MotionGlyphs: Visual Abstraction of Spatio-Temporal Networks in Collective Animal Behavior

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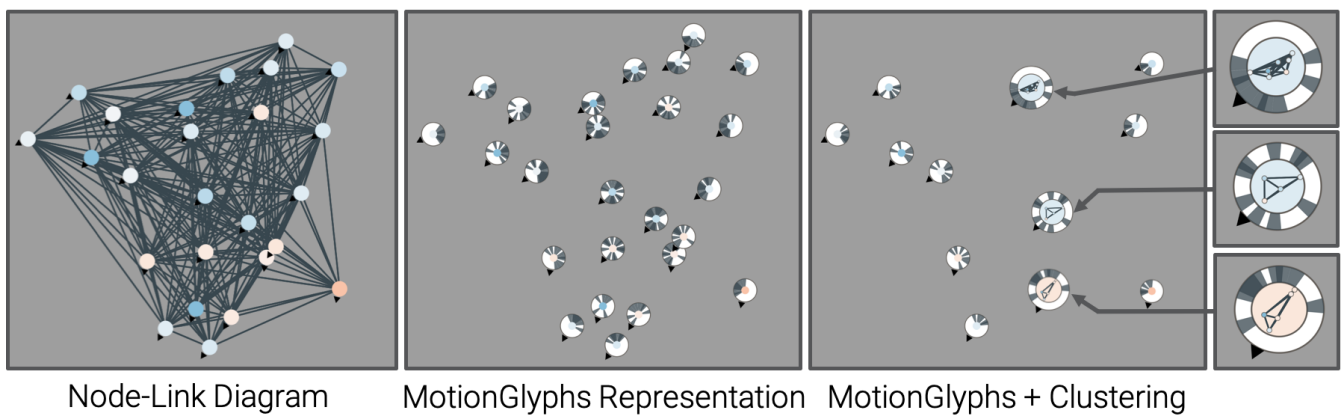
Figure 1: *MotionGlyphs allows biologists to visually explore and abstract dense spatio-temporal network data in collective animal behavior. The figure presents the same time instance of golden shiner fish data in a node-link diagram (left), MotionGlyphs representation (middle), and with additional clustering (right). The color of the movers displays the speed (blue to red), and the links (light blue to dark blue) encode the similarity between movement properties (direction, speed, distance to each other). The example above shows how MotionGlyphs abstract relationships and aggregate movers into groups to reduce visual clutter and highlight different group structures.*

Abstract

Domain experts for collective animal behavior analyze relationships between single animal movers and groups of animals over time and space to detect emergent group properties. A common way to interpret this type of data is to visualize it as a spatio-temporal network. Collective behavior data sets are often large, and may hence result in dense and highly connected node-link diagrams, resulting in issues of node-overlap and edge clutter. In this design study, in an iterative design process, we developed glyphs as a design for seamlessly encoding relationships and movement characteristics of a single mover or clusters of movers. Based on these glyph designs, we developed a visual exploration prototype, MotionGlyphs, that supports domain experts in interactively filtering, clustering, and animating spatio-temporal networks for collective animal behavior analysis. By means of an expert evaluation, we show how MotionGlyphs supports important tasks and analysis goals of our domain experts, and we give evidence of the usefulness for analyzing spatio-temporal networks of collective animal behavior.

1. Introduction

Collective animal behavior is an intriguing phenomenon appearing in nature in many forms. Prominent examples are the collective movement of fish schools, insect swarms, or flocks of birds [Gor14]. Research in biology and other fields aims to explain the mechanisms by which group motion patterns emerge in natural and social sciences [Cou09]. Such patterns can be, for instance, relationships among multiple animals (e.g., social influences), temporal trends

(e.g., migrations), and sub-group behavior of animals (e.g., group of leaders). These group patterns are yet not fully understood since the movement depends strongly on influences and interactions between possibly many animals (movers) [Cou09]. Recent research has modeled collective behavior as spatio-temporal network data to analyze the emergent properties of groups [FW15]. For example, Rosenthal et al. [RTH*15] analyze evolving interaction networks in which they map movers to nodes and the sensory information

of a mover to weighted links (edges). A purely statistical analysis of such spatio-temporal networks (e.g., networks metrics) should be avoided as the interpretation in the context of collective animal behavior remains challenging [FW15]. The field, therefore, requires tailored visual metaphors to analyze the evolving network structure and highlight correlations between movers [FW15].

Spatio-temporal network data is a particularly challenging type of data as it consists of evolving relationships between spatially positioned entities (attribute-driven layout) [NMSL19]. Real-world applications are, for instance, traffic [PHT15], network security [SSG11], and migration analysis [SBW15]. The visualization of such data promotes the identification of spatial, as well as topological patterns over time (e.g., spatio-temporal network clusters). However, two main challenges limit the visual exploration of such evolving patterns. First, the fixed network topology of spatial networks often leads to node overlaps as well as edge crossings in dense areas [WCG03]. Therefore, Nobre et al. [NMSL19] recommend displaying spatial networks only for small and sparse networks. Second, the additional temporal dimension poses a challenge to present the data in a readable, scalable, and expressive manner [BBDW17]. Visualization techniques for multivariate [NMSL19] as well as dynamic networks [BBDW17] aim to reduce the complexity of such data (e.g., aggregation [Wat06, DS13, KLS*17] or filtering [PHE*17, vdEvW13]). Yet, such methods either change the positions of movers or reduce data characteristics (e.g., filtering), which should be avoided in collective animal behavior analysis as it can hide potential sub-patterns and consequently decrease the interpretability [FW15]. An uncluttered overview visualization of spatio-temporal networks in collective animal behavior, therefore, can help domain experts analyze single movers (ego-centric) and groups of movers (socio-centric).

In contrast to earlier work, our prototype (MotionGlyphs) focuses on reducing visual clutter by abstracting a spatio-temporal network to glyphs. We demonstrate the usefulness of our approach by conducting expert interviews and pair analytics sessions [AHKGF11]. In summary, the primary contributions of this paper are: (1) A design study with problem characterization, findings, and lessons learned within the domain of collective animal behavior. (2) A glyph design for the summarization and depiction of spatio-temporal networks at multiple levels of granularity. (3) A visualization prototype for experts to explore local as well as global network properties over time.

2. Related Work

The visual identification of patterns (e.g., clusters or trends) in spatio-temporal network data remains challenging due to the high dimensionality and the scalability issues in space, time, and network characteristics. We cover related visualization research, addressing these challenges from different perspectives in the fields of spatial, dynamic, as well as spatio-temporal network data.

2.1. Spatial Networks Analysis

Spatial networks (also known as geographic networks) are a way to model relationships between spatial locations. Real-world examples include the analysis of air traffic [KAW*14] and transportation data [AAFW16]. Nobre et al. [NMSL19] defined spatial network data as a special type of multivariate network data (attribute-driven layout). Multivariate network visualization can be

applied to spatial networks such as Pivot-Graphs [Wat06], Semantic Substrates [SA06], GraphDice [BCD*10], or dimensionality reduction [DCW11]. However, the listed approaches focus on either node or edge (link) attribute comparisons or abstract the spatial positions. Matrix visualizations using geographical embeddings (e.g., Yang et al. [YDGM16]) are not suited for the application domain as the approaches do not scale to many time steps, and the matrices grow quadratically with the number of movers. Other visualization approaches for spatial networks aim to reduce the complexity and visual clutter by either filtering [PHE*17, vdEvW13], aggregation [Wat06, DS13, KLS*17], clustering [EDG*08], edge bundling [LHT17], deriving new attributes [DCW11] (e.g., node degree), or converting edges to nodes [JKZ13]. Filtering, aggregation, clustering, and edge bundling techniques enable to reduce the number of displayed nodes or links. However, this results in information loss, which may lead to misinterpretations in the application domain [FW15]. Furthermore, deriving new attributes (e.g., node metrics) can lead to misleading information [FW15], and the conversion of edges to nodes is not applicable in our application domain as it would produce additional movers. For spatial network visualization, Ko et al. [KAW*14] analyzed flight journeys as origin-destination data and introduced a petal glyph which displays multivariate network features. The glyph enables to assess, for example, the number of flight delays or security delays for airports. However, the proposed glyph does not scale for dense areas. Zou and Brooks [ZB19] present a visualization system to aggregate nodes into hubs, which enables to display local and global information. The authors propose a dynamic circular layout with new edge curving and node positioning algorithms. The approach is, however, unsuited for our application as the method does not allow displaying the exact spatial position or adapting the applied aggregation method.

2.2. Dynamic Network Visualization

Recently, the visualization of dynamic (temporal) networks has gained research interest [BBDW17]. The automatic analysis of such data enables to examine structural properties of the network, for example, the temporal analysis of static network metrics (e.g., node degree, centrality [BW04]) as well as dynamic network metrics (e.g., change centrality [FPA*12]). However, only analyzing such automatically extracted structural properties in collective animal behavior might hide specific local dynamic patterns and how such local changes affected the overall dynamic phenomena [FW15]. Interactive visualizations try to overcome these challenges by allowing users to visually analyze the changing relationships in their evolving structural context. Beck et al. [BBDW17] categorized dynamic network visualization into: animation (time-to-time mapping) [DG02, PHG06, APP11], timeline (time-to-space mapping) [GBD09, BPF14, HBW14] and hybrid visualizations [HSS11, BBV*12, BHRD*15]. Timeline mappings map the temporal dimension to a spatial axis (e.g., small multiples), which, however, does not scale to long sequences [BBDW17]. Other approaches from this category (e.g., NodeTrix [HFM07]), furthermore, do not preserve the position of each node (mover) over time. Similarly, the usefulness and effectiveness of animation is still controversial [TMB02, RFF*08]. While animation has been shown to be effective in some domains such as flow visualization [WBM*16], it does not scale to large quantities of nodes and links, often higher cognitive load [TMB02]. For further reading, we refer to the survey of Beck et al. [BBDW17].

In summary, the current visualization techniques either change the positions of the movers (timeline mapping) or animate the temporal evolution of the underlying dynamic data. Therefore, the field of collective animal behavior requires new visual metaphors that combine spatial and temporal abstraction methods to reduce the presented data and highlight temporal and structural changes (e.g., clusters splitting).

2.3. Spatio-Temporal Network Visualization

Recently, techniques for the analysis of spatio-temporal networks (dynamic geographic networks) have been proposed (e.g., for collective movement in transport [AAPS19]). These approaches focus mainly on the study of origin-destination data. Frequently in flow map visualization, movement data is discretized to highlight the direction and magnitude of mobility patterns [AAFW16]. Kim et al. [KJW*17] propose a heatmap to display origin-destination data, which can, for example, highlight the origins of disease outbreaks. The approach, however, discards the movement (trajectory) data, which is crucial in the analysis of collective animal behavior. Zhu and Guo [ZG14] apply a hierarchical clustering method to identify significant and dense flows in the traffic data. The approach scales to large spatial data but does not scale for large time periods. Andrienko et al. [AAFW16] proposed a method for spatial and temporal abstraction, including a composite glyph to reduce clutter and occlusion in the origin-destination data. The proposed composite glyph displays for each location the flow angle and the distance between the locations to reveal regional mobility trends. The approach highlights periodic patterns by aggregating overall spatial events and then clustering the temporal dimension into periods. A limitation of the approach is the information lost due to spatial as well as temporal aggregation, and with an increasing number of spatial locations, the glyph becomes challenging to interpret.

In summary, the listed approaches for spatio-temporal networks focus on the visualization of flows in specific applications, for instance, mobility trends in the form of flows between locations (origin-destination data) [AAFW16]. In contrast to these approaches, we focus on the visual exploration of changing relationships in collective animal behavior, for which no design studies have been carried out. In this design study, we address the needs of biologists and propose a design to tackle the challenge of visualizing evolving relationships between single movers, and groups of movers.

3. Application Background

The goal of this design study is to create a visual analysis design supporting the identification of group patterns over time in a large set of moving entities. We conducted interviews with two domain experts (postdoctoral researchers) to clarify the user needs, understand the workflow and requirements in the targeted domain. The domain experts analyze spatio-temporal networks to discover similar behavior, evolving group structures, and outliers.

3.1. Collective Animal Behavior

Collective animal behavior aims to understand the social influence (relations) as well as information flow between individuals and groups [Cou09]. The research field is lately observing and tracking animal groups at larger scales in lab experiments or field studies due to technological advances (e.g., small GPS devices) [KKA*13].

Purely statistical approaches are usually used to analyze data generated by such experiments [SVL16]. While they support to verify a single hypothesis, they are typically unable to observe potentially interesting patterns in the data which fall outside the chosen parameters and scope of the selected statistics [DBC*15]. In the research field, a lot of effort is put into revealing evolving groups (clusters) of animals that influence individual groups and vice versa how individuals affect internal group characteristics (e.g., through local influences) [Cou09]. The analysis of influences between animals (e.g., interactions) requires methods that display the spatial data accurately and preserve local neighborhoods as this helps to follow and interpret emerging group properties [CKJ*02]. Clustering local interactions enable, furthermore, to distinguish movers with similar behavior [PAA*12] at the loss of some spatial accuracy and summarize group structures to reduce the complexity of the data. The similarity between all movers for each time step is essentially a weighted network (distance matrix). The visual exploration of such evolving similarities can reveal underlying group characteristics of collective animal behavior [DBC*15]. For example, Rosenthal et al. [RTH*15] displayed communications networks to study behavioral changes and social influences in collective evasion maneuvers. For instance, we are visually exploring a real-world dataset consisting of 151 Golden Shiner fish swimming through a depthless fish tank (2.1m x 1.2m) for 12 minutes (18000 frames). The two-dimensional dataset consists of 2.7 million data records and 18000 similarity matrices with more than 410 million links. A similarity matrix is computed using the weighted Euclidean distance between the features of a mover (see Sec. 4.1).

3.2. Problem Description

During the interviews, we investigated how domain experts analyze data, which tools they use, and what potential high-level problems have to be addressed to understand collective animal behavior. We considered movers (nodes) with similar behavior over time a group, for instance, the aligned movement of multiple movers towards a food source. The analysis of an appropriately constructed distance matrix (based on similarity) for each time step provides a possibility to identify groups of similar behavior and to investigate socio-centric patterns (e.g., group leaders). For the visual analysis of such socio-centric patterns in collective animal behavior, we have to address the following high-level problems (P):

P1. Display the ego-centric relationships In the application domain, it is crucial to investigate the relations of one mover to all other movers (ego-network). For example, to examine if there are similar ego-networks in space or if ego-networks increase and decrease simultaneously over time. The visual analysis of relationships between multiple evolving movers, however, remains challenging due to visual clutter in spatially dense networks [ZB19]. A visualization of the ego-centric network, therefore, should aim to provide an uncluttered overview (summary) of such relations. A compact ego-network visualization can help domain experts to identify similar movers, compare movers, and to detect outliers.

P2. Identify groups of movers with similar behavior The visualization of movers is challenging as with a growing number of movers, the clutter and overlap in dense areas increase, which can hide spatio-temporal patterns [DBC*15]. For such cases, often visual data aggregation (e.g., clustering, density maps) is applied

	Spatial Representation			Temporal Aspects			Scalability						Explorability & Comparability					Relational Representation	
	Accurate	Inaccurate	Displaced	Animated	Timeline / Static	none	Small (<100) Nodes	Small Edges	Medium (<1000) Nodes	Medium Edges	Large (>1000) Nodes	Large Edges	Nodes	Edges	Neighbors	Clusters	Sub-networks	Nodes	Edges
MotionGlyphs	•			•			•	•	•	•	•	•	•	•	•	•	•	explicit	implicit
Scheepens et al., 2014 [SVDWVW14]	•			•			•		•				•		•	•		explicit	none
Ko et al., 2015 [KAW*14]	•				•		•	•					•	•	•	•		explicit	explicit
Kim et al., 2018 [KJW*17]	•				•					•		•		•		•		implicit	aggregated
Li et al., 2017 [LBW17]	•					•			•	•	•	•		•	•	•	•	explicit	explicit
Andrienko et al., 2016 [AAFW16]		•		•					•	•	•	•	•	•		•		aggregated	aggregated
Andrienko & Andrienko, 2010 [AA10b]		•			•		•	•	•	•				•		•	•	aggregated	aggregated
Park et al., 2017 [PNK19]		•			•		•	•					•	•	•	•		explicit	order-based
Guo & Zhu, 2014 [GZ14]		•			•			•		•		•		•				none	explicit
Dunne & Shneiderman, 2013 [DS13]		•				•	•	•	•	•	•	•		•	•	•	•	aggregated	aggregated
Yao et al., 2019 [YWZ*19]		•				•	•	•	•	•			•	•	•			aggregated	aggregated
Dörk et al., 2011 [DCW11]			•	•			•	•	•				•	•	•	•	•	explicit	explicit
Huang et al., 2019 [HSS*19]			•	•			•	•					•	•	•	•	•	explicit	explicit
Zou & Brooks , 2016 [ZB19]			•			•	•	•	•	•	•	•		•	•	•	•	explicit	explicit

Figure 2: *Comparison of key properties of related techniques, ordered by kind of spatial representation and presentation of temporal aspects: Scalability concerning depictions of nodes and edges in small, medium and large networks; Exploribility and Comparability of Nodes, Edges, Neighbors, Clusters and Subnetworks, which denotes whether these network structures are explorable and comparable with the respective technique; Temporal Representation, which describes how time is represented; Spatial Representation, which describes whether spatial aspects are reproduced accurately, inaccurately (e.g., by aggregation) or displaced (e.g., by layout). Relational Representation explains, whether nodes and edges are visualized explicitly, which means specific visual representation of nodes or edges as such, or implicitly, or whether there is no visual reference for edges or nodes at all.*

to reduce the number of movers [AA10a]. We consider two types of clustering based on the spatial-temporal data and the evolving network structure. The visual analysis of such clustering methods should also involve domain experts to explore different parameter settings for grouping elements together [AAFW16].

P3. Present the socio-centric relations in groups The display of groups of movers, for example, through a meta-node, can help to reduce the number of displayed movers and reduce clutter in dense areas. However, through such a clustering, relevant information within dense areas themselves, such as internal group dynamics, is lost [AAFW16]. The visualization of intra-cluster relationships of groups can present underlying socio-centric processes.

3.3. Requirements

Slingsby and van Loon [SVL16] held a workshop with multiple animal movement ecologists and described the requirements necessary for the initial visual analysis of movement ecology. The research disciplines of movement ecology and collective animal behavior are related as both disciplines work on the analysis of collective movement [WBTB18]. In discussion with our domain experts, we selected and adapted key requirements, which are relevant for the identification of group patterns in collective animal behavior, form the proposed requirements of Slingsby and van Loon [SVL16]. As well, we identify related key properties a technique needs to support in order to satisfy these requirements, denoted in italic for each item.

R1: Display the original data Group patterns in collective animal behavior emerge from local spatio-temporal interactions between movers. Displaying the raw data is, therefore, essential as it helps to interpret and understand the emergent group properties. This means, the *node representation* needs to be explicit and *spatially accurate* to enable *node and neighbor comparability*. Also, since typical use cases range from small to large amounts of movers, *scalability* towards a broad range of network sizes is required.

R2: Relate the time, space, and attribute dimensions Define and present a summary of the multivariate relationships between the

dimensions space, time, and attributes of a mover (node). To do so, *node exploration* by attributes and a dynamic *temporal representation* need to be provided.

R3: Enable the aggregation into groups Enable the aggregation into "ecologically-meaningful" units, which is crucial to abstract and simplify large movement datasets. Consequently, the technique needs to support the *cluster and subnetwork explorability and comparability*.

R4: Allow the exploration of the spatio-temporal network at different scales Networks can be observed from an ego-centric (low-level) perspective or a socio-centric (high-level) perspective. The technique needs to support both perspectives, both for the global view and local groups (*subnetwork*).

3.4. Gaps in Related Approaches

To illustrate the gap we intend to close, we compare a selection of current approaches (see Fig. 2) to the key properties as specified in the requirements (see Sec. 3.3). The compared publications were selected as a sample of established techniques based on recursive scanning of references from the visualization technique surveys for group structures in networks [VBW17], dynamic networks [BBDW17], and multivariate networks [NMSL19].

The comparison provides several insights. First, it becomes apparent that techniques which scale to large networks often do not regard a temporal dimension (**R2**, e.g., [DS13, ZB19, LBW17, YWZ*19]), or resort to a static time representation such as timelines (e.g., [DCW11, AA10b, HSS*19, PNK19, KAW*14, AAFW16, GZ14, KJW*17]), which is not adequate to display live group dynamics. If animation is provided (e.g., [AAFW16, SVDWVW14]), node or edge aggregations are introduced to reduce the visual complexity at the loss of some spatial accuracy (**R1**) between the moving entities. In animation, however, the identification of temporal trends over short timescales remains difficult [RFF*08]. It becomes apparent that the focus of aggregation-based approaches does not lie in the display of dynamic movements. Rather, many of these
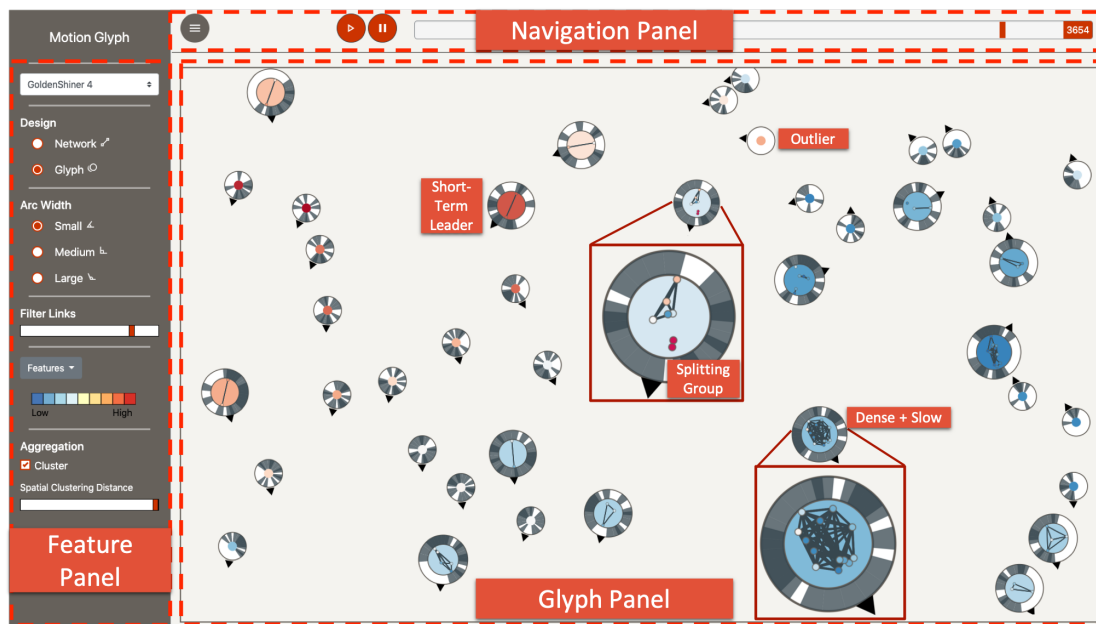
Figure 3: *The glyph panel shows a subset of the 151 golden shiner fish school data, the attribute color displays the speed (blue to red), and clustering is applied. The fish school has a fast (red group on the left) and a slower subset (blue groups on the right). Multiple groups with different characteristics are visible (e.g., number of movers, density, number of links), which enables to analyze them over time. The granularity of the aggregation can also be changed at any time to allow analyzing detailed group structures or abstract movers into larger groups.*

techniques use aggregation to summarize static spatial contexts or the developments on a global scale, neglecting individual nodes ([DS13, AA10b, YWZ*19, AAFW16]). Yet, being able to explore clusters and to identify what properties they share are essential tasks when trying to identify common behavior (**R3**). Finally, those approaches considering temporal aspects are often more catered explicitly to either larger or smaller networks, which violates **R4**, requiring that the method needs to be scalable towards different sizes of networks and to enable the exploration of substructures as well. For example, techniques that only work for smaller networks may employ network layouting to optimize the depiction of clusters, coming at the cost of losing some spatial accuracy.

In summary, the comparison shows that there is a gap concerning approaches that satisfy the requirements fulfilled by MotionGlyphs: Most related approaches are not suitable for the exploration of temporal dynamics of movers, or they do not support an accurate spatial representation of participating nodes. Other properties, such as node aggregation or fixed spatial clusterings as an integral part of an approach, further restrict the usefulness of related approaches in the context of the described requirements. In contrast, MotionGlyphs is designed to fulfill the requirements, coming only at the cost of implicit edge representations and some spatial accuracy for interactive exploration of group structures.

4. Visual Design

MotionGlyphs was designed over the course of five months in close collaboration with two domain experts from the field of collective animal behavior. We followed the design guidelines by Lloyd and Dykes [LD11] to make the design process interactive, including real-world data, developed digital sketches, allowing the free exploration

of prototypes, and think-aloud protocols. MotionGlyphs is a web prototype to visually explore group patterns spatio-temporal network data, which consists of two components for data modeling and visualization. The data model is responsible for feature extraction (e.g., speed of a mover), computation of similarities matrices, and spatio-temporal clustering. The visual interface of the prototype (see Fig. 3) consists of the navigation panel to change the temporal dimension, feature panel to adapt the visual variables (e.g., clustering scale), and the glyph panel to display the single and cluster glyphs.

4.1. Data Model

We briefly describe the functionality and choices we made for the feature extraction, spatio-temporal networks, spatio-temporal clustering. The data model component aims to model interactions between movers by enabling domain experts to compute specific evolving networks and clusters. The input file for the prototype has a standard domain-specific format (time, animal-id, x, y). Domain experts suggested data cleaning methods (e.g., interpolation) and feature extraction (e.g., average speed, direction, and distance to the centroid). For the extraction of features, domain experts have to define the temporal scales (e.g., per second, per minute), which usually depends on the tracking resolution. A network for each time step can be defined by a user-defined similarity metric based on the extracted features (e.g., weighted euclidean distance) or the segmented trajectories of the mover (e.g., Fréchet distance). Such a similarity metric can be, for instance, the weighted euclidean distance between all (or a subset) of the extracted features. Varying combinations of weights in the euclidean distance metric generate different networks, which can be used to highlight specific patterns. For example, using the direction, speed, and acceleration of each mover, the aligned movement of a group towards a particular target can be emphasized.

The network for each time step includes the temporal information as derived features (e.g., average speed) are computed using a rolling window approach. The usage of temporally smoothed features (e.g., average heading changes per second) improves the interpretation as noise is smoothed out (e.g., small tracking errors).

Domain experts can, furthermore, use either the network weights (distance matrices) or another similarity metric for the computations of spatio-temporal clusters. The spatio-temporal clustering helps to summarize as well as examine the temporal evolution of relationships and highlight the changes of group properties in the data. We apply the density-based clustering proposed by Peca et al. [PFV*12] as the algorithm scales to large datasets. The proposed algorithm has two parameters ε_{time} and ε_{space}, which we discussed in detail with the domain experts. By default, the ε_{time} is set to the temporal scale of the extracted features (e.g., average speed per minute). Additionally, the clustering is applied several times with a varied ε_{space}, which results in clusterings with different spatial densities. The default values of ε_{space} are defined by the maximum distance a mover can travel between two consecutive time steps, which is a useful heuristic to determine the possible spatial changes between two points in time.

4.2. MotionGlyphs

MotionGlyphs allows visualizing single (single glyph) and groups of movers (cluster glyph) (see Fig. 4). The single glyph displays the spatio-temporal network using the spatial positions (geospatial-layout) (**R1**) and abstracts network links by mapping them to a radial representation (outer-ring) of the glyph. The inner-circle of the glyph allows to display characteristics of the mover (e.g., speed), and the glyph arrow depicts the movement direction (**R2**). The outer-ring of a single glyph is essentially a doughnut chart with segments (link abstraction arcs) that aim to summarize the direction and median link weights to other movers that lie in that direction. The segments preserve link characteristics, such as the direction and strength (weight) (**R2**). By default, we segment the outer-ring into 12 segments of 30 degrees. Domain experts can, furthermore, adapt at any time the segment width. The abstraction of links to segments prevents edge crossings, and was inspired by the work of Ko et al. [KAW*14] in which the authors simplify origin-destination. Two color scales from ColorBrewer [HB03] are used to encode values: For the inner-circle attributes, a divergent color scale from blue to red is used to highlight low and high attribute values. For example, in some fish schools, the animals are continually moving, therefore usually values below and above the mean speed are interesting for domain experts. The link weights are mapped to the outer-ring using linear light blue to dark blue color scale.

MotionGlyphs allows to abstract groups of movers into a cluster glyph (see Fig. 4) to present the underlying group structure (**R3**). The cluster glyph is a disjoint flat group structure visualization, which is, to the best of our knowledge, the first node glyph proposed for this category [VBW17]. The cluster glyph size is normalized and mapped to the number of nodes in the group. The maximum size (all movers) of the cluster glyph is five times the size of a single glyph. The outer-ring of the cluster glyph displays the abstracted links to all other glyphs. The inner-circle depicts the underlying spatio-temporal network of the group as an animated node-link diagram. We visualize the underlying group structure as an additional
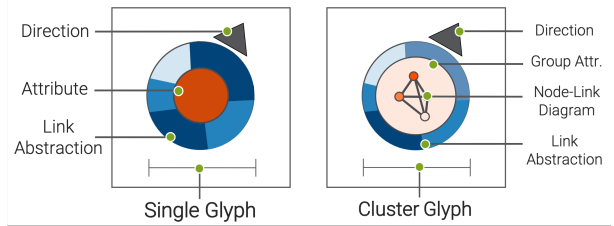

Figure 4: *Glyph for single movers (left) and for group of movers (right). The inner-circle display attributes (e.g., speed) and the outer-ring abstracted links to other movers.*

level of detail view for cluster interpretation to allow the exploration of the data at different scales (**R4**). The spatial centroid of the group defines the position of a cluster glyph. The inner-circle also enables to display average attributes of the group (e.g., average speed) as the background color of the inner-circle (**R2**). The node-link diagram in the center of the cluster glyph is also colored and encodes attribute information (e.g., speed) for the nodes and the links (weights) (**R2**). The color encoding in the cluster glyph allows comparing the group nodes with the average attribute values of the spatio-temporal group (**R4**). The cluster glyph also has an arrow, which indicates the average movement direction of the group (**R2**). By default, the prototype only uses the spatial positions for the spatio-temporal clustering [PFV*12] due to the preference of domain experts (**R1**). Domain experts can, furthermore, adapt, and explore the spatial scale of the clustering as we pre-compute the clustering with varying input parameters (**R4**).

4.2.1. Design Rationale

In the following, we describe our design rationales to facilitate transferability to other domains with similar tasks and requirements.

Why are we using a glyph visualization? The complexity of spatio-temporal networks poses a challenge for the visual exploration of group patterns in collective animal behavior. Typically, methods like clustering [AAB*10], which aggregate and abstract the nodes into meta-nodes, and edge-bundling techniques [LHT17], which display flow patterns in dense areas, are used to reduce the complexity of such data. In edge-bundling, the links between pairs of nodes are difficult to perceive [GZ14], and the artifacts produced by such methods often lead to misinterpretations [AAFW16]. Glyph-based visualizations depict multivariate data as visual objects to enable the discovery of patterns (e.g., anomalies, clusters) [BKC*13]. A glyph maps data characteristics to visual variables to provide a compact view of such multivariate records and to enable interpretation as well as comparison of the data records (e.g., star-glyph [FIB*14]). Recent approaches of Scheepens et al. [SVDWVW14] and Andrienko et al. [AAFW16] highlight how glyphs can be used to reduce visual clutter for scalable visualization of large datasets (e.g., through aggregation). Dunne and Shneiderman [DS13] also show how different glyphs can be used to improve network readability. Based on these methods, we decided together with domain experts to develop sketches and design a glyph [LD11] to reduce visual clutter and to highlight group structures in collective animal behavior.

Visual variables used: Multiple visual variables (e.g., size, color) can be used to design a glyph. We chose to keep the number of visual variables low to maximize the discriminatory factor between

such visual variables. We decided to use a circle for the single glyph design and to display the temporal dimension of the data using animation. We choose not to adapt the shape and size of the single glyph as such distortions modify the spatial positions of movers (nodes) and could be misinterpreted as physical sizes of movers. We also incorporated two other visual variables, an arrow for direction, and color the circle based on movement characteristics (e.g., speed). The visual variable color (hue) is selective and associative [Ber83]. These features are usually used in the visualization of movement data [SVDWVW14] and the application domain [LLEK10]. We use color and orientation as visual variables to draw attention to changes in these attributes [BKC*13]. We abstract and encode the links in an outer-ring of the glyph to summarize and highlight the relationship characteristics of a node (direction and weight). For the design choice of the outer-ring, we used the design space described by Andrienko et al. [AAFW16] and decided to use the combination of a circle and juxtaposition components (CJ flow diagram). A drawback of abstracting the links is that the detailed connection information (e.g., the distance between movers) is lost, which can be incorporated by using multiple outer-rings that also encode the distance to the target node (e.g., CJ glyph [AAFW16]). In collective animal behavior, however, showing multiple outer-rings is not useful as movers are usually uniformly distributed and retain similar distances to each other [Sum10, Chapter 2]. We chose to keep the complexity of the glyph low and only to display one ring.

Why is a cluster glyph useful? Based on the requirements **R3** and **R4**, we iteratively designed another glyph to allow domain experts to abstract movers into groups. The goal of the cluster glyph is to reduce the number of displayed glyphs, clutter in dense areas, and the cognitive load for the user. The cluster glyph, furthermore, summarize and presents the structural properties of the group, the segments of the nested glyphs, and displays internal links in such groups. We discussed with our collaborators the idea to aggregate, and show multiple single glyphs in the inner-circle of a bigger group glyph (nested design) and created a digital sketch as proposed by Lloyd and Dykes [LD11]. This first alternative cluster design (see Fig. 5), however, was complex as the nested glyphs were hardly readable and difficult to interpret since the segments of nested glyphs could be misinterpreted as links to movers outside of the group. Additionally, there is a minimal amount of space required to communicate color, which is not given in such a small-sized glyph [FFM*13]. We chose to show and animate a simple node-link diagram in the inner-circle of the glyph, which downsizes and displays all the movers of the cluster. For this, we map the spatial extent of the nodes in a cluster to the inner-circle of the cluster glyph. Using such a mapping, we retain the spatial distances between movers (**R1**). The node-link diagram also encodes additional attributes (e.g., speed) and link weight (**R2**). The directional arrows for the internal node-link diagram are not displayed, as they are barely readable after mapping the movers to a smaller scale.

Why do we use animation? We display data by animation, as this is the conventional method to display temporal data in the domain of collective animal behavior (e.g., in Rosenthal et al. [RTH*15]). Visualizing the data through animation remains challenging due to change blindness [SFR00] and our limited short-term memory [HE11]. We aim to overcome these challenges by reducing the number of nodes through clustering, and we highlight merges

or splits of movers in groups by coloring the single glyph (merge) or a node in a cluster glyph (split) pink (0.5 seconds). The goal of the highlighting is to help experts to maintain a mental map of the changes. The identification of such group changes, such as split, merge, and swappings between groups, remains challenging due to noisy real-world data and the animation speed.

How to interact with the glyph? To further facilitate the visual exploration of group patterns, MotionGlyphs enables a set of interactions. The glyph depicts the abstracted links during a mouseover to investigate the links of a specific node, which was suggested by domain experts in a free exploration of the prototype [LD11]. The prototype also enables filter links, limit the overall presented number of segments in the outer-ring, and modify the width (in degrees) of the displayed segments. The prototype implements a zoom and the option to adapt the spatial clustering scale using a slider (**R4**).

4.3. Design Alternatives

Many glyph visualization techniques for either spatio-temporal or network data have been proposed. A possible design alternative to simplify the spatio-temporal network is to apply motif simplifications [DS13]. The approach replaces motifs in the networks (e.g., fan and cliques) with glyphs (e.g., rhomboids or circles sectors). The primary problem of motif simplification for collective animal behavior is that the interpretation of such motif glyphs over time is difficult as the approach abstracts structural motifs (fan and parallel motif). The single glyph has a similar design as the proposed petal glyph [KAW*14], rose or sunburst diagrams [EST08, SM08, AAFW16] which are used to present origin-destination data [KAW*14]. The design space analysis by Andrienko et al. [AAFW16] for origin-destination data provided us with a structured way of thinking about the possibilities of abstracting links. The proposed variants of flow diagram designs examine different glyphs to reveal mobility trends between regions. The usage recommendation for the CJ glyph (circle and juxtaposition), which is similar to the single glyph design, is to highlight details for individual regions [AAFW16]. We discussed many alternative sketches and designs with domain experts to encode attributes as visual variables. For example, we explored different background colors, different hues, shapes, and the usage of small multiples. Through the usage of these digital sketches [LD11] we learned that the domain expert (biologists) prefer rather simple glyph designs to identify behaviorally similar movers. Two examples of such design alternatives for the encoding of the links can be seen in Fig. 5. Off-screen visualization techniques inspire the first alternative glyph in which the linked movers are mapped to circles in the outer ring. The design was inspired by the work of Farrugia et al. [FHQ11] in which they displayed ego-network neighborhoods in concentric circles, which are mapped to a time step. In contrast to a single glyph, the first design alternative animates and places the ego-network nodes based on the distance and the direction to the linked mover. The color of each node in the outer-ring encodes the weight of the abstracted link. The second design alternative extends the first alternative further and displays the whole ego-network with links. The two design alternatives allow displaying evolving ego-networks of movers in more detail. However, identifying changes and comparing values in the relatively small and complex outer-rings would have been difficult due to clutter resulting from the detailed information.
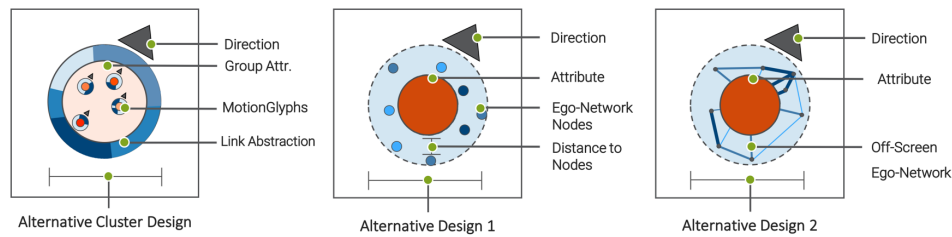
Figure 5: *The first design of the cluster glyph (left) and two alternative designs for single glyph (middle, right) which also enables to encode the distance information to other nodes and present the ego-network in an off-screen outer-ring.*

4.4. Design Process

We conducted contextual interviews to understand the data analysis workflow of our collaborators. During these interviews, our collaborators described examples of challenges as well as common features and methods (e.g., spatio-temporal clustering) used in the domain. We identified that the main focus of the domain is to verify a single hypothesis with statistical tools, with only a few tools to display spatio-temporal data (e.g., Animal Ecology Explorer [SBJ*11]). Standard network visualization tools (e.g., Gephi [BHJ09]), furthermore, have limited support for dynamic networks and do not support any abstraction methods over time. We did not find any specifically tailored visualization tools to present and analyze spatio-temporal data in the application domain. Afterward, we discussed potential abstractions methods and designs in the form of slides with our collaborators [LD11]. Based on the feedback we received, we implemented a prototype to visualize the spatio-temporal network by a first simple glyph design. In later iterations, we redesigned the cluster glyph based on the feedback we received and added more features (e.g., filter links) to the prototype. Finally, we conducted a user evaluation to understand how users perform real tasks.

5. Evaluation

To show the effectiveness and usability of the MotionGlyph system, we conducted audio-recorded interview sessions of 60-90 minutes with five expert participants. Before using the application, we interviewed the participants on their background, expectations for the application, and their impressions of the design. Then, the application was used during a screen-recorded pair analytics session [KF14]. After the pair analytics session, we reviewed the initial expectations in comparison to the actual tool.

5.1. Participants

All participants (P1-P5) are involved in researching the collective behavior of animals. None of the participants had used or seen the tool before entering the study. The gender distribution was four male and one female participant. The educational distribution was one master's student, three PhD researchers, and one postdoctoral researcher. Four of the five participants were between 20 and 30 years old, and one between 30 and 40.

5.2. Dataset and Tasks

To provide a realistic setting for the pair analytics session, we prepared a dataset of 151 golden shiner fish moving inside a tank. To facilitate the exploration of all application aspects, we provided the participants with a list of six tasks to be solved:
1. Introduction - Familiarize with all interactions using a test dataset

2. Temporal - Identify and analyze an interesting point in time
3. Spatial - Find an outlier fish and analyze its characteristics
4. Network - Find a group and analyze its characteristics
5. Find at least one meaningful single behavior pattern
6. Find at least one meaningful group behavior pattern

The first task aimed at exploring all facets and interactions of the application. Additionally, the participants were encouraged to compare the network and glyph view. All other tasks 2-6 should be conducted on the real-life dataset of 151 fish. The second task should encourage the exploration of the animation feature. The third task aimed at filtering the network connections and changing the features to get insights into one mover/glyph. The fourth question encouraged the use of the cluster glyphs at different granularity levels. Finally, task five and six aimed at interpreting the results of the visual analysis concerning real animal behavior.

5.3. Background and Domain Characteristics

Of the five participating experts, three had already worked with data on fish behavior, while two had only worked on insects and mammals. All five experts were familiar with the analysis of collective behavior, but only three focused explicitly on the movement of a collective. The main goals of data analysis were split between finding clusters (2), finding interactions of individuals (3), and finding differences between groups (2). The majority of experts solved their tasks by programming analyses (4). Some experts had used visual tools for exploring their data (3), while others had primarily used visualization to present the final analysis outcomes (3). The most critical variables for either analyzing the data were social interactions (5), movement metrics (2), and vision fields (2).

5.4. Expectations and First Impressions

The main goals for using an explorative visualization were the identification and extraction of essential data subsets (5), the interactive filtering of relevant information (3), and the comparison between different groups or subgroups of the cohort (3). Other aspects that were mentioned concerning confirmative visualization were aggregation/comparison of data subsets (2), prediction of behavior (2), and analysis of contextual influence (2). When first shown the design of the individual and cluster glyphs, all participants agreed that the design is clear and intuitive. Two questions that were raised were the interpretability of the glyph within the collective (2) and the possibility of extensions. Two critical interaction features were the adaptability of the view using zooming (3) and the adaptability of the glyph using self-defined parameters (3). Some of the participants stated that the design is similar to their current approaches at exploring the data (3).
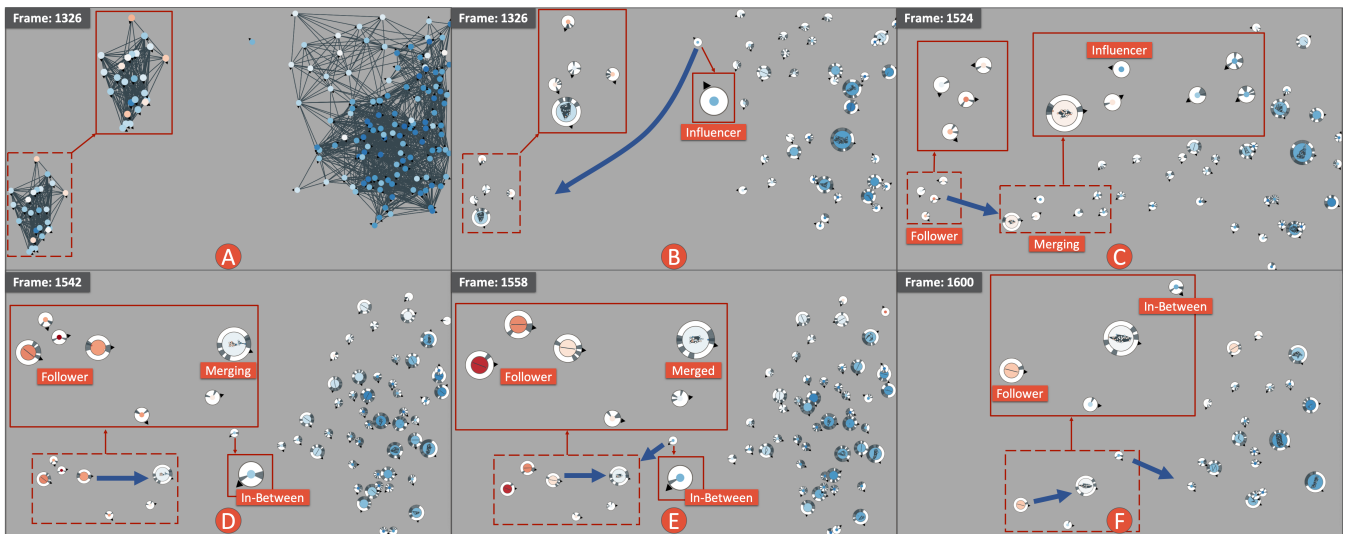
Figure 6: *The presented use case in Sec. 5.7 from the 151 golden shiner. The color of the glyph is mapped to the speed of movers. The time steps show how two groups merge initiated by an influencer fish. The example illustrates how the designed glyphs display relations between movers and group structures to identify patterns and generate new insight using the proposed glyphs.*

5.5. Pair Analytics Session

The relevant features that were discussed are the temporal representation via animation, the comparison between node-link and glyph representation, and the clustering of groups. The animation was seen as a central element of the analysis. To finetune the findings, the speed of animation should be adaptable (4). Furthermore, interesting movers or groups need to be followed during the animation (4) either by highlighting them or by centering them in a zoomed view. Finally, the details of an individual behavior need to be retrieved from the original video (4), which should be synchronized with the animation. Most participants agreed that the network is too confusing and overloaded with information (4). However, while some appreciate the glyph design as a clean solution (2), others were happy to include the edge information on hovering a glyph (2). Despite some differences in the overall acceptance of the glyphs, all participants agreed that the aggregation is helpful and necessary in large groups or dense areas of the network (5). One participant summarizes this nicely: "Even when proper filtering is applied, there is no way to see the interactions of a fish in the center [of a cluster]. Then the glyph is way better. [...] In high-density formations, the glyphs are awesome. In low-density formations, the network is much more important". The cluster glyph was helpful for the participants to identify the groups and outliers in their analysis.

Some improvements were suggested to increase the benefit of the cluster glyph. Due to the scaling of the internal cluster network within the cluster glyph, the spatial extent of the cluster was not easily visible in the overall dataset (3). The scale of clustering strengths should be adaptable (2). Finally, opinions diverged between too little or too much information on the representation of the internal cluster network, leading to a wish for further adaptability in both cases (2). The most common extension suggestion was an interactive parametrization of the links (4), distance metric (4), and their granularity (3). A second extension was the labeling or individuals, groups, and timestamps for tracking and comparison (4). Other wishes regarded the selection of sweet spots on each of the scales

via distribution and unit information (2), the scalability to long time sequences (2), and the display of exact values on hovering nodes in the network (2).

5.6. Expectation Review and Future Use

Overall the participants' experience with the application was positive. They were able to identify several interesting patterns. Most commonly, they could easily spot outliers (4), larger groups (3), and transitions in groupings (split or join) (3). Some participants went even deeper into the analysis and identified roles such as leader and follower (2), and behaviors, such as outlier groups joining the larger group (2), groups circling a center point (2), and groups following a formation (2). Regarding their projects, most participants saw the applicability of MotionGlyphs (4), and some were especially intrigued by the use of a simple web interface (2). However, all participants requested additional contextual information (5), such as 3D movement, in place motion, or geographical context, and some wanted to export the identified relevant subsets of data into statistical programs for retrieving their final results (2).

5.7. Use-Case

The selected use-case (see Fig. 6) highlights the merging process of two fish groups and shows how MotionGlyphs can be used to identify structural and temporal patterns. The use-case is adapted from a pair analytics session and shows the 151 Golden Shiner fish data (color mapped to speed). (A-B) display the same time moment as a node-link diagram (A) and as MotionGlyphs with clustering (B). The left group in (A) and (B) reveals how MotionGlyphs helps to reduce clutter and emphasizes movers with different behaviors (see left red box in (B)). Also in (B), there is an apparent mover (influencer) who is going to initiate the merging process of both groups. The influencer mover leads between (B-C) a subgroup from the main group (right) towards the smaller group (left). The merging process between the two groups is reflected by the movers being added into the left cluster glyph (see merging in (C-E)), which indicates that the

in-between subgroup of movers imitates the behavior from the left group. The merged group moves, afterward, towards the larger group on the right (see (E-F)). In (C-F), furthermore, a group of followers trying to catch up with the left cluster glyph is visible. The follower movers in (C-F) group accelerate, and some followers catch-up with the group and merge into the cluster glyph. However, in (F) still, two follower movers, as well as an outlier fish below, are visible, which did not yet manage to catch up and integrate into the merging cluster group. In (C-F), a fish in-between the groups is apparent, and the temporary influences onto the in-between mover are visible through the as abstracted links. The in-between fish moves in (D-E) towards the left group and adapts his behavior in (F) towards the direction of the right group. In Fig. 6 (F), the cluster granularity was also adjusted to aggregate the movers further into groups to reduce overlapping glyphs and presents higher-level patterns in the merging fish swarm.

The use-case shortly describes how MotionGlyphs can be utilized to analyze the temporal evolution of interactions and group structures in collective behavior. In the use-case, more patterns are visible (e.g., outlier movers), which allows further detailed analysis to understand the influences among the movers. Experts can perform such an investigation by tracking the movers or groups over time and examining the links between them.

5.8. Lessons Learned

Domain experts are used to testing hypotheses and applying familiar visualizations (e.g., heatmaps) for presenting statistical results. The interactive aggregation and disaggregation of data helps them to unveil behavior processes in space and time. Domain experts, however, need the original video in addition to the animation, as the individual behavioral traits of movers are also dependent on the posture and visual field of movers. The animation rate seems to influence the perceived patterns heavily and should, therefore, automatically adapt to a user-defined metric so that the animation plays faster for intervals in which the change is minimal. There was also an emphasis to include an export functionality for data subset to verify the identified pattern with statistical tools. This shows that visual exploration and statistical analysis are seen as complementary and require new methodologies combining both perspectives.

6. Limitations

The cornerstone of our design is the visual abstraction of spatio-temporal network links and group structures. The approach consists of the basic steps, (1) to define a spatio-temporal network based on a similarity metric, (2) the spatio-temporal clustering, and (3) the visual exploration using MotionGlyphs. There are multiple parameters to set for the steps (1-2), for example, choosing what features to use in the similarity metric and the range of spatial densities for the clustering. The meaningfulness of the network and the clustering, therefore, depends on the input parameters and the similarity metric (Euclidean or cosine distance) [RT14]. Many of these parameter choices have to be defined by a domain expert and depend on the data characteristics (e.g., tracking resolution). We consider the flexibility of computing different networks and clusterings an advantage of our approach and a possibility for future work to explore which similarity metric works best for particular patterns (e.g., following of a leader).

The choice of encoded attribute poses another challenge, as there are multiple alternative designs possible. The downside of the link abstraction is that the aggregated segments are harder to interpret and that minimal variations and changes in segments are hardly readable. In the application domain, however, such minimal variations result from noise, and the main focus of domain experts is rather to visually identify evolving structural properties (e.g., group changes). The identification of changes (e.g., movers frequently swapping between groups) in the evolving data poses a challenge and requires further visual support (e.g., temporal smoothing of the animation). The cluster glyph aims to reduce clutter and the number of displayed movers, however, the mapping results in a small visual space in which changes are difficult to interpret. Visual indicators such as highlighting changes (e.g., mover leaving a group) intend to point out evolving structural properties in the group. The cluster glyph placement (centroid of the group) distorts the positions of the individual movers and can create overlaps between groups and single movers. Such an overlap between a group and a single mover is an indicator that the single mover is a local outlier as the movement characteristics differ from the spatially related neighbors.

We consider two types of scalability: the network size and the number of time steps. The approach is robust to a larger group of movers (e.g., 800 movers) as the proposed glyph designs reduce the number of displayed network links. MotionGlyphs is, however, currently not fully able to cover datasets with different spatial distributions, which can be supported by applying other density-based clusterings (e.g., ST-OPTICS [AGSP16]). We also used agent-based models (e.g., Couzin et al. [CKJ*02]) to investigate the temporal scalability (6000 time steps) of the approach and identified that the current prototype scales up well to 25 million network links. The glyphs are less useful in the application domain if the number of movers and links is below a certain threshold as we rely on the visual abstraction of links as well as groups.

7. Conclusion

We present a design study for the visual exploration of spatio-temporal networks and group structures in collective animal behavior. The result of our iterative design process is a glyph that enables us to display a visual summary of dense spatio-temporal network data, which are typically hard to visualize. MotionGlyphs is iteratively designed by a series of discussions with our collaborators. We validate our design with an expert evaluation, which highlights how the design and prototype can be used to gain insights about the underlying evolving data. We learned that the glyph design is appropriate and can be extended for a range of potential analysis use cases (e.g., context analysis). Even though the application domain motivated the design of MotionGlyphs, the design is suitable to visualize any spatio-temporal networks. We plan to, furthermore, evaluate the designed glyph for similar analysis tasks (e.g., identification of network attacks) in other domains (e.g., network security). Finally, we also plan to combine a semantic zoom with a hierarchical clustering by modifying AGNES [KR90] to work with spatio-temporal data to split groups interactively during a semantic zoom into smaller subgroups and to adapt the proposed glyph to the size of the groups.

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