning in games,” in Proc. of the 3rd Int’l Workshop on Planning in Games (PG’13), pp. 11–14, 2013.

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A huge challenge is to simulate tens of thousands of characters in real-time where they pro-actively and realistically avoid collisions with each other and with obstacles present in their environment. Such simulations are required for e.g. deciding whether crowd pressures do not build up too much during a festival, finding out how to improve crowd flow, training emergency personnel to deal with evacuation scenarios, or populating a game environment with realistic characters. This environment contains semantic information (e.g. roads and bicycle lanes, dangerous and pleasant areas), is three- dimensional (e.g. contains bridges where people can walk over and under as well) and can dynamically change (e.g. a bridge

partially collapses). We currently study how to create a generic framework centered around a navigation mesh, for such environments and how it can be updated dynamically and efficiently. Next, we study how (groups of) people move and avoid collisions in such environments, based on character profiles and semantics. We run our simulations in realistic environments (e.g. soccer stadiums or train stations) and game levels to study the effectiveness of our methods. Finally, we have created a software package that integrates this research.

I gave a talk with the following messages:

- For simulating complex motions and behaviors, we need
  - an abstract representation of the navigable areas;
  - a framework of (at least) 5 complexity levels.
- Methods must be compatible with surface-based navigation at all levels (paradigm shift!), so a graph-based approach is not going to be sufficient
- A path planning algorithm should not compute a path
- Algorithms for complex motions have difficulties with force-based models
- Our simulation software is freely available for researchers

See <http://www.staff.science.uu.nl/~gerae101/> for more information.

### 4.3 Flocking and turning of starling flocks

*Asja Jelic (ISC-CNR – Rome, IT)*

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**Joint work of** Alessandro Attanasi, Andrea Cavagna, Lorenzo Del Castello, Irene Giardina, Tomas S. Grigera, Asja Jelic, Stefania Melillo, Leonardo Parisi, Oliver Pohl, Edward Shen, Massimiliano Viale

Turning flocks of starlings are a paradigm for a synchronized, rapid change of direction in moving animal groups. The efficiency of the information transfer during such a collective change of direction is the key factor to prevent cohesion loss and preserve robustness of a flock. However, the precise mechanism by which natural groups achieve such efficiency is currently not fully understood. I will present an experimental and theoretical study of starling flocks undergoing collective turns in which we analyze how the turning decision spreads across the flock. Using newly obtained 3D trajectories of every individual bird in a flock for the entire duration of a turning event, we find sound-like propagation with no damping of information. This is in contrast with standard theories of collective animal behavior based on alignment, which predict a much slower, diffusive spread of information. We propose a novel theory for propagation of orientation in flocks based on the rotational symmetries and conservation laws of the problem. The new theory also provides a quantitative prediction for the speed of propagation of the information, according to which transfer must be swifter the stronger the group's orientational order. This is confirmed by the experimental data. The link between strong order and fast transfer of information we found may be the adaptive drive for the high degree of behavioral polarization observed in many living groups.



## 4.4 Going with the flow: Towards In-Situ Human Behavior Modeling

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**Joint work of** Nishino, Ko; Kratz, Louis  
**URL** <http://www.cs.drexel.edu/~kon/>

Computer vision research, in the past few decades, has made large strides toward efficient and reliable processing of the ever increasing video data, especially for surveillance purposes. Automated visual analysis of crowded scenes, however, remains a challenging task. As the number of people in a scene increases, nuisances that play against conventional video analysis methods surge. People will occlude each other, the notion of foreground and background collapses, and most important the behavior of the scene content especially of those of people will change to accommodate the clutter in the scene. These are nuisances not only to the computer algorithms but also to human operators that will have to squint through the clutter for hours and days to find a single adverse activity. In other words, automated video analysis is most needed in crowded scenes where it is hardest to do.

The crowd, however, does in turn give rise to invaluable visual cues regarding the scene dynamics. The appearance of a large number of people densely packed in the scene adds texture to the emerging movement of the people as a group—the crowd flow. If we can model the crowd flow while faithfully encoding their variability both in space and time, we may use it to extract important information about the dynamic scene. In this talk, I discussed about learning a statistical model of the spatially and temporally varying local motion patterns underlying the crowd flow and showed how we can use it to achieve challenging video analysis tasks, in particular anomaly detection and pedestrian tracking, in extremely crowded scenes.

## 4.5 How many insects does it take to make a swarm?

*Nicholas Ouellette (Yale University, US)*

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**Joint work of** Ouellette, Nicholas T.; Puckett, James G.

Aggregations of social animals, such as flocks of birds, schools of fish, or swarms of insects, are beautiful, natural examples of self-organized behavior far from equilibrium. They tend to display a range of emergent properties, from enhanced sensing to the rapid propagation of information throughout the aggregate, that have made them a potentially valuable template for bio-inspired design. But how large must a group be before showing these emergent properties? I will address this question by presenting measurements of laboratory mating swarms of the non-biting midge *Chironomus riparius*. We measured swarms of various numbers of individuals and studied how their statistical properties changed with group size. Surprisingly, by about 10 individuals, all statistical properties of the swarms saturate. These results both provide a strong constraint on collective-motion models and also suggest that swarm robotics may indeed be feasible.

## 4.6 Model-based Segmentation and Classification of Trajectories

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**Joint work of** Alewijnse, Sander P.A.; Buchin, Kevin; Buchin, Maïke; Sijben, Stef; Westenberg, Michel A.

**Main reference** S. P. A. Alewijnse, K. Buchin, M. Buchin, S. Sijben, M. A. Westenberg, “Model-based Segmentation and Classification of Trajectories,” Extended Abstract of a presentation given at the 30th European Workshop on Computational Geometry (EuroCG’14), 4 pages, 2014.

**URL** [http://www.cs.bgu.ac.il/~eurocg14/papers/paper\\_36.pdf](http://www.cs.bgu.ac.il/~eurocg14/papers/paper_36.pdf)

We present efficient algorithms for segmenting and classifying a trajectory based on a parameterized movement model like the Brownian bridge movement model. Segmentation is the problem of subdividing a trajectory into parts such that each part is homogeneous in its movement characteristics. We formalize this using the likelihood of the model parameter. We consider the case where a discrete set of  $m$  parameter values is given and present an algorithm to compute an optimal segmentation with respect to an information criterion in  $O(nm)$  time for a trajectory with  $n$  sampling points. Classification is the problem of assigning trajectories to classes. We present an algorithm for discrete classification given a set of trajectories. Our algorithm computes the optimal classification with respect to an information criterion in  $O(m^2 + mk(\log m + \log k))$  time for  $m$  parameter values and  $k$  trajectories, assuming bitonic likelihood functions.

## 4.7 Algorithms for Hotspot Computation on Trajectory Data

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**Joint work of** Gudmundsson, Joachim; van Kreveld, Marc; Staals, Frank;


**Main reference** J. Gudmundsson, M. van Kreveld, F. Staals, “Algorithms for Hotspot Computation,” in Proc. of the 21st ACM SIGSPATIAL Int’l Conf. on Advances in Geographic Information Systems (SIGSPATIAL’13), pp. 134–143, ACM, 2013.

**URL** <http://dx.doi.org/10.1145/2525314.2525359>

We study one of the basic tasks in moving object analysis, namely the location of hotspots. A hotspot is a (small) region in which an entity spends a significant amount of time. Finding such regions is useful in many applications, for example in segmentation, clustering, and locating popular places. We may be interested in locating a minimum size hotspot in which the entity spends a fixed amount of time, or locating a fixed size hotspot maximizing the time that the entity spends inside it. Furthermore, we can consider the total time, or the longest contiguous time the entity spends in the hotspot. We solve all four versions of the problem. For a square hotspot, we can solve the contiguous-time versions in  $O(n \log n)$  time, where  $n$  is the number of trajectory vertices. The algorithms for the total-time versions are roughly quadratic. Finding a hotspot containing relatively the most time, compared to its size, takes  $O(n^3)$  time. Even though we focus on a single moving entity, our algorithms immediately extend to multiple entities. Finally, we consider hotspots of different shape.

## 4.8 The dilemma of foraging in a group, studied by on-board audio and GPS monitoring of bats in the wild

Yossi Yovel (*Tel Aviv University, IL*)

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How animals move and forage in the presence of conspecifics is one of the most fundamental questions in social behavior. Even though bats account for more than a fifth of mammalian species, they are very hard to monitor in the wild because of their small size and their agile nocturnal behavior. Here, we present a new system which allows full night monitoring of an echolocating bat's movement and foraging activity. We mount bats with miniature devices which include GPS and an ultrasonic microphone. This system takes advantage of the bat's reliance on active sensing (echolocation) which requires emitting sound to perceive the environment. The setup thus allows studying how bats forage with conspecific competition. For the first time, we tracked bats flying along hundreds of kilometers in the wild while following their foraging behavior. Data shows that bats group and are attracted to conspecifics but that their foraging success decreases when they are too close to each other. We show that the decrease in foraging does not result from sensory jamming by the echolocation of other bats, as has been previously suggested, but from the need to localize other bats in order to avoid collision. We therefore found strong evidence for the existence of a classical group foraging dilemma between the need to forage together to improve success and the need to keep a distance apart to avoid interference.

## 5 Working Groups

### 5.1 Collective Behaviour and Interactions with the Environment

Edward A. Codling (*University of Essex, GB*)

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Joint work of Codling, Edward A.; Geraerts, Roland; Löffler, Maarten; Nishino, Ko; Perna, Andrea; Yovel, Yossi

The working group considered the open problem of how to determine the role and extent of environmental interactions in collective group behaviour and movement. The group considered the open problem from different perspectives and discussed more specific open questions such as “How can one determine important landscape features or the distribution of an unknown resource given known group behavioural rules and group movement data?”. Or “How can one determine the most efficient set of behavioural rules for the collective group in order to maximise the utilisation of a known resource or minimise the time taken to move through a known landscape?”. The group discussed various techniques and approaches that could be used to address these open questions. Some of these approaches require novel methodology and the development of such tools was discussed within the group. The group considered how to address the open problem in the specific context of groups of foraging bats. In addition, wider contexts for the open problem were also considered. Examples include better understanding of human crowd behaviour in urban landscapes, improved algorithms for simulated agents in computer games, and general ecological problems such as migration and navigation of schools of fish or flocks of birds. While the open problems considered were not solved directly during the workshop, the group made some useful progress in designing

a conceptual framework for further study. Members of the working group have agreed to continue collaborating on the open problems considered at the workshop and this may lead to future publications.

## 5.2 Dynamic Behaviour Indices to Explore Movement of a Goose Family Group

*Andrea Kölzsch (MPI für Ornithologie – Radolfzell, DE)*

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**Joint work of** Kölzsch, Andrea; Jelic, Asja; Theraulaz, Guy; Buchin, Maïke; Duckham, Matt; Laube, Patrick; Purves, Ross; Sjiben, Stef; Lopez, Ugo; Wang, Yusu

Being initiated by the general interest on dynamic social movement analyses, this group focused on discussing possible data analyses for a data set of high resolution GPS positions and accelerometer measures of a family of geese in their breeding grounds. A main point of interest was how to extract dynamic leadership from the data and test if goose parents were indeed leading the chicks. First, the group discussed previously used methods that had been used to determine leadership in large flocks of e.g. fish, starlings or pigeons. It became clear that in those studies coordinated turning of the animals was a main property exploited to determine leadership. For the goose tracks, however, such turning events were very infrequent and less pronounced. Thus, other possibilities of identification of critical events are needed, and we discussed the possibilities of using distance, speed, direction or behavioral states. Second, we tested some of our ideas on the goose data set (2 parents + 5 chicks, one day) that was provided for this workshop. It became apparent that the data had several weaknesses that the data owners had not been aware before, ranging from gaps at night for some individuals to shifts in time alignment. Exploration of the GPS and accelerometer data sets led to initial insights in the differences of behaviour of the different members of the goose family by e.g. speed and energy spent. A first idea of leadership by spatial position within the family was implemented and seemed a promising way forward for further investigations. Future collaboration ideas were discussed within the group. We aim to (i) improve data visualization methods for small groups of animals moving in a coordinated way, (ii) explore mathematical properties of and use methods for analysis of accelerometer data of animal groups and (iii) develop leadership indices by position rather than turning.

## 5.3 Subgroup Coordination

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**Joint work of** Nathan, Ran; Buchin, Kevin; Engel, Anael (via Skype); Giuggioli, Luca; Ouellette, Nicholas; Snoeyink, Jack; Bettina, Speckmann


Studies of collective movement commonly assume that all individuals are identical. This assumption simplifies investigating the most basic properties of collective movement itself, that is, those arising from the tendency of individuals to move together. Yet, real-life individuals often differ in various important features, including size, sex or social ties, as well as being from different species identity. These difference could impact the way each individual

perceives its neighbors, and hence alter their decisions how, when and where to go. For example, many collective movement systems involve social groups in which several features of the social structure, such as dominance and various associations, could play a key role in shaping the resulting movement patterns. Basic models developed to investigate collective movement show how collective motion can arise from simple rules and local interactions, such as repulsion, alignment and attraction. A much smaller set of studies have relaxed the assumption of identical individuals, demonstrating how variation in social identity can affect the movement patterns of individuals within the group, and the entire group itself. Preference to move near certain other individuals, can give rise to spatiotemporal subgroups within a group. Subgroups prevail in human crowds, and are crucial for understanding and modeling the behavior of the pedestrians. Overall, although subgroups occur in many systems of social animals, they have been scarcely incorporated in modeling and empirical studies of animal collective movement.

In this group, we discussed some key challenges in studying subgroup coordination, such as rather ambiguous terminology and lack of basic concepts. We also discussed the use of several possible indices (e.g. Simpson’s diversity index) and algorithms (e.g. re-parameterization surface) to identify subgroups, and how to develop null models for this purpose (e.g. randomized trajectories around the mean center-of-mass path). We shared movement tracks of 5 flocks of jackdaws, for which subgroup coordination is expected given the known pair-based linear social hierarchy in this species. Practically, we set a goal of preparing a joint synthesis paper highlighting this topic for scholars of animal movement, and set specific writing tasks among group members.

## 5.4 On the Quality of Trajectory Data, Trajectory Analysis, and Trajectory Cleaning

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**Joint work of** Blanke, Ulf; van Kreveld, Marc; van der Spek, Stefan; Staals, Frank; Tredan, Gilles; Wenk, Carola

In the two working group sessions we discussed two related topics: (i) the quality of trajectory data and its influence on the quality of the analysis, and (ii) the role of cleaning the data, e.g. removal of outliers etc, on the analysis.

**Quality of Trajectory Data and its Analysis.** We started by identifying properties and characteristics of (loss in) the quality of trajectory data. We identified different kinds of errors in trajectory data (e.g. lack of geometric precision, missing data-points, etc.), and in its analysis. We discussed how to measure the quality of both trajectory data, and analysis tasks on trajectories. Furthermore, we considered a typical “pipeline” for the analysis of trajectory data in a GIS setting, in which we identified where these types of errors show up. We discussed how the quality of the data influences the quality of those steps in the analysis, and how this propagates to subsequent steps.

**Cleaning Trajectory Data.** From discussions with the workshop participants that worked with real trajectory data it became clear that for virtually any analysis task some “data cleaning” is required, e.g. detection and removal of outliers, removing trajectories with too few data points, etc. We discussed how to measure the amount of cleaning that has been done, and is still “required”. Finally, we considered the quality of the analysis as a function

of the amount of cleaning that has been done. We investigated the desired shape of such a function, and how to formalize this.

While we did not solve a concrete problem during the workshop, we have made some interesting observations on the topic of “quality and trajectories”. We continue to work on this, and expect it will lead to future publications.

## **6** Concluding Remarks

On Friday afternoon the participants reviewed the seminar and discussed potential followup seminars. All participants enjoyed the interdisciplinarity of the seminar. Several participants mentioned that they were unaware of the research and results in different fields, yet relevant for their own work. Therefore, a number of interdisciplinary collaborations have started up. While all participants would be happy to return to a similar seminar later, it was agreed that the focus will slightly shift to keep this cross-fertilization of the different research fields.

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