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Detecting reaction movement patterns in trajectory data

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Abstract

Movement patterns structure large trajectory data sets and allow a better understanding of the dynamics amongst moving objects. This paper proposes patterns that model the reaction behavior between two individuals of different types of moving objects, as in predator-prey or female-male behavior patterns. Inspired by behavioral ecology, reaction movement patterns for pursuit and escape, avoidance, and confrontation are conceptualized, formalized, and algorithmically detected. The approach is evaluated through a set of numerical experiments with simulated and observed trajectory data.
Keywords: Movement pattern mining, trajectory data, reaction patterns, spatial collectives, Lagrangian and Eulerian movement.

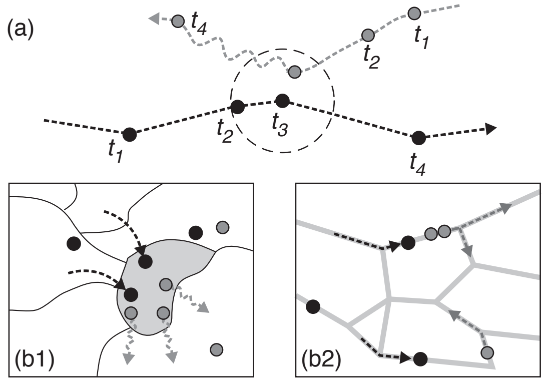
1 Introduction

Movement patterns detect structure in large trajectory data sets and thereby help understanding the involved processes [11]. With rapidly growing repositories of fine-grained trajectory data capturing the movement of animals, pedestrians, or motorists, Geographical Information Science has seen a growing interest in movement pattern analysis. The pattern *flock*, where a certain number of objects move together for a specified time period, is a prominent example [13]. However, work on movement patterns so far focussed on homogeneous groups of moving objects (a flock of sheep). By contrast, this paper specifically addresses movement patterns that capture interactions between different object types, e.g., predator vs. prey, male vs. female, or police officer vs. burglar (see Figure 1).

In this paper we draw on a large body of literature in movement ecology, a branch of behavioral ecology, where the study of the spatio-temporal footprint of behaviors has a long tradition. For decades, this community has developed techniques for meticulously capturing the behavior of animals, acting and interacting in and with their habitats. Often, such research features detailed descriptions of the geometric and topological arrangements of actors and the temporal sequences of the actions, all of which crucial building blocks shaping behaviors [3, 6]. It is exactly this knowledge that we capitalize on for a formalization of more generic interaction movement patterns. Inspired mainly by behavioral ecology we focus here on three interaction movement patterns, namely *pursuit and escape*, *confrontation*, and *avoidance*, which we conceptualize, formalize, and algorithmically detect. Our framework is evaluated with experiments, based on trajectory data both from agent-based simulation and real observation data emerging from an outdoor game for children.

Finally, movement can be perceived from the Lagrangian or the Eulerian perspective, respectively [17]. Most movement analysis in GIScience takes the Lagrangian perspective, adopting the perspective of the moving object as it moves along a trajectory through space and time (Figure 1a). For example, animal tracking based on GPS localization devices attached to moving individuals adheres to the Lagrangian perspective. By contrast, the Eulerian perspective focuses on specific locations fixed in space and observes objects passing by (Figure 1b). Tracking customers in a mall through following their RFID-tagged shopping trolleys as they pass by fixed beacons illustrates this alternative perspective. As a further contribution of this paper, we argue that movement patterns can be conceptualized and formalized adhering to both the Lagrangian or the Eulerian perspective. We furthermore argue that interaction movement patterns make an excellent case for this dual perspective, and illustrate and investigate both perspectives in this movement pattern mining study.

Figure 1: (a) Lagrangian perspective: The grey object reacts on the approach of the black object and moves away. (b) Eulerian perspective with fixed space compartments observing passing moving objects: Grey entities avoid sharing space compartments with black entities, space being represented as habitat polygons in b1, and edges of a transportation network in b2.



In detail, this paper investigates the following three research questions regarding reaction movement patterns in trajectory data:

- **RQ1:** How can reaction behaviors found in the behavioral ecology literature be formalized and algorithmically detected?
- **RQ2:** Which parameters are most important when parameterizing reaction movement patterns?
- **RQ3:** To what extent does the choice of either the Lagrangian or the Eulerian perspective of movement influence the pattern mining process?

2 Related Work

2.1 Geographical Information Science

Movement patterns in GIScience describe *flocking* objects [13, 2], moving objects lined-up like pearls on a string in a *single file* formation [5], or identify *leaders* and *followers* in a coordinated group [1]. Often, simple arrangement patterns serve as primitive building blocks for more complex compound patterns [12, 7]. Wood and Galton [18] discuss ontological ramifications for representing collective phenomena, and therefore present a range of appropriate classification phenomena. One of these criteria is the differentiation of roles. For interaction patterns roles are key. Finally, Orellana *et al.* [14] present one of the few studies explicitly focusing on interaction movement patterns. In their study the authors investigate *approximation*, *attraction*, and what they call *suspension* (stops) based on flows and density maps.

2.2 Behavioral Ecology and Surveillance

From the large behavior ecology body of literature we mainly focus on work featuring explicit descriptions of spatial arrangements in the footprints of observed behaviors. Relevant for this study is work on predator and prey [8], confrontation and territorial interaction [3], as well as avoidance [6]. More detailed descriptions about these behaviors can be found in the respective theory sections below. Similar approaches based on spatio-temporal descriptions of suspicious behavior, however much less elaborate, are used in video surveillance and security applications [10].

3 Theory

3.1 Lagrangian vs. Eulerian perspective

As stated in the introduction, movement can be perceived from the Lagrangian or the Eulerian perspective [17]. In this study we adopted both perspectives as it was an explicit goal of the study to illustrate how the choice of perspective may influence the pattern formalization and detection process, as well as consequently the result of the movement mining process.

The formalization of reaction movement patterns in the Lagrangian perspective is straightforward, as the conditions, the building blocks of the patterns can be expressed with geometric or topological relations between the involved moving objects or their trajectories respectively. Examples for such relationships include Euclidean distance, turning angle, front regions, to name but a few. The Eulerian perspective is modeled for objects moving in a constrained fashion on a transportation network [11]. Note that instead of areal compartments of space (Figure 1b1), objects enter and leave linear edges of a network (Figure 1b2). So, two objects occupying the same space compartment are indeed moving on the same edge.

3.2 Reaction Movement Patterns

In this study we refer to *reaction movement patterns* as the spatio-temporal footprint of the movement behavior occurring when individuals of two different kinds (e.g., predator and prey) react on their spatial co-occurrence. Following Laube *et al.* [12] and Dodge *et al.* [7], reaction movement patterns can be conceptualized as sequences of pattern primitives. For example, a *pursuit and escape* pattern consists of the building blocks of actions *approach, following, separation*, with each of this being formally described (Figure 2).

As will be shown in the experimental section, the temporal sequence and indeed the temporal spacing of the events is crucial for detecting reaction movement patterns. The delay d, that may or may not separate two actions, is crucial. This can be illustrated with the example of a sprinter getting out the starting blocks in track and field. For it to be an (regular) interaction, the reacting time of the event leaving the blocks' must not be too short (false start), and will normally not extend a certain time interval.

In the following, three movement interaction patterns are described and their formal definitions are given. Even though reaction movement patterns could involve complex $n:m$ interactions, for the sake of simplicity this study focusses on $1:1$ interactions. Although both Lagrangian and Eulerian perspectives have been formalized for all patterns, for reasons of brevity in this short paper only for *pursuit and escape* they are both included in this theory section.

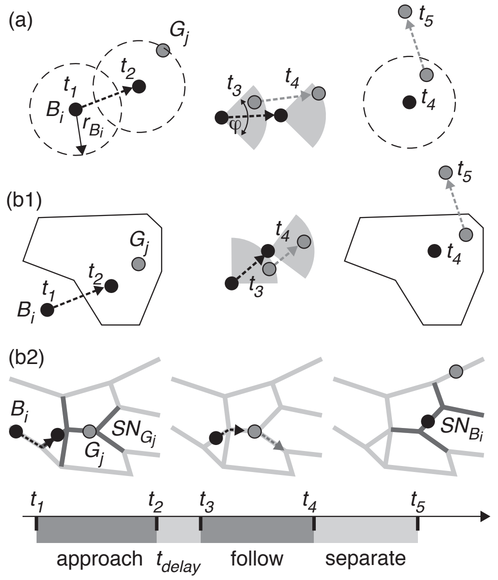
3.2.1 Pursuit and Escape

The first pattern is very much inspired by predator and prey behavior, where individuals of different species, one prey one predator, interact. As has been pointed out by [8], this interaction involves the individuals perceiving each other. For this pattern a perception area of a given radius r is hence modeled (Figure 2a).

As a further arrangement criterium, this pattern involves the notion of a front region as introduced in [1], see Figure 2a in the middle. Assuming that the perception of an animal is built by its field of view, two objects are said to be following each other if the following individual is located in a wedge-shaped region of radius r and including the angle φ for a certain time interval i. This study adopts this notion of following, see [1] for detailed formal definitions. The final separation of the two objects is crucial as it distinguishes this pattern from *flocking* [13] or *leadership* [1]. The pattern is described, formalized in the following, and illustrated in Figure 2.

Pursuit and Escape, Lagrangian (PE_L). Let n black objects B and m grey objects G move in Euclidean space $\mathbb{R}^2$. Actor B_i enters the perception area of radius r_{B_i} of object G_j (**C1**). Reacting object G_j is located in the front region of B_i enclosing φ for the duration of t_{follow} (**C2**). The delay between the approach action and the escape reaction is below $t_{critDelay}$ (**C3**). The distance between acting object B_i and reacting object G_j is again increased beyond the radius of the perception area r_{B_i} (**C4**).

Figure 2: Pursuit and escape pattern. A black actor approaches a grey reactor, they follow each other (front region φ), and finally they separate again. (a) Lagrangian perspective, (b1) Eulerian perspective, (b2) Eulerian perspective for network bound movement.



C1: $\| B_i(x,y,t_2) - G_j(x,y,t_2) \| = d(B_i,G_j,t_2) < r_{B_i}$
C2: $G_j \in front(B_i,t,\varphi), t \in [t_3,t_4]$ and $t_4 - t_3 \geq t_{follow}$
C3: $t_3 - t_2 = t_{delay} < t_{critDelay}$
C4: $\| B_i(x,y,t_5) - G_j(x,y,t_5) \| = d(B_i,R_j,t_5) > r_{B_i}$

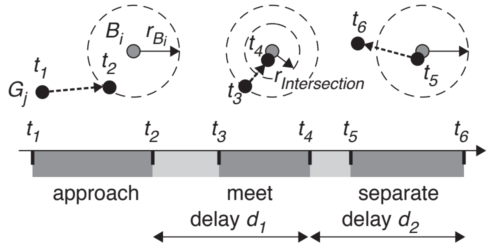
Pursuit and Escape, Eulerian (PE_E). Let n black objects B and m grey objects G move on a network $N = (V,E)$, featuring vertices V and edges E. At time t_2 a black object B_1 enters the segment neighborhood of a grey object G_j, termed the approach event (**C1**). From t_3 the movement azimuth φ_{B_i} equals φ_{G_j} for at least t_{follow}, termed the follow event (**C2**). The delay d between the approach event and the follow event is below the critical delay $t_{critDelay}$ (**C3**). The grey object G_j leaves the segment neighborhood of the black object B_i (**C4**).

C1: $B_i \in E_m, E_m \in SN_{G_j}$ at time t_2
C2: $\varphi_{B_i}(t) = \varphi_{G_j}(t), t \in [t_3,t_4]$ and $t_4 - t_3 \geq t_{follow}$
C3: $t_3 - t_2 = t_{delay} < t_{critDelay}$
C4: $G_j \in E_n, B_i \notin E_n$ and $E_n \notin SN_{B_i}$ at time t_5

3.2.2 Confrontation

For a confrontation, the involved individuals need to meet, not just approach each other [3]. Whereas the event *meeting* in the Lagrangian perspective is modeled as an approach beyond a minimal separation distance $r_{Intersection}$, in the Eulerian perspective *meeting* refers to occupying the same space compartment (here the same edge or an edge neighborhood, in dark grey in Figure 3.b2). A typical confrontation is concluded with the objects separating. For the Lagrangian perspective, the pattern is described and formalized in the following and illustrated in Figure 3.

Figure 3: Confrontation pattern in the Lagrangian perspective. A black object approaches a grey one, they meet, and finally separate again.



Confrontation, Lagrangian (C_L). Let n black objects B and m grey objects G move in Euclidean space $\mathbb{R}^2$. Object G_j enters at time t_2 the perception area of the object B_i with a radius r_{B_i} (**C1**). Objects B_i and G_j approach closer than meeting distance $r_{Intersection}$ within the temporal interval $t_{Intersection}$ (**C2**). The delay d_1 between the approach action at time t_2 and the meet action at time t_4 is below $t_{critDelay1}$ (**C3**). Within the temporal interval $t_{Separation}$, the distance between the two objects is raised above the radius r_{B_i} of the perception area of B_i (**C4**). The delay d_2 between the meet action at time t_4 and the separation action at time t_6 is below $t_{critDelay2}$ (**C5**).

C1: $\| B_i(x,y,t_2) - G_j(x,y,t_2) \| = d(B_i,G_j,t_2) < r_{B_i}$
C2: $\| B_i(x,y,t) - G_j(x,y,t) \| = d(B_i,G_j,t) < r_{Intersection}$, $t \in [t_4,t_5]$ and $t_5 - t_4 \geq t_{Intersection}$
C3: $t_4 - t_2 = d_1 < t_{critDelay1}$
C4: $\| B_i(x,y,t) - G_j(x,y,t) \| = d(B_i,G_j,t) \geq r_{B_i}, t \in [t_6,t_7]$ and $t_7 - t_6 \geq t_{Separation}$
C5: $t_6 - t_4 = d_2 < t_{critDelay2}$

3.2.3 Avoidance

Avoidance, finally, includes the explicit modeling of the objects trying to get out of each other's way [6]. In this study, such avoidance is modeled as a swift change of movement direction, expressed as a change in movement azimuth exceeding a critical angle α_{crit} (Figure 4). For the Lagrangian perspective, the pattern is described, formalized, and illustrated in the following.

Avoidance, Lagrangian (A_L). Let n black objects B and m grey objects G move in Euclidean space $\mathbb{R}^2$. Object G_j enters at time t_2 the perception area of the object B_i with a radius r_{B_i} (**C1**). Object B_i changes its movement azimuth $\varphi_{B_1}(t_2)$ to $\varphi_{B_1}(t_3)$ by at least α_{crit} (**C2**). Between t_2 and t_4 the distance between the two objects does not drop below $r_{minAvoid}$ (**C3**). The distance between the two objects is then raised above the radius r_{B_i} of the perception area of B_i for at least the temporal interval $t_{Separation}$ (**C4**). The delay d between the meet action at time t_4 and the separation action at time t_6 is below $t_{critDelay}$ (**C5**).

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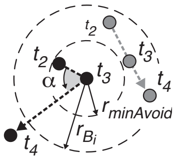
Figure 4: Change of movement direction for A_L. From t_3 to t_4 the black object moves away from the grey object.



C1: $\| B_i(x,y,t_2) - G_j(x,y,t_2) \| = d(B_i, G_j, t_2) < r_{B_i}$
C2: $| \varphi_{B_1}(t_1) - \varphi(t_3) | = \varphi_{B_1}(t_1, t_3) > \alpha_{crit}$
C3: $\| B_i(x,y,t) - G_j(x,y,t) \| > t_{minAvoid}, t \in [t_2, t_4]$
C4: $\| B_i(x,y,t) - G_j(x,y,t) \| = d(B_i, G_j, t) \geq r_{B_i}, t \in [t_4, t_5]$ and $t_5 - t_4 \geq t_{Separation}$
C5: $t_4 - t_2 = d < t_{critDelay}$

3.3 Algorithmic pattern detection

The algorithmic framework bases on a straightforward implementation of the criteria listed above. For every time step, spatial arrangements are evaluated and then temporal persistence and sequence of the given criteria is computed. Even tough the development of efficient algorithms was not a goal of this study, most solutions base on pairwise comparisons and hence feature a complexity of $O(n^2 t)$, with n being the number of moving objects and t the number of time steps.

4 Evaluation

The conceptualized interaction movement patterns and the algorithms for their detection were evaluated in a series of experiments. Both simulated and observed movement data was used. For both data sources semantic knowledge about actually happening behaviors (e.g. a *confrontation*, simulated or observed) was available (at least partially) and used for the evaluation of the pattern detection process. To this end, the agent-based simulation environment Repast Symphony (version 1.2.0, Java 6.0) was used for simulations and numerical experiments.

4.1 Data

Simulated data ($data_{SIM}$) For a first set of experiments, trajectories of interacting agents were simulated using the Steering Behavoir Model [15, 16]. Initially, this agent-based model was developed for the simulation of coordinated movements as are found in fish schools or flocks of birds. The model is especially useful for this study as it allows the explicit simulation of *pursuit*, *escape*, and *separate* behaviors. Movement was simulated for eight individuals interacting in a space of $640 * 480$ units. Trajectories were generated for (a) unconstrained movement, (b) movement that is constrained by walls (see Figure 5), and (c) movement along a topological network representing the wall design in Figure 5. Several simulation runs lasting several thousand time steps each, produced a number of test data sets, each featuring a list of logged interaction patterns.

Figure 5: Some objects in the steering behavior model, constrained by walls.

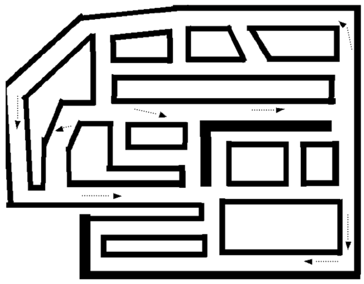


Figure 6: Topological network of Amsterdam's historic center, generalized from Bing-Maps, five moving teams.

Real data ($data_{OBS}$) The second data set emerged from an urban outdoor mobile game, allowing students a pilgrimage through 1550 medieval Amsterdam [14]. The students' goal was to collect points from distributed check-points, or by raiding points from confronting competing groups. Given these game rules, the trajectories of the players express *pursuit and escape*, as well as *confrontation* patterns. Preprocessing of the data included filtering with a minimal trajectory duration, as well as map-matching to a street network according to [9, 4]. The resulting data set of ten gaming days had a sampling rate of 10 seconds for maximally 6 concurrently moving teams (Figure 6). Also for this data source, semantic information could be gathered. A list of 33 observed and documented confrontation behaviors could be scraped from the project web site[1] through a HTML-parser.

4.2 Experiments

The evaluation was conducted as an error analysis, combined with a sensitivity analysis. The algorithms' reliability was evaluated by comparing the number of found patterns with the number of documented behaviors (Section 4.1). Two forms of error were investigated: First, *errors of omission*, or the number of documented behaviors that were not detected (*eoo*, 'missed patterns'); Second, *errors of commission*, or the number of wrongly detected patterns when no behavior was documented in the first place (*eoc*, 'false positives'). Note that *eoc* can raise above 1.0 when the number of false positives exceeds the number of real pattern. The original study included a inclusive wide range

[1] test.frequentie1550.nl/results

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of experiments for all patterns, for both data sets $data_{SIM}$ and $data_{OBS}$, as well as for both the Lagrangian and the Eulerian perspective. In this short paper, however, we focus on the following selection of experiments only:

- **Exp #1** Error analysis (*eoo*, *eoc*) for selected algorithms, for both Lagrangian and Eulerian perspectives and for both data sets.
- **Exp #2** Sensitivity analysis. (a) Parameter *front angle* when detecting the pattern *pursuit and escape*, with $data_{SIM}$, (b) parameter *delay* when detecting the pattern *avoidance*, with $data_{OBS}$.
- **Exp #3** Comparison of the Lagrangian vs. the Eulerian perspective when detecting *avoidance*, with $data_{SIM}$.

4.3 Results

Exp #1 Table 1 summarizes a series of results of the error analysis. The presented table summarizes *eoo* and *eoc* for optimal parameters for perception area and delay found in the sensitivity analysis (Exp #2). Note that especially for PE, short delays yield the best results, as short delays indicate causal interrelation (as with the sprinter's starting time). PE_L and A_L achieve the lowest *eoo* values, missing the least patterns, with very low *eoc*. For two reasons, C_L expresses rather high error rates: First, low positional accuracy of GPS signal undermines the distance criterion. Second, the formalization given in Section 3 only partially matches the annotated patterns in the semantic log. Figures 7 depicts two successfully detected PE_L patterns, with teams red (pursuer) and purple (fugitive).

Table 1: Exp #1. Error analysis. Perception area is given for the Lagrangian perspective as the radius r_{B_i}, and for the Eulerian perspective as the number of neighboring segments, 0 = same edge, 1 = same and adjacent edge.

algo	data	per.area	delay	#behav	#found	eoo	eoc
PE_L	$data_{SIM}$	75	40	35	34	0.03	0.06
PE_E	$data_{SIM}$	1	35	18	12	0.33	0.22
C_L	$data_{OBS}$	50m	100s	33	13	0.6	0.39
C_E	$data_{OBS}$	1	120s	33	20	0.39	0.60
A_L	$data_{SIM}$	35	45	33	32	0.03	0.03
A_E	$data_{SIM}$	0	120	33	27	0.18	0.54

Exp #2 This experiment shall illustrate the sensitivity of the interaction movement pattern algorithms to their parameterization. (a) First, the error analysis with $data_{OBS}$ from Exp #1 (third row in Table 1) is diversified by systematically varying the parameter delay d. Figure 8 illustrates that *eoc* can be reduced by increasing the delay d. This, however, is achieved by a linked drop of *eoo*. Such sensitivity analysis may be used, together with indispensable domain knowledge, for a selection of suitable parameter values. (b) A second error analysis focuses on the sensitivity to the inclusive angle φ of the front region in PE_L. Figure 9 shows a similar convergence of curves as Figure 8, however with

Figure 7: Successful detection, $data_{OBS}$, PE_L.

φ growing towards 90 degrees, *eoc* gets out of hand, as objects just happening to move in roughly the same direction are misclassified as pursuit and escape.

Figure 8: Effect of delay d, $data_{OBS}$, C_L.

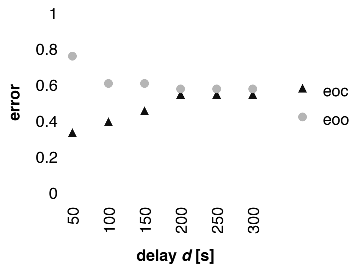
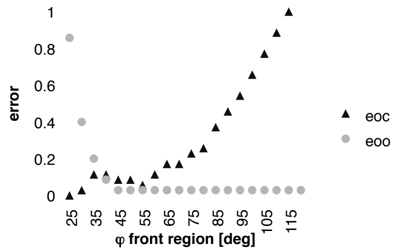


Figure 9: Effect of φ, $data_{SIM}$, PE_L.



Exp #3 Finally, the third experiment investigates the sensitivity of the presented approach to the choice of perspective, be it Lagrangian and Eulerian. Here, the parameter angle of the direction change α_{crit} is varied for detecting both A_L and A_E (Figure 10). Whereas trajectories of randomly meeting objects tend to simply cross paths without changing their direction, objects showing an avoidance pattern must move away from each other, modeled through a sudden change of direction, expressed with the angle α (Figure 4). In the Lagrangian perspective, the angle criterion is very selective. It is very unlikely that large direction changes happen by chance, so *eoc* remains low for large α. In the Eulerian case this angle criterion must be treated with care, as the geometry of the street network imposes rather abrupt direction changes. Hence, from 60 degrees onwards this criterion

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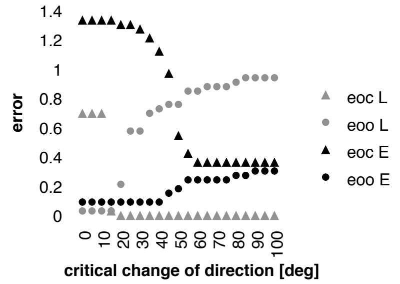
Figure 10: Avoidance Lagrangian (A_L) vs. Eulerian perspective (A_E), change of direction α_{crit}, $data_{SIM}$.



has no further influence and other criteria need to be used for the network case.

5 Discussion and conclusions

This study confirms previous findings that complex movement patterns can be conceptualized from linking primitive building blocks of geometrical or topological arrangement patterns (RQ1). However, focusing on interaction movement patterns, this study also suggests, that the sequencing and especially the temporal timing of lined-up primitives, that is the temporal spacing captured in the delay d, plays a crucial role when distinguishing interaction patterns from related patterns (such as flocking or converging). Exp #2 also showed the importance of the parameter front angle φ (RQ2). The reduced flexibility of the Eulerian perspective, however, constrains the potential effect of parameters. Clearly, when moving objects must move in a street, the sensitivity of a pattern to its front region angle φ is limited. In concrete application cases a careful combination of sensitivity analysis and domain knowledge is expected to yield the most adequate values for such crucial parameters (RQ3).

Future work will extend interaction movement patterns allowing for $m : n$ relations and investigate further fine-grained trajectory data sets as they come about.

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