Report from Dagstuhl Seminar 16022

Geometric and Graph-based Approaches to Collective Motion

Edited by

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- Abstract

This report documents the program and the outcomes of Dagstuhl Seminar 16022 "Geometric and Graph-based Approaches to Collective Motion".

The seminar brought together a group of enthusiastic researchers with a diverse background. To create a shared body of knowledge the seminar featured a number of survey talks that were planned early in the week. The survey talks were rather engaging: the audience learned for instance at what scale one should look at a painting of Van Gogh, how bats chase each other, what size of clumps mussels make and why, and how to interact with a computational geometer.

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1 **Executive Summary**

Giuseppe F. Italiano Marc van Kreveld Bettina Speckmann Guy Theraulaz

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A trajectory is a time-stamped sequence of locations which represents the movement of entities in space. Trajectories are often created by sampling GPS locations and attaching a time-stamp, but they can also originate from RFID tags, video, or radar analysis. Huge data sets exist for entities as diverse as birds, deer, traveling humans, sports players, vehicles, and hurricanes.

During recent years analysis tools for trajectory data have been developed within the areas of GIScience and algorithms. Analysis objectives include clustering, performing similarity analysis, segmenting a trajectory into characteristic sub-trajectories, finding patterns like flocking, and several others. Since these computations are mostly spatial, algorithmic



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solutions have been developed in the areas of computational geometry and GIScience. Although trajectories store only the location of a single point of reference on a moving entity, this is acceptable for the common large-scale analysis tasks. However, for the study of more complex phenomena like interaction and collective motion, it is often insufficient and the basic trajectory representation must be extended.

Simultaneously, in the area of ecology the study of motion of animals has also become a topic of increasing interest. Many animal species move in groups, with or without a specific leader. The motivation for motion can be foraging, escape from predators, changing climate, or it can be unknown. The mode of movement can be determined by social interactions, energy efficiency, possibility of discovery of resources, and of course the natural environment. The more fascinating aspects of ecology include interaction between entities and collective motion. These are harder to grasp in a formal manner, needed for modelling and automated analysis.

The seminar brought together a group of enthusiastic researchers with a diverse background. To create a shared body of knowledge the seminar featured a number of survey talks that were planned early in the week. The survey talks were rather engaging: the audience learned for instance at what scale one should look at a painting of Van Gogh, how bats chase each other, what size of clumps mussels make and why, and how to interact with a computational geometer.

Probably the main research result was a momentum started up by interaction and awareness of an exciting direction of research where a lot can still be accomplished.

More specific research accomplishments included a methodology for evaluating whether fish or other animals have their movement mostly influenced by closest neighbors, and how to reconstruct movement just based on counts at different time steps.

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3 Overview of Talks

3.1 Multidisciplinary challenges concerning self-organization in ecological systems.

Johan van de Koppel (Royal Netherlands Inst. for Sea Research – Yerseke, NL)

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I discussed the emergence of theory of spatial self-organization in ecology, focussing on the formation of regular spatial patterns. Past research on for instance arid systems or mudflats have highlighted Turing's activator-inhibitor principle to explain pattern formation. I have highlighted a different form of self- organization in mussel beds, where mussels aggregate to form regular patterns. This form of pattern formation follows a different mechanism that is similar to the physical process of phase-separation, as formulated by Cahn and Hilliard in 1958. Individual-based models of pattern formation in mussel beds indicate that patterns have a important effect on ecosystem functioning, increasing mussel bed resilience.

I finished with highlighting a number of outstanding challenges in the field of spatial self-organization of ecosystems:

- Understanding critical transitions: How to distinguish ecosystems with and without tipping points?
- Can we determine the process driving self-organization from the observed patterns?
- How do patterns affect ecosystem functioning?
- Can we find self-organization in "everyday", human modified ecosystems?
- How do organisms adapt to/in self-organizing systems?
- How can we best translate individual behavior to population dynamics?

Technical issues

- Multidisciplinary bridging the culture gap between physics, computer sciences, mathematics, and biology.
- How do we overcome scale differences in ecosystems?
- Communication how to explain our results to the general public?

3.2 Multiscale inference in collective behaviour

Richard Philipp Mann (University of Leeds, GB)

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How do groups of animals act cohesively and make collective decisions? How do complex patterns of collective motion emerge in groups of individually simple organisms? Simulation studies show that simple interaction rules between individuals and their local neighbours are sufficient to produce complex group behaviours, but the specific nature of these interactions is often unclear. Large scale group behaviours often fall into generic 'universality' classes such as spinning balls or polarised flocks, obscuring the precise interactions at the individual level.

In this talk I demonstrate a technique of theory-driven model comparison based on individual agent motions alongside group level observations. I phrase alternative hypothesised interactions as models which predict the behaviour of individuals, using a Bayesian model

comparison to select between competing theories, and combine this with model simulations to detect emergent effects. I show examples of this approach in the context of the collective motion of glass prawns and decision-making in damselfish, and discuss how to take this method forward.

3.3 Self-Organization in Complex Systems

Nicholas Ouellette (Stanford University, US)

Complex systems – that is, systems that consist of many simple but coupled degrees of freedom – generically and spontaneously form structure. Over the past several decades, this process of self-organization has been identified as driving the formation of patterns and structure at nearly every scale in nature. Here, I will give a brief overview of some of the key results that have come out of the study of self-organization from a physicist's perspective. I will then connect these ideas to the study of collective behavior in animals, as well as outlining some caveats. Finally, I will pose some questions that deserve future study.

3.4 Dynamic Graph Algorithms

Giuseppe F. Italiano (University of Rome "Tor Vergata", IT)

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Guiseppe F. Italiano

In my talk, I will survey dynamic graph algorithms. In particular, I will consider a fundamental problem in this area: the dynamic maintenance of shortest paths. Although research on this problem spans over almost 50 years, progress has been achieved only recently through the introduction of many novel algorithmic techniques. I will make a special effort to abstract some basic combinatorial properties that are at the base of some of those techniques. This will help presenting some of the most efficient algorithms in a unifying framework so that they can be better understood and deployed also by non-specialists.

3.5 Topological Data Analysis in Real Applications

Brittany Terese Fasy (Montana State University – Bozeman, US)

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Persistent homology is a method for probing topological properties of point clouds and functions. The mathematical concepts stem from Morse theory, but the use of topology in data analysis is fairly recent. In this talk, we draw an analogy between looking at homology at different parameter values and at a painting at different distances. These parameters (distances) give different insights as the values change. Persistence tells us which of these insights lasts through large intervals of the parameter. For example, the parameter can be time and the persistence may explain the dynamics of animals moving in a collective motion. After giving an intuition for persistent homology, we briefly explain how it can be sued to describe, compare and analyze data.

3.6 Analysing spatio-temporal patterns of delayed alignment interactions

Luca Giuggioli (University of Bristol, GB)

Animal coordinated movement interactions are commonly explained by assuming unspecified social forces of attraction, repulsion and alignment with parameters drawn from observed movement data. Very little is done to connect the sensory ecology with the movement and interaction of the individuals. On trajectories of two interacting trawling bats flying over a water pond we have shown how to extract delays with which individuals respond by copying each other's heading. Using that information it is possible to reconstruct the echolocation field strength and directionality of the bats [1].

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3.7 Computational Geometry for Collective Motion

Maarten Löffler (Utrecht University, NL)

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The main challenge in applying techniques from computational geometry to solve real-world problems in collective motion analysis is deciding on the correct mathematical model. A mathematical model, or problem description, in this context, is a precise description of the input and output of a problem. In particular, given the problem description and an input, it must be clear (unambiguous) what the resulting output is.

On the one hand, a problem description must then be validated in the application. Both the input and output can be interpreted in collective motion – for instance biological or ecological – terms, and the ability to convert the input to the output has a clear value.

On the other hand, given a problem description, we can design efficient and provably correct algorithms to arrive at the desired output. For this, we leverage 50 years of research in geometric algorithms, combined with new solutions that are tailored to the unique challenges in the problem at hand.

3.8 Challenges for movement analytics: A GI science perspective

Matt Duckham (RMIT University – Melbourne, AU)

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This talk examined three of the key challenges and trends in movement analytics, from the perspective of the field of GI science. The first challenge concerns the structure of movement data. Whilst there has in the past been a strong focus on the Lagrangian trajectory data view of movement, Eulerian checkpoint or "cordon-structured" data is often

under researched. A wide range of familiar and voluminous data sources, including social media check-ins, electronic tolling, public transport smart cards, generate data structured as Eulerian checkpoints, rather than Lagrangian trajectories. The second challenge concerns the integration of information about the drivers of movement into movement analytics. In particular, the context and causes of movement are often of overriding importance in understanding movement. The third challenge relates to the interaction between moving objects in the production of collectives. These collectives are more than the sum of there parts, and so cannot be adequately captured purely by looking at the movement of individuals in the collective. Underlying these challenges is the maxim that there is "more to movement than geometry", and a comprehensive approach to movement analytics must incorporate non-geometric movement structure, the context and causes of movement, and the role of collectives.

4 Extra Event

4.1 DYNAMO: Dynamic Visualization of Movement and the Environment

Somayeh Dodge (University of Colorado – Colorado Springs, US)

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Movement is highly influenced by its embedding spatiotemporal context, a geographic context that changes over time, such as the ambient environment, terrain, and landscape. In essence, movement occurs in both spatiotemporal space and a multidimensional attribute space (i.e. environmental and geographic context of movement). The syntheses of these two spaces need new tools suitable for dynamic visualization of the traversal through these dimensions. These tools can play a major role as a fundamental component of spatiotemporal processes and patterns of movement. This presentation provides an overview of a visualization tool, called "DYNAMO: Dynamic Visualization of Movement and the Environment" (http://dynamovis.com), developed for the exploratory analysis of movement in relation to the environment and geographic context. DYNAMO applies visual variables such as point and line width, color, and directional vector to visualize and animate movement tracks in their attribute space (e.g. movement parameters and context attributes).

5 Working groups

5.1 Analysis on Check-in Data

Karl Bringmann (MPI für Informatik – Saarbrücken, DE), Oliver Burkhard (Universität Zürich, CH), Brittany Terese Fasy (Montana State University – Bozeman, US), Giuseppe F. Italiano (University of Rome "Tor Vergata", IT), Martin Nöllenburg (TU Wien, AT), Frank Staals (Aarhus University, DK), Goce Trajcevski (Northwestern University – Evanston, US), and Carola Wenk (Tulane University, US)

Most current work in trajectory and movement analysis assumes that the input trajectories are precise enough to capture the exact movement of the entities, that is, it is assumed that the trajectories are either (piecewise linear) functions mapping time to a location, or a dense sample of (time,location) pairs from such a function. A large amount of such trajectory data is available. However, systems such as cell towers, wireless sensor networks, electronic travel cards (e.g. Oister card, ov-chipkaart), and social networks such as Foursquare generate much sparser trajectory data. They capture the location of an entity only at very few, and often wide spread, times. This means that the usual assumption that the entity moves linearly in between two trajectory vertices does not make sense, and thus the traditional algorithms and analysis techniques are not applicable. We refer to such sparse trajectory data as *check-in data*, and identify several interesting questions and analysis tasks for check-in data.

We assume that the entities move in a network, which we model as a (planar) directed weighted graph, where the edge weights model travel time. Some of the edges are equipped with a *beacon* that registers when an entity traverses the edge. Beacons register the time at which an entity starts traversing the edge, and the identity of the entity. For every moving entity, we thus obtain a *(sparse) trajectory*, a sequence of (time,edge) pairs. Note that not every edge is equipped with a beacon, hence the trajectory of an entity will, in general, not be known completely. We are then interested in the following problem:

Given all sparse trajectories, an edge e of the graph, and a time interval I, compute how many entities start traversing edge e during I.

We identified and formalized several subproblems toward solving the above problem. Furthermore, we discussed variations of the model, e.g. incorporating uncertainty, delay, placing beacons at vertices rather than at edges etc. We aim to solve these problems in the near future.

5.2 Detecting Avoidance Interaction in Trajectory Data

Luca Giuggioli (University of Bristol, GB), Johan van de Koppel (Royal Netherlands Institute for Sea Research – Yerseke, NL), Andrea Perna (Paris Diderot University, FR), Robert Weibel (Universität Zürich, CH), and Carola Wenk (Tulane University, US)

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The purpose of the working group was to explore ideas and methods to detect avoidance behaviour by looking at trajectories of an habitauted population of dwarf mongoose in the wild. The data consists of gps tracking at approximately 30 second sampling based on each

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of the location on the researchers following simultaneously different groups of mongooses of 5–7 individuals. Biologists expect a scent-mediated interaction to occur as individuals detect fresh scent left by other groups and move away to avoid costly confrontations. As we played with the dataset at our disposal, we realized that the locations of individuals were potentially too far apart for scent to be detected and no-delayed crossing of the trajectories appeared. We hypothesized that individuals may respond instantaneously through visual detection of other groups from a distance. By looking at the vegetation in South Africa where data were collected we saw that trees and high bushes may constrain the distance at which such detection occurs. We thus concluded that sentinels on trees, usually used for detecting predators, may also be involved in identifying the presence of other mongoose groups.

5.3 Detecting Interactions Given Trajectory Information

Somayeh Dodge (University of Colorado – Colorado Springs, US), Brittany Terese Fasy (Montana State University – Bozeman, US), Tim Ophelders (TU Eindhoven, NL), Nicholas Ouellette (Stanford University, US), and Kevin Verbeek (TU Eindhoven, NL)

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 \odot Somayeh Dodge, Brittany Terese Fasy, Tim Ophelders, Nicholas Ouellette, and Kevin Verbeek

Our group was tasked with developing strategies to answer a question that seems straightforward but that in practice is quite difficult: given trajectory information from one or more individuals, can we identify where and when interactions occurred?

This question is particularly difficult given that in general we do not know what the signature of an interaction is; and indeed, it will likely be different for different specific problems. We therefore modified the question to something we felt was more tractable. If we make the hypothesis that interactions result in some (possibly transient) change in behavior, then identifying these interaction events becomes a problem of segmenting the trajectory. This approach will miss interactions that do not result in a measurable change in behavior; such events, however, will likely never be detectable without additional information.

We had some discussion as to whether considering single trajectories is sufficient for this problem, or whether we must look at explicitly pairwise or higher-order quantities. Although we did not reach a general consensus on this point, we settled on considering only single trajectories initially, as in general the signature of interactions should be reflected in single trajectories as well as in pairs.

The problem is thus one of trajectory segmentation into "normal" and "unusual" parts. How to do this in a meaningful, objective way, however, is not obvious. We considered approaches based on simple global statistics, such as segmenting based on the mean speed or the velocity variance, but found these to be unsatisfying. Instead, we proposed a kind of "auto-segmentation", which we expressed as an optimization problem. The ideal segmentation for our purposes would cut the trajectories into pieces that are as different as possible. That is, if we cut a trajectory into segments of type A and B, the information content in the A and B segments should be as different as possible. To accomplish this, we thought of taking an iterative approach. Suppose we begin with some initial, arbitrary segmentation. We can then calculate the statistics of the A and B segments separately, and define a cost function based on the difference between these statistics (the mutual information, for example, or the Kolmogorov distance between their PDFs). By then optimizing this cost function, one could come up with an objective segmentation, which could then hopefully be interpreted.

5.4 Distinguishing Real and Artifactual Social Interactions

Martin Beye (Universität Düsseldorf, DE), Oliver Burkhard (Universität Zürich, CH), Brittany Terese Fasy (Montana State University – Bozeman, US), Richard Philipp Mann (University of Leeds, GB), Bettina Speckmann (TU Eindhoven, NL), and Kevin Verbeek (TU Eindhoven, NL)

We started by considering whether one could use purely trajectory data from groups (e.g. pairs) of animals to decide whether a social interaction took place, as opposed to correlated responses to an environmental stimulus.

In general the problem appears insoluble, since an arbitrary unseen stimulus could exactly mimic another animal. Therefore in principle the two could not be distinguished.

However, if we have some idea what the external stimuli might look like we can either:

- Do experiments to determine response to these, and look for differences in later data. This is the approach taken by Gautrais et al. in PLoS Comput. Biol. 2012.
- Try to theorise what a response might look like, e.g. a fleeing response to a point source might be spherically symmetric around that point

We considered whether there would be differences in the noise structure between two individuals following each other versus two individuals following a common route, since the noise from one would become part of the signal the other follows. This might lead to an entangled noise signature that would be indicative of interactions.

Then we moved onto larger scale observations of collectives and whether we could assess whether an aggregation was due to self organisation rather than an environmental cue. This led us onto a detailed discussion of to what extent persistent homology methods could be used to classify different groups collective behaviour as being distinct from each other. Unfortunately it seems necessary to be quite sure what types of structure you want to pick out in the combined trajectories before designing a persistent homology metric to find them.

5.5 Identifying Influential Neighbors in Animal Flocking

Martin Beye (Universität Düsseldorf, DE), Anael Engel (The Hebrew University of Jerusalem, IL), Ramon Escobedo (Université Paul Sabatier – Toulouse, FR), Luca Giuggioli (University of Bristol, GB), Marc van Kreveld (Utrecht University, NL), Andrea Perna (Paris Diderot University, FR), Frank Staals (Aarhus University, DK), Guy Theraulaz (CNRS and Université Paul Sabatier – Toulouse, FR), and Goce Trajcevski (Northwestern University – Evanston, US)

One important issue that is largely discussed in the community dealing with collective motion in animal groups concerns the number of neighbors each individual in a flock of birds or a school of fish is interacting with. Indeed, it has been shown that the properties that emerge at the level of a flock or a school largely depend on the number and position of neighbors each individual is paying attention to. Is it possible to analyze the trajectories of individuals moving in groups in such a way to get access to this information?

To identify the influential neighbors, we propose first to detect the correlation between the velocity changes of a focal individual and the corresponding velocity changes of individuals moving in its close vicinity. Obvious choices are to compute: (1) the normalized cross-velocity correlation (difference in headings) and (2) the non-normalized cross-velocity correlation. In addition one has to take into account the fact that the focal individual will also react with a certain time delay. One good method to extract the values of delays as a function of time from one or all of the correlation plots would be to use the pairwise method developed by Giuggioli et al. (2015). The problem with that method is that it is only pairwise, and in some instances of time the extracted delays have inconsistencies (the order is not maintained if one looks at all pairwise possibilities). Another method recently developed by Kevin Buchin (Konzack et al., 2015) that we also intend to use is in principle capable of extracting delays for N animals without these inconsistencies.

Then, we will analyze the time-average correlation value between a focal individual as a function of either the distance or the number of neighbors. This analysis should also distinguish individuals that are located either in the centre or in the periphery of the flock. The results can then be used to get histograms of the maximum correlation values as a function of the k-nearest neighbor or distance for each moment of time. If each individual pay attention to only a limited number of individuals within their perception field, one can expect that it can strongly affect the distribution of correlation values on these histograms. However one cannot know if a given individual focuses its attention on only one of its close neighbors at a time or if it responds to some "average information". In order to test this hypothesis, one can perform the same analysis as the one described before, but with some average quantity associated with the (linear or non-linear) combinations of neighbors, e.g. the simplest one is the average.

In order to test our method, we will use controlled simulations of a model of collective movement with known rules (i.e. how many influential neighbors, if they influence by rank or by distance) and use our method to test if it can detect and distinguish between the different rules. In addition we will perform this analysis on trajectory data on groups of fish, moving in an annular arena and we will only focus on spontaneous U-turn events to minimize the effects of the constraining geometry.

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5.6 Mussel Bed Connectivity and its Influence on Survival

Johan van de Koppel (Royal Netherlands Inst. for Sea Research – Yerseke, NL), Maarten Löffler (Utrecht University, NL), and Tim Ophelders (TU Eindhoven, NL)

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Johan van de Koppel, Maarten Löffler, and Tim Ophelders

We want to understand how the spatial structure of a mussel bed influences the survival or persistence of groups of mussels. It seems that net-shaped structures may provide a more stable landscape, with less vulnerability to waves. Models that account for the effect of such grouping structure on mussel survival may provide a better understanding of 1) self-organization in mussels, and 2) stability of mussel beds as a key habitat to many species.

Giuseppe F. Italiano, Marc van Kreveld, Bettina Speckmann, and Guy Theraulaz

Waves put force on a limited section of the bed (say 25x25 cm). Small clumps of mussels get dislodged easily, while larger clumps that are connected to the larger bed, are not dislodged. A binary test is needed, that checks which of the mussels are sufficiently connected not to break free after a wave impact.

Given a geometric graph of mussels and a disk representing the wave impact zone, we define a score F(M) for each set of mussels M. If F(M) is above a certain threshold H, the set M gets dislodged. In order to define this F(M), we are going to count three things:

- 1. C The number of connections between M and the rest of the mussels;
- 2. I The number of mussels of M that are inside the disk;
- 3. O The number of mussels of M that are outside the disk.

In addition, we define three weights:

- 1. W_C The strength of the glue between connected mussels;
- 2. W_I The force applied by a wave to the mussels inside the disk;
- 3. W_O The force required to move a mussel that is outside the disk.

We define $F(M) = W_C C(M) - W_I I(M) + W_O O(M)$, and take the minimum of F(M) over all sets M to compare with our threshold H.

If the mussel connections are directed, we can model this as a minimum closure problem. Minimum closures can be computed in quadratic time using an approach based on MinCut. One way to get a directed graph is to direct all edges to the center of the wave impact zone. It is likely that undirected graphs can be handled by a similar approach.

6 Schedule

Monday

- 09.00–10.30: Survey lectures: Johan van de Koppel, Richard Mann
- 10.50–12.00: Quick introductions of participants, Dagstuhl explanations
- = 14.00–15.30: Survey lectures: Nicholas Ouellette, Giuseppe Italiano
- \blacksquare 16.00–18.00: Open problems + break-out

Tuesday

- 09.00–10.15: Survey lectures: Brittany Therese Fasy, Luca Giuggioli
- \blacksquare 10.40–12.00: Continue break-out
- 13.00–15.30: Personal discussions with colleagues at Dagstuhl on collective motion
- \blacksquare 16.00–18.00: Continue break-out

Wednesday

- 09.00–10.15: Survey lectures: Maarten Löffler, Matt Duckham
- 10.40–12.00: Reporting back from break-out, discussion
- Afternoon excursion

Thursday

- 09.00–10.15: New open problems and groups
- 10.40–12.00: Second break-out set
- 14.00–15.30: Break-out
- 16.00–17.30: Break-out
- **17.30–18.00:** Extra event

Friday

- 09.00–10.15: Reporting from second break-out
- 10.40–12.00: Future plans of research in collective motion



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