An Event-Based Conceptual Model for Context-Aware Movement Analysis

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Current tracking technologies enable collection of data describing movements of various kinds of objects, including people, animals, icebergs, vehicles, containers with goods, etc. Analysis of movement data is now a hot research topic. However, most of the suggested analysis methods deal with movement data alone. Little has been done to support the analysis of movement in its spatio-temporal context, which includes various spatial and temporal objects as well as diverse properties associated with spatial locations and time moments. Comprehensive analysis of movement requires detection and analysis of relations that occur between moving objects and elements of the context in the process of the movement. We suggest a conceptual model in which movement is considered as a combination of spatial events of diverse types and extents in space and time. Spatial and temporal relations occur between movement events and elements of the spatial and temporal contexts. The model gives a ground to a generic approach based on extraction of interesting events from trajectories and treating the events as independent objects. By means of a prototype implementation, we tested the approach on complex real data about movement of wild animals. The testing showed the validity of the approach.

Keywords: trajectories, movement data, movement behaviour, spatio-temporal context, relations, events, spatio-temporal data, spatio-temporal analysis, geovisualization

1 Introduction

Recent technological progress has enabled tracking of various moving objects and collection of data about the movement. In some domains, such as traffic management or tourism, movement data may be used to study general characteristics of mobility: space use, spatial and temporal variation of objects' presence, major flows, etc. In other domains, movement behaviours of individuals and/or groups are in focus. Examples are animal research, iceberg studies, and sports analysis.

It should be emphasized that movement behaviours can only be understood by considering various *relations* occurring between moving objects and the environment in which they move. The *environment*, also called *spatio-temporal context*, includes

- complex and heterogeneous physical *space*, in which characteristics vary from place to place and change over time,
- complex and heterogeneous physical *time*, in which day differs from night, summer from winter, and so on,
- static and dynamic *objects* existing in space, as well as
- *events* occurring over time.

Tomaszewski and MacEachren (2010) suggest a conceptual model that encompasses three aspects of context, spatial (geographical), temporal (historical), and conceptual. From these three, the spatial and temporal aspects are in the focus of our current research. Since many kinds of objects and phenomena are simultaneously spatial and temporal, we do not separate the spatial and temporal aspects but join them into a single concept of spatio-temporal context. This paper deals particularly with the spatio-temporal context of movement. For the sake of brevity, we shall sometimes use the single word "context" to refer to the spatio-temporal context.

Although extensive research on analyzing movement has been made in recent years, most of the existing methods and tools focus on movement data per se with little or no consideration of the spatio-temporal context. Our current research aims at finding ways to involve context information in analysis of movement data. We have developed a general approach based on treating occurrences of various relations between moving objects and elements of the context as spatial events, i.e., objects localized in space and time. These events are extracted from movement data and context data by means of computations and interactive filtering. Extracted events are then visualized and analyzed using suitable methods. As a proof of concept, we have done a prototype implementation of the approach and tested it on real-world datasets.

In the next section of the paper, we give an overview of the research on movement analysis and demonstrate that quite little has been done so far on joint analysis of movement data and context data. Next, we introduce the conceptual model underlying our approach and the approach itself. After a brief description of our prototype implementation, we show how the approach works by example of real data about movement of wild animals. This is followed by a discussion of the results and a conclusion.

2 State of the art

A cartographic map can convey to some extent the heterogeneity of the geographical space and various relations occurring within it (Andrienko et al. 2008). Hence, a visual representation of movement on a map enables a human analyst to see some of the relations between the movement and the spatial context. However, maps are weak in representing temporal information. The existing techniques and tools for the visualization and exploration of spatio-temporal data are reviewed by Andrienko et al. (2003). The most common approach to dealing with space and time together is map animation; however, its effectiveness is quite limited (Tversky et al. 2002). Another approach is the space-time cube, where the horizontal plane represents space and the vertical dimension represents time. The idea was introduced by T. Hägerstrand in the 1960s (Hägerstrand 1970) but software implementations appeared relatively recently (Kraak 2003, Andrienko et al. 2003, Kapler and Wright 2005). Both a map and a space-time cube are limited with respect to the number of trajectories that can be effectively explored, the length of the time period, and the capacity to represent various aspects of the movement context: when much information is included in a display, it becomes illegible due to the visual clutter.

As larger and larger collections of movement data become available, researchers work on devising computational analysis methods that could cope with these amounts. One of the possible approaches is data aggregation. A survey of the aggregation methods used for movement data is done by Andrienko and Andrienko (2010). To study the distribution of movement characteristics over space, movement data are aggregated into continuous density surfaces (e.g. Dykes and Mountain 2003, Willems et al. 2009) or discrete grids (e.g. Forer and Huisman 2000, Andrienko and Andrienko 2010). Mountain (2005) further processes density surfaces generated from movement data to extract their topological features: peaks, pits, ridges, saddles, and so on. Brillinger et al. (2004) aggregate movement data into a vector field using a regular grid: in each grid cell, a vector is built with the angle corresponding to the prevailing movement direction and the length and width proportional to the average speed and amount of movement, respectively. Wood and Dykes (2008) build spatially-ordered treemaps combining spatial, temporal, and attributive aggregation. To study links between places, movement data are aggregated into origin-destination matrices (Guo 2007) and flow maps (Tobler 1987, 2005, Andrienko and Andrienko 2011). Wood et al. (2010) suggest two-level spatial treemaps to represent flows among locations. The existing aggregation methods operate on movement data only, i.e., do not involve any data about the spatio-temporal context. Investigation of relations between the movement and the context is only supported by showing aggregated data on a cartographic background for visual inspection.

Various computational analysis techniques for movement data are developed in the area of data mining. Most of them deal with movement data alone and do not take the context into account. Extensive research is done around the concept of similarity of movement trajectories. A number of similarity measures and respective algorithms for computing the similarity have been proposed (Andrienko et al. 2007, Pelekis et al. 2007, Trajcevski et al. 2007). These measures and algorithms are used for querying trajectory databases (Vlachos et al. 2002, Pelekis et al. 2007) and for clustering trajectories (Gaffney and Smyth 1999, Li et al. 2004, Nanni and Pedreschi 2006, Rinzivillo et al. 2008). Another research direction is extracting particular types of movement patterns, such as frequent sequences of visited places and transition times between them (Giannotti et al. 2009).

There are relatively few methods for analyzing relations between moving objects and elements of the movement context. Crnovrsanin et al. (2009) visualize the dynamics of the distances of moving objects to selected locations. Lundblad et al. (2009) attach data about weather conditions to positions of ships and visualize the data on interactive linked displays. Yu (2006) computationally detects occurrences of three types of spatio-temporal relations among moving objects: co-location in space, co-location in time, and co-location in both space and time. Orellana et al. (2009)

detect and visualize occurrences of proximity between moving objects. Laube et al. (2005) propose methods for finding certain types of relative movements of several objects such as concurrence, opposition, dispersion, following, flocking, etc.

ArcGIS Tracking Analyst (ESRI 2010) is a commercially available tool for movement analysis allowing the user to visualize tracks of moving objects, modify the display by means of highlighting, filtering, and other operations, and create map animations. Nothing specific is suggested for analyzing movement in context; however, the user can employ the analytical functionality of the ArcGIS Desktop system, in particular, perform queries and computations on two or more map layers.

Hence, despite the existence of extensive literature and a large number of methods and tools for analyzing movement data, quite little research and development has been done so far concerning the analysis of movement in context. Furthermore, while there are a few methods for detection of certain types of relations (mostly relations of moving objects to other moving objects), no attempts have been made to support context-aware movement analysis in a more systematic and comprehensive way. Our research aims at filling this gap. The next two sections introduce the main concepts we deal with and explain our approach to supporting movement analysis.

The concept of spatial event plays a key role in our approach. Beard et al. (2008) review the definitions of events occurring in the literature and note that a common theme among them is that events are associated with change and localized in space and time. Our definition of spatial events includes only the spatial and temporal localizations as essential features; change is not a necessary part of the meaning.

3 Conceptual model

There are three fundamental sets pertinent to movement: space *S* (set of locations), time *T* (set of instants or intervals, jointly called time units), and objects *O* (Peuquet 1994, 2002). Elements of each set may have their properties, which can be represented by values of attributes. Among others, there may be attributes whose values are elements of *T*, *S*, or *O*, or more complex constructs involving elements of *T*, *S*, or *O*. Attributes that do not involve time or space will be called ‘thematic’.

The set of objects includes various physical and abstract entities. Objects can be classified according to their spatial and temporal properties. Table 1 contains the definitions and examples of the types of objects relevant to our work: *spatial object*, *temporal object*, also called *event*, *spatial event*, *static spatial object*, *moving object*, also called *mover*, and *moving event*.

Table 1: Types of objects according to their spatial and temporal properties

Concept	Superior concepts	Properties	Examples
Spatial object	Object	Has a certain position in space (a location or a set of locations, not necessarily continuous)	Building, village, river, rainfall, deer, lynx, a deer at a river, a lynx chasing a deer
Event (temporal object)	Object	Appears and/or disappears during the time period under analysis, i.e., has a certain position in time (a time unit or a sequence of time units)	Rainfall, a deer at a river, a lynx chasing a deer, sunset, winter

Spatial event (spatio-temporal object)	Spatial object, event	Has certain positions in space and in time	Rainfall, a deer at a river, a lynx chasing a deer
Static spatial object	Spatial object	The spatial position is constant; exists during the whole time period under analysis	Building, village, river
Mover (moving object)	Spatial object	The spatial position changes over time	Deer, lynx, a lynx chasing a deer
Moving event	Mover, event	Exists during a sequence of time units (i.e., not instant); the spatial position changes over time	A lynx chasing a deer

Changes of the spatial position of a mover over time can be represented by a mapping $T \rightarrow S$ (in mathematical terms, a *mapping*, or *function* from set P to set Q, denoted as $P \rightarrow Q$, is a correspondence between elements of P and Q such that for any $p \in P$ there is at most one $q \in Q$). A mapping $T \rightarrow S$ is called *trajectory*. A trajectory is an object having a certain position in space, which is the set of locations visited by the mover. Hence, a trajectory is a spatial object, by the definition given in Table 1. When the mover is considered as a point (i.e., the shape and size are ignored), the spatial position of the trajectory is a line in S. A trajectory may also have a certain position in time, which is the time interval when the positions of the mover were observed. This interval does not necessarily coincide with the whole time of the mover's existence. Hence, a trajectory, generally, is a spatial event, by the definition given in Table 1.

Furthermore, a trajectory $T \rightarrow S$ consists of pairs (t,s), $t \in T$, $s \in S$. Each pair has a particular position s in space and a particular position t in time; in our classification, it is a spatial event. Hence, a trajectory $T \rightarrow S$ is a complex spatial event consisting of a sequence of elementary spatial events (t,s).

Movers may also have thematic attributes, which may be static (i.e., values do not change over time) or dynamic. The values of a dynamic attribute, such as movement speed or direction, are mappings $T \rightarrow A$, where A is the set of possible values of the attribute, for example, [0,100] km/h for the speed and [0,360] degrees for the direction. The pairs (t,a) in $T \rightarrow A$ can also be considered as objects having temporal positions, i.e., as events, for example, speed events, direction events, etc.

Instead of dealing with the mappings $T \rightarrow S$ and $T \rightarrow A$ separately, one can consider their join $T \rightarrow S \times A$ consisting of triples (t,s,a). Hence, an occurrence of an attribute value a at time t has a corresponding spatial position s. More generally, when a mover has several dynamic thematic attributes $A_1, \ldots, A_n$, the temporal variation of the mover's position and thematic characteristics can be represented by a joint mapping $T \rightarrow S \times A_1 \times \ldots \times A_n$ consisting of tuples $(t,s,a_1,\ldots,a_n)$. We shall use the notation (t,s,a) as a compact form of $(t,s,a_1,\ldots,a_n)$, meaning that a may stand for a combination of values of several thematic attributes. Each tuple (t,s,a) is a spatial event.

A sequence of temporally consecutive events may be regarded as one larger event, which, in turn, may be included in a higher level event. One of the possible reasons for uniting consecutive events (t_1,s_1,a_1), (t_2,s_2,a_2), …, (t_k,s_k,a_k) into one event may be constancy of s ($s_1=s_2=\ldots= s_k$) and/or a ($a_1=a_2=\ldots= a_k$). We shall use the term *movement events* to refer to elementary and composite spatial events involved in the movement. We shall use of the notations (t,s) and (t,s,a) both for elementary and for composite movement events. This means that t may stand either for an element of T ($t \in T$) or for a continuous subset of T ($t \subset T$), i.e., a sequence of consecutive time units. In both cases, s is the set of spatial locations ($s \subset S$) and a is the set of attribute values ($a \subset A$, $A = A_1 \times \ldots \times A_n$) corresponding to t by the mapping $T \rightarrow S \times A$. The dependence of s and a on t may be emphasized by transforming (t,s,a) to $(t,s(t),a(t))$. To denote that movement event (t,s,a) belongs to moving object o, the notation (o,t,s,a) may be used.

Figure 1 schematically represents our view of movement as a collection of spatial events. This extends the conceptual model of movement as a combination of stops and moves suggested by Spaccapietra et al. (2008). In the latter model, stops are important parts of trajectories associated with domain-specific semantics while moves are merely transitions between consecutive stops. In our model, stops and moves are particular types of spatial events among other types. Any of the possible types of movement events may be important from the application point of view.

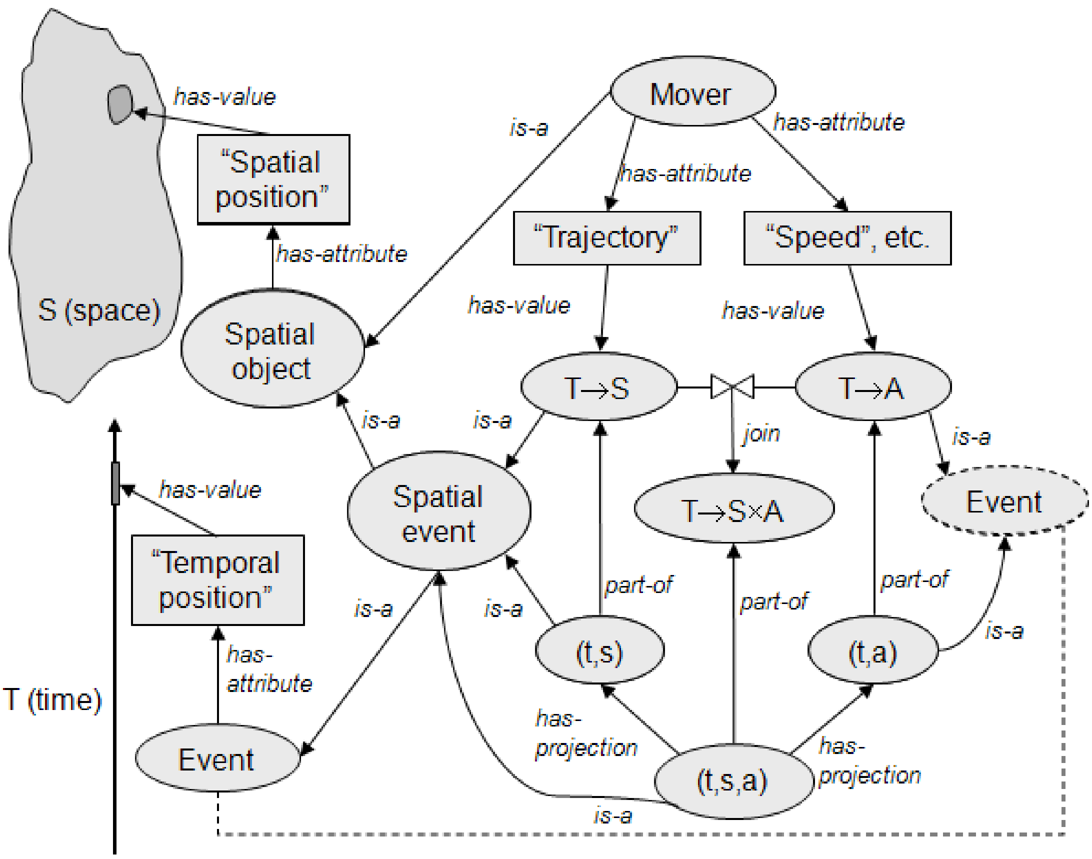

Figure 1: Movement as a composition of spatial events.

For a selected moving object o, the *spatio-temporal context C* consists of the space, time, and other objects positioned in the space and/or time: $C = S \cup T \cup O \setminus \{o\}$.

As we argued before, movement of an object consists of spatial events, called movement events. Each event is linked to elements and subsets of the context by relations. *Spatial relations* link movement events through their spatial positions to elements and subsets of S. Other spatial objects also have positions in S; hence, spatial relations link movement events to other spatial objects. *Temporal relations* link a movement event through its temporal position to elements and subsets of T. Other events also have positions in T; hence, temporal relations link movement events to other events. Figure 2 schematically represents the spatio-temporal context of object's movement and how the movement is related to the context.

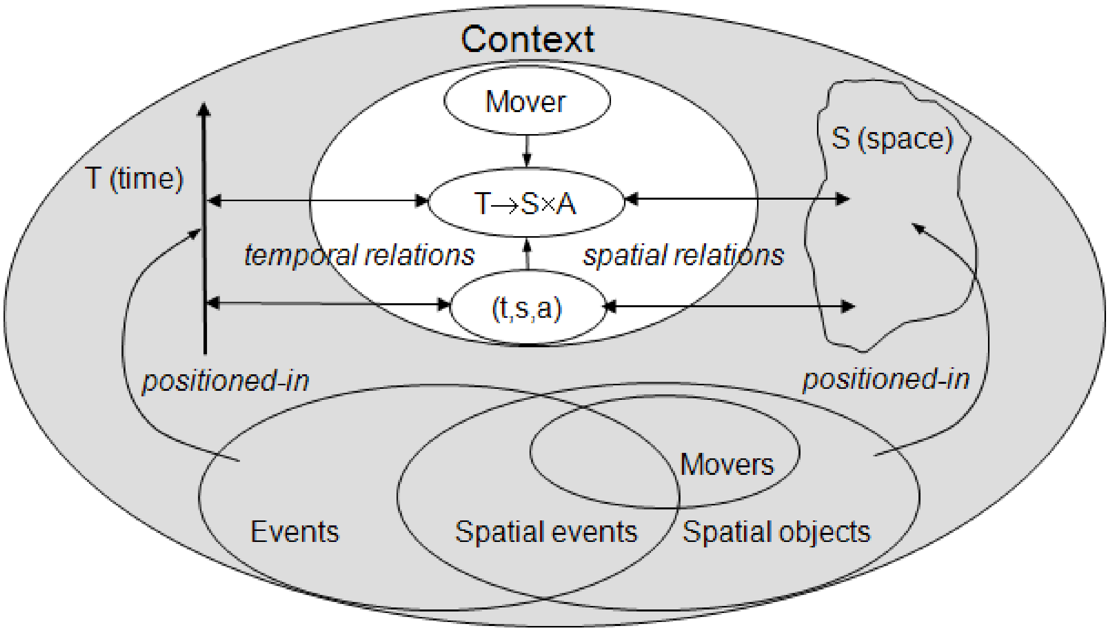

Figure 2: Spatio-temporal context of object's movement and relations between the mover and elements of the context.

The possible types of spatial and temporal relations are considered in the literature on temporal and spatial reasoning (e.g. Allen 1983, Egenhofer 1991, Frank 1992) and on geographic information systems (e.g. Jones 1997, Longley et al. 1999). The basic types of temporal relations include binary topological, ordering, and distance relations. The basic types of spatial relations include binary topological, directional, and distance relations. Topological and ordering relations are formally represented by predicates, i.e., boolean-valued functions $P \times Q \rightarrow \{\text{true,false}\}$. Distance relations can be represented by numeric-valued functions $P \times Q \rightarrow [0,\infty]$ expressing spatial or temporal distances in suitable units, e.g. metres or seconds. Directional spatial relations can be represented by a numeric function representing the spatial direction, e.g. in degrees. Directional and distance relations can also be represented qualitatively, i.e., by predicates such as "near", "far", "north", etc. (Frank 1992). In fact, any such predicate stands, explicitly or implicitly, for a certain range of values of a numeric function. Reciprocally, for any range (or, more generally, subset) of values of a numeric function, one may introduce a predicate. Hence, we assume that distance and direction relations can always be represented by a set of predicates defined according to the specifics of the application domain and the goals of the analysis.

From the basic types of relations, more complex types of relations are built such as density (clustering, dispersion), arrangement (e.g. sequence in time or alignment in space), and spatio-temporal relations. The latter are composed of spatial and temporal relations and represent changes of spatial relations over time: approaching or going away, entering or exiting, following, keeping distance, concentrating or dissipating, etc. Some researchers call such relations "movement patterns" (Dodge et al. 2008) or "interactions" (Orellana and Renso 2010).

Let a movement event m be linked to some element or subset c of the context by relation R, which means that $R(m,c)$=true. For example, the spatial position of a deer in some time unit is at a river. Here, the deer is the mover, the combination of the time unit and the respective spatial position is the movement event, the river is an element of the context, and "at" is a type of spatial relation. A combination (m,c,R) where $R(m,c)$=true is called an *instance*, or *occurrence* of the relation type R.

Movement data are records associating movers with respective trajectories and, possibly, values of thematic attributes. Most often, movement data have the form (object identifier, time reference, spatial coordinates, attribute values). Movement data available in other forms can be transformed to this form. *Context data* describing the spatio-temporal context of the movement may have diverse forms depending on the nature of the respective context elements. For example, geographical datasets may describe the spatial context. Movement data containing trajectories of multiple objects describe simultaneously the movement of each object and a part of its context consisting of the movements of the other objects. Context data may also be implicit, i.e., exist in the mind of an analyst. For example, there may be no dataset describing which time of the day is light and which is dark, but analysts may use their professional knowledge or common sense.

4 General approach

Context-aware analysis of movement implies consideration of relations between object's movement and the context. The number of instances of various spatial, temporal, and spatio-temporal relations between movement events and the context is infinite; it is impossible to consider them all. Usually, not all instances are interesting to analysts, i.e., relevant to analysis goals. Analysts need tools that support finding interesting instances among all possible (*m*,*c*,*R*). A set of potentially interesting instances may be defined by imposing constraints on *m*, *c*, and/or *R*. Based on which elements of the triad (*m*,*c*,*R*) are given (constrained) and which of them needs to be found, we distinguish three types of tasks. They can be symbolically represented by formulas (*?*,*c*,*R*), (*m*,*?*,*R*), and (*m*,*c*,*?*), where the question mark stands for the unknown element. In Table 2 we give text interpretations to these formulas, suggest the kinds of tools and techniques that can support the tasks, and provide examples.

Table 2: Types of queries about relations between movement and context

Task	Interpretation	Support	Examples
(*?*,*c*,*R*)	Find movement events (parts of trajectories) that have relation *R* to context element(s) *c*.	Extraction of movement events from trajectories: for each *m*=(*t*,*s*) compute predicate *R*(*m*,*c*); extract such *m* that *R*(*m*,*c*)=true. <u>Note</u>: the extracted events make a part of the spatio-temporal context	Extract the parts of deer's trajectories in open areas. Extract the parts of deer's trajectories in 6 hours after the events of deer's proximity to lynxes.
(*m*,*?*,*R*)	Find context elements that have relation *R* to movement event(s) *m*.	Visualization of the events and the context; aggregation of events by context elements they are related to.	Find in what spatial context the events of deer's proximity to lynxes occurred. Find in what temporal context the deer appeared in open areas.
(*m*,*c*,*?*)	Find relations that exist between movement event(s) *m* and context	Visualization of the events and the context; queries (filtering) to select the context elements of interest.	How are the events of deer's proximity to lynxes located in space in relation to the open areas? When did the events of deer's appearance in open

	element(s) *c*		areas occur in relation to the sunrise and sunset times?

The tasks (*m*,*?*,*R*) and (*m*,*c*,*?*) imply that movement events *m* have been previously extracted from movers' trajectories. In particular, extracted movement events may be a result of the task (*?*,*c*,*R*). As suggested in Table 2, the task is supported by a tool that extracts parts of trajectories having relation *R* to context elements *c*. However, not only such events may be interesting to analysts. Analysts should also be able to extract movement events according to values of dynamic thematic attributes, for example, events of low speed, northward movement, etc.

Hence, we suggest a *general approach* to context-aware movement analysis based on extraction of interesting events from trajectories:

- Interactive query tools allow the analyst to define what movement events are of interest in terms of relations to elements of the context and/or in terms of values of dynamic thematic attributes.
- The events are extracted from the trajectories and added to the database as new objects. In the following analysis, they may be treated as elements of the spatio-temporal context for other movement events.
- The extracted events are visualized together with their context on spatial, temporal, and spatio-temporal displays.
- The extracted events are analyzed using spatial and temporal queries, aggregation, clustering, and other analytical techniques suitable for spatial events as data type.

Orellana and Renso (2010) have recently suggested an approach based on representing movement data as a collection of interactions with the context (the term "interaction" corresponds to "relation" in our paper). The main idea is to define possible types of interactions in a knowledge base (ontology) and use automatic inference to extract interaction instances from specially prepared data. As the authors admit, populating the ontology with data is a difficult task requiring further research.

5 Prototype implementation

As a proof of the concept, we have implemented this general approach within a geospatial visual analytics system for interactive exploration and analysis of diverse types of spatial and spatio-temporal data. Describing the entire system is out of scope of the paper. We focus on the tools used for the extraction of interesting movement events from trajectories.

5.1 Basic visualization and interaction tools

The basic visualization tools available in the system include cartographic map display and space-time cube. In both displays, trajectories of movers are represented by lines. Spatial events can be represented by points, lines, or areas, depending on their spatial extent. Events extracted from movement data are represented by singular points or multi-points (i.e., several points represent one event). In addition to map and space-time cube, diverse non-cartographic displays can be created, including scatterplots, parallel coordinate plots, frequency histograms, time graphs, and others.

A set of interactive tools for data filtering allows the user to select portions of movement data and/or context data to be visualized and analyzed. A *temporal filter* limits the temporal scope of the data. A *spatial filter* selects spatial objects fitting in a user-defined area, e.g. bounding rectangle. An *attribute filter* selects objects according to values of thematic attributes. A *class-based filter* selects classes or clusters of objects. An *object filter* allows the user to directly select specific objects. Several filters are combined by the logical operation AND. All visual displays dynamically react to changes of the filter conditions made by the user. The filters also affect the extraction of events from trajectories: only the data satisfying the filters are used.

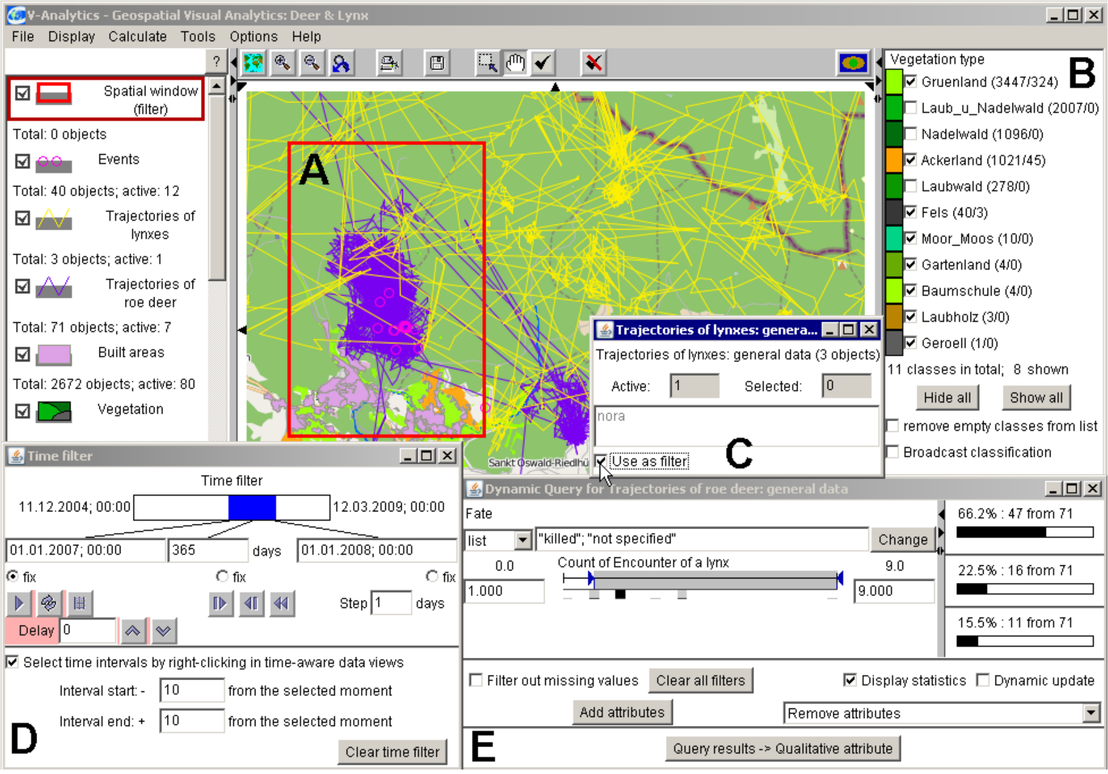

Figure 3: Interactive data filters. A) Spatial window. B) Class-based filter. C) Object filter. D) Temporal filter. E) Attribute filter.

Each kind of filter has its specific user interface, as illustrated in Figure 3. To set a spatial filter, the user draws a rectangle in the map display (A). A class-based filter is controlled through a list of classes with checkboxes (B), which are activated or inactivated by the user. For an object filter, a list of object names is provided. The user selects one or more list items and activates the checkbox “Use as filter” (C). The user interface of the temporal filter (D) includes a time slider (blue bar) manipulated by mouse dragging, which moves the whole bar or its left or right end. There are also text fields for entering the exact start and/or end times of the chosen interval or the desired interval duration. The latter can be specified in user-preferred time units, from seconds to years. To choose the time unit, the user clicks on the label denoting current unit and receives a list of possible units for selection. Time intervals for the temporal filter can also be selected by clicking on graphical elements representing temporal objects in spatial and temporal displays, for example, on points of trajectories in a map. The times corresponding to these elements are used as reference times for setting the filter. In the time filter window (D), the user specifies the relative positions of the start and end of the selected interval with respect to the reference time. For the relative positions, the same time units are used as for the length of the time interval. In the user interface of an attribute filter (E), conditions for numeric attributes are specified by entering the desired minimum and/or maximum values in text fields or by dragging sliders (blue triangles). For non-numeric attributes, the user may either select one or more of the existing values from a list, or enter the values of interest in the text field, or specify a substring that must be contained in attribute values.

The specific interactive query tools used for event extraction from trajectories are described in the following sections.

5.2 Temporal view of trajectories

Temporal view of trajectories is a visual display used in one of two modes: *time graph* and *time bars*. In both modes, the horizontal dimension of the display represents time. In the time graph mode, the vertical dimension represents the value range of some time-dependent numeric variable, which may be one of the following:

- Spatial distances: to specific trajectory points (start, end, midpoint, or any other computationally extracted point), to selected locations, to selected spatial objects (static objects, movers, or events);
- Temporal distances: to the trajectory start or end, to values of a temporal attribute (i.e., an attribute whose values are time moments), to selected events;
- Dynamic thematic attributes: any attribute available in the movement data; attributes derivable from positions: speed, direction, distance travelled from the beginning of the movement, remaining trip length, distance travelled in time intervals of specified length, etc.

Each trajectory is represented by a polygonal line (Figure 4) reflecting the temporal variation of the values of the variable. This is similar to the visualization suggested by Crnovrsanin et al. (2009); however, our display is not limited to showing distances to selected locations. The display includes controls for choosing the variable to be currently visualized. If the values are not available in the original data, they are immediately computed, and the display is updated. A detailed description of the contents of Figures 4 and 5 is given in section 6.2.1.

A disadvantage of the time graph view is overplotting of the lines. The time bar view (Figure 5) removes the overplotting at the cost of precision in representing the numbers. In this mode, which is a variation of the Gantt chart technique, trajectories are represented by horizontal bars positioned one below another, i.e., the vertical dimension does not convey any meaning but is used for arranging display elements. The horizontal positions and the lengths of the bars correspond to the temporal positions and durations of the respective trajectories. Values of the currently selected variable are represented by colours of bar segments. For this purpose, the value range of the variable is interactively divided into intervals. Each interval gets its colour according to one of the Color Brewer colour scales (Harrower and Brewer 2003). Colourless segments correspond to intervals of data absence. A similarity to the approach taken by Laube et al. (2005) and Kincaid and Lam (2006) can be noted; however, our visualization is suited to different life times of the trajectories and to temporally irregular data. We do not assume that values for different objects refer to the same regularly spaced time moments or intervals.

When the user moves the mouse cursor over the temporal view, the respective temporal position is marked by a vertical line. The same temporal position is simultaneously marked in all instances of the temporal view that are currently present on the screen. When the mouse cursor points on a display element representing a trajectory, the spatial position corresponding to this temporal position is marked in the map display by a cross-shaped cursor and in the space-time cube by a vertical line (this can be seen in Figure 8). The time and the corresponding value are shown by text on the top of the temporal view. Additionally, a popup window displays general information about the trajectory.

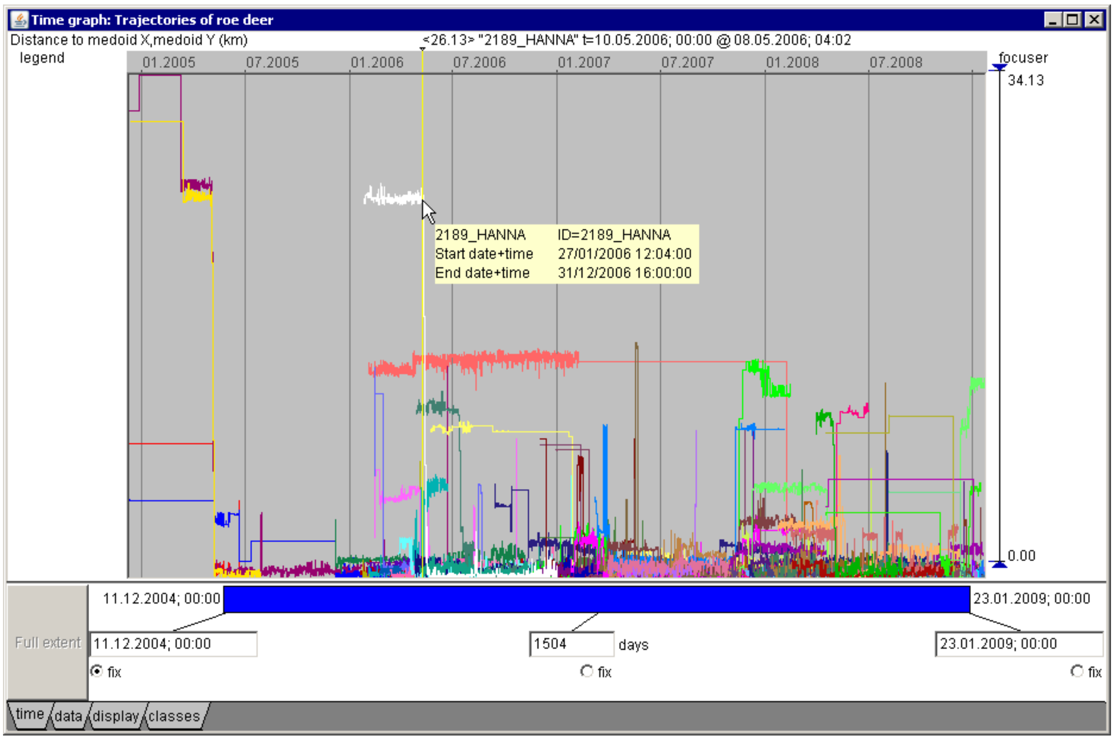

Figure 4: The time graph mode of the temporal view of trajectories.

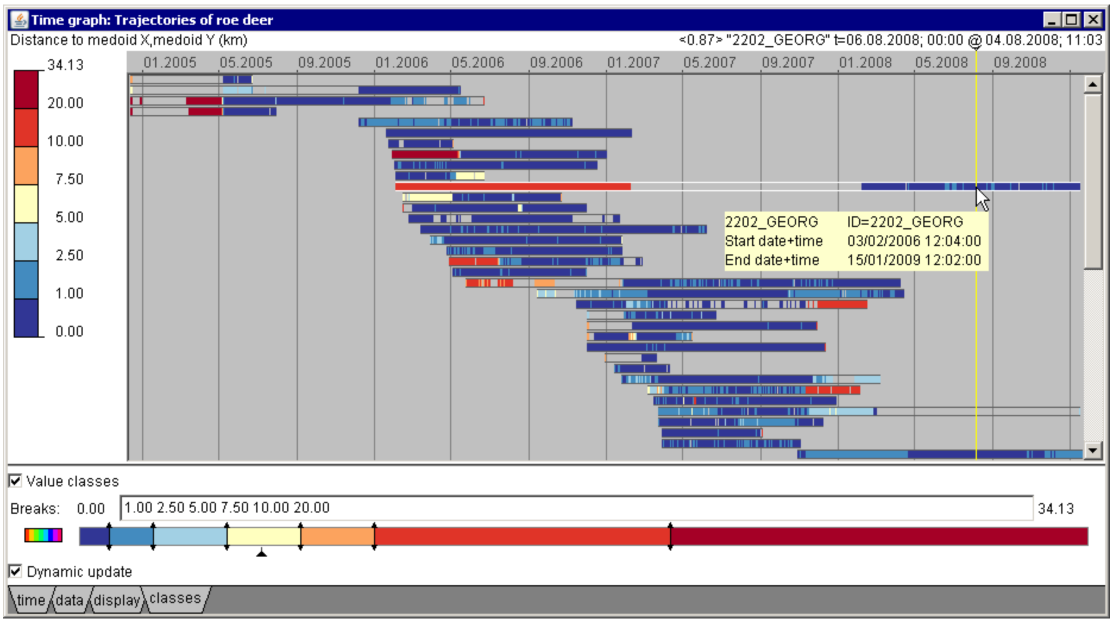

Figure 5: The time bar mode of the temporal view of trajectories.

5.3 *Event extraction*

Our interactive query tool for event extraction works in two stages. The first stage is filtering: only the parts of the trajectories that satisfy the query conditions are shown in the visual displays. This specific filter for trajectories is called *segment filter*. The user can preview the events that will be extracted according to the current query and decide whether to proceed with the extraction or to change the query conditions. The second stage, which occurs upon pressing a special button, creates a new dataset consisting of the extracted events.

The user interface of the segment filter is embedded in the temporal view of trajectories: this is the colour legend on the left of the plot area (Figure 5). Clicking on the coloured rectangles unselects and selects the respective value intervals, which sets query conditions on the values of the currently visualized variable. Hence, the user may define which movement events are of interest either in terms of distances to elements of the context or in terms of dynamic thematic attributes. The user can open several temporal views showing different variables and set two or more segment filters simultaneously. This operation is called *cross-filtering* (Weaver 2010). The filters are combined by the logical operation AND. For example, cross-filtering may find the appearances of deer in open areas within 6 hours after encountering lynxes.

It can be noted that the segment filter is limited concerning the types of spatial and temporal relations that can be used in query conditions. The tool allows the user to define arbitrary predicates on the basis of spatial and temporal distances; however, predicates in terms of topological and directional relations are not directly supported. These limitations are not pertinent to the approach in general but refer only to the current version of our prototype tool, which, in principle, can be extended to other types of relations. However, as will be shown by example, queries by spatial and temporal distance relations are sufficient for rather sophisticated analyses.

Our prototype implementation is oriented to a discrete model of the movement context, i.e., the context is represented as a combination of discrete spatial, temporal, and spatio-temporal objects with their attributes. Another possibility is to consider the context as a spatio-temporal continuum, in which properties vary from location to location. This view is appropriate for spatially and temporally continuous phenomena, such as weather. In the continuous data model, the continuum is divided into compartments by means of a grid, and the properties are represented by attribute values associated with the grid cells. Our approach can be applied to a continuous representation of the context in the following way. Each position of a trajectory is located in a certain cell of the space-time continuum. The attribute values from the cell are attached to this position; hence, the movement data are enriched with additional attributes representing the context. These context attributes are visualized in the temporal view of trajectories. By applying the segment filter, movement events co-occurring with selected attribute values of interest are extracted, for example, movements during harsh weather conditions.

5.4 Extraction of event-related statistics

Using the temporal view of trajectories, the analyst may obtain statistics of the values of the currently visualized variable for specified time intervals around selected events. The statistics include the minimum, maximum, median, mean, and standard deviation of the values. These are attached to the events as new thematic attributes, which allows the analyst to investigate the impact of the events on the movement.

For getting event-related statistics, the user selects the dataset with the events and specifies the starts and ends of the time intervals of interest in relation to the start or end times of the events, for example, from 6 hours before the event start till 12 hours after the event end. When the events have references to trajectories among their thematic attributes, the user may request that the statistics for each event are extracted only from the relevant trajectory. In particular, movement events previously extracted from trajectories always have references to these trajectories. The other available options are to extract event-related statistics from all trajectories or from the parts of trajectories being within a chosen range of spatial distances from the events.

6 Example scenario of movement analysis

6.1 Example dataset

The dataset we use for our example scenario was collected by GPS-tracking of 72 roe deer and 3 lynxes in the Bavarian Forest National Park (Bayerischer Wald) in Germany. The animals wear special collars with devices that measure the positions at chosen time intervals and transmit the measurements via radio networks (Bavarian Forest 2010). Unfortunately, the amounts of data that can be collected are strongly limited by the battery lives of the tracking devices. Thus, a collar suitable for roe deer can collect about 3500 positions and a collar suitable for lynxes about 1200 positions. In order to track animals over longer time, the researchers increase the time intervals between the position measurements. Therefore, the collected records are quite sparse in time. Furthermore, transmitted measurements are often lost; hence, the time intervals between the records may be irregular, and large temporal gaps may occur.

These problems are typical for data obtained by tracking wild animals. Many of the existing methods for movement data analysis assume regular sampling of position records and, moreover, high sampling frequency, which allows interpolation between known positions. Such methods would not be applicable to animal tracking data. Our methods based on event extraction do not assume temporal regularity and/or high temporal frequency of the position records. However, in applying these methods, it should be borne in mind that an extracted set of events of a certain type does not necessarily include all events of this type that might have occurred in reality. The analyst should treat any extracted set of events as a sample of real events.

The Bavarian Forest dataset contains 90571 position records for the roe deer and 2604 for the lynxes within the period from 11/12/2004 to 21/01/2009. The time spans of the data about individual animals vary from 5 to 1077 days. The time intervals between the position records vary from a few minutes to several months; the median interval length is about 5 hours for the roe deer. For the three lynxes, the time intervals are about 12 hours, 45 minutes, and 24 hours.

The analysis has been done in cooperation with the domain experts from the Bavarian Forest national park, who provided their interpretations of the findings.

6.2 Analyzing relations to spatial locations

6.2.1 Preferred places

Visualization of the trajectories of the animals on a map display and in a space-time cube gives us an initial insight about their movement behaviours in relation to the space. We see that the roe deer mostly make small movements within spatially limited areas and very seldom travel to more distant places. The lynxes move much more actively over wide territories.

The next questions are how far the roe deer can travel from their habitual places and when and how often this happens. We compute the medoid of each trajectory, i.e., the point with the smallest sum of distances to all other points. It can be expected that the medoid is located in the place of concentration of the trajectory points or in one of such places, if there are more than one. We use the temporal view of trajectories to visualize the spatial distances of the trajectory points to the respective medoids (Figures 4 and 5). The time graph in Figure 4 shows that the typical pattern of value variation is small fluctuations reflecting small moves within limited areas. Long vertical lines indicate travels on large distances. The lines look vertical because the horizontal dimension of the display represents a very long time period (1504 days). An interval of several days, during which a long travel is made, is represented by just one or two pixels. When temporal zooming is applied, the lines representing the long trips do not look straight vertical any more. The horizontal lines correspond to temporal gaps in the data. In the time bar mode (Figure 5), the gaps appear as colourless segments. As can be seen, such cases are quite numerous.

Figure 4 shows us that the largest distance of a roe deer from the trajectory medoid, which represents the most habitual place, was 34.14km, but only a few animals made long travels. In Figure 5, we see that a great part of the roe deer never moved for more than 2.5km from their habitual places. The bars representing the trajectories that include long travels (more than 7.5km) are distinguished by orange- and red-coloured segments. The times of the distant travels can be ascertained by mouse-pointing. Unfortunately, we cannot get reliable temporal information about the travels in the cases of long time gaps between the position records. For the remaining cases, we found out that five travels were in May, four in November, two in December, and one in July. We can conclude that the roe deer tend to change their places before summer and before or in the beginning of winter.

Domain expert's comment: This corresponds to two types of migration of roe deer: (1) migration after leaving the mother's territory, as in the case highlighted in Figure 4; (2) winter migration when animals come to valleys with less snow cover.

6.2.2 Locations with specific properties

The next analysis task is to investigate the relations of the roe deer to open areas, i.e., not covered by forest. This is the case when movement data need to be combined with context data. We use a dataset (map layer) with vegetation types. Applying the attribute filter to it, we select non-forest areas. We use the interface of the temporal view to compute and visualize the spatial distances to the selected areas (for each trajectory point, the nearest area is found). We observe that many roe deer appeared quite often in the open areas whereas some roe deer almost never did this (of course, this refers only to the areas that are defined in the available vegetation data).

We set the segment filter to the value 0 (interval from 0 to 0) and commit the event extraction query. As a result, we obtain a dataset with 16537 open area events represented as a new layer in the map display. We can now apply various analytical tools available in the system, such as spatial clustering. Figure 6 shows a map fragment where the spatial clusters are represented by colouring of the circle symbols representing the events. The symbols are drawn with 20% opacity. One of the visible clusters is located in a valley of a river (bright purple cluster in the centre of the map fragment) while the others are near villages or farms or other places of human activities. It is striking that the animals seem to have no fear of entering such places.

Domain expert's comment: Roe deer would probably not go into a village because they are afraid of people. But they might go for feeding to open areas like fields or meadows that surround villages.

Our hypothesis is that roe deer may tend to appear in open areas in dark times. To see how the open area events are distributed over times of the day, we use spatio-temporal aggregation: for each spatial cluster, the system counts the events by hourly intervals of the day. The yellow-coloured diagrams in Figure 6 show the variation of the event counts over a day in each cluster. The horizontal dimension of the diagrams represents hours of the day from 0 to 23 and the vertical dimension shows the event counts. It can be seen that much more events occurred in the early morning and night hours than in the middle of the day. Note that the cluster located at a river does not have so big differences in the number of events between the night and day hours.

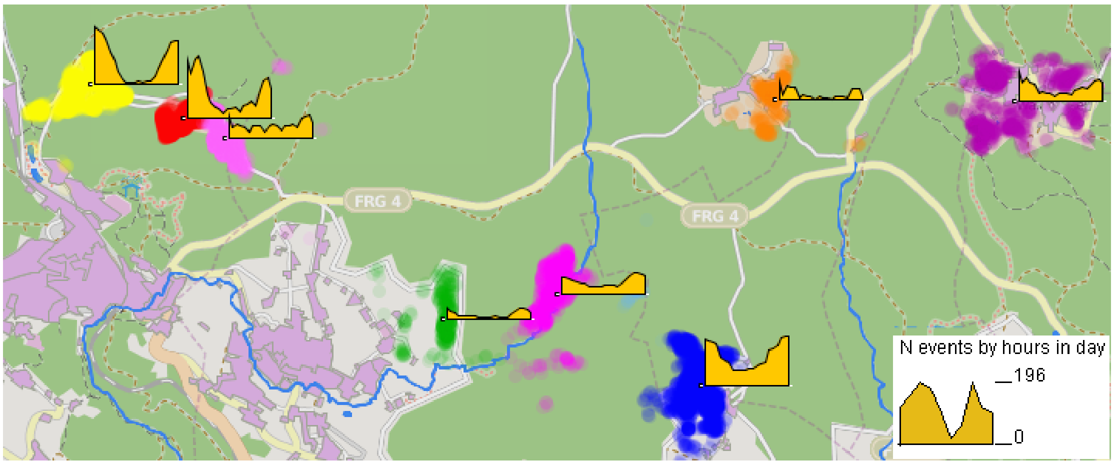

Figure 6: A fragment of the map showing the spatial clusters of the open area events and diagrams representing the variation of the event number by the hours of the day.

Since the same time of the day may be dark in the winter but light in the summer, it is reasonable to look whether the times of the open area events vary over a year. We are particularly interested when the roe deer appear in the areas near the places of human activities. Using one more dataset with context data, namely, a dataset describing built areas (the areas are shown in Figure 6 as polygons filled in light pink), we select those open area events that occurred in 50m or less from the nearest built area. There are 3707 such events. We visualize the frequencies of the events by the hours of the day and the months of the year in a two-dimensional histogram as shown in Figure 7. The horizontal axis corresponds to the hours of the day from 0 to 23 and the vertical axis to the months of the year from 1 (January) to 12 (December). The frequencies of the events are represented by the circles with the areas proportional to the values. The maximal circle size corresponds to 75 events.

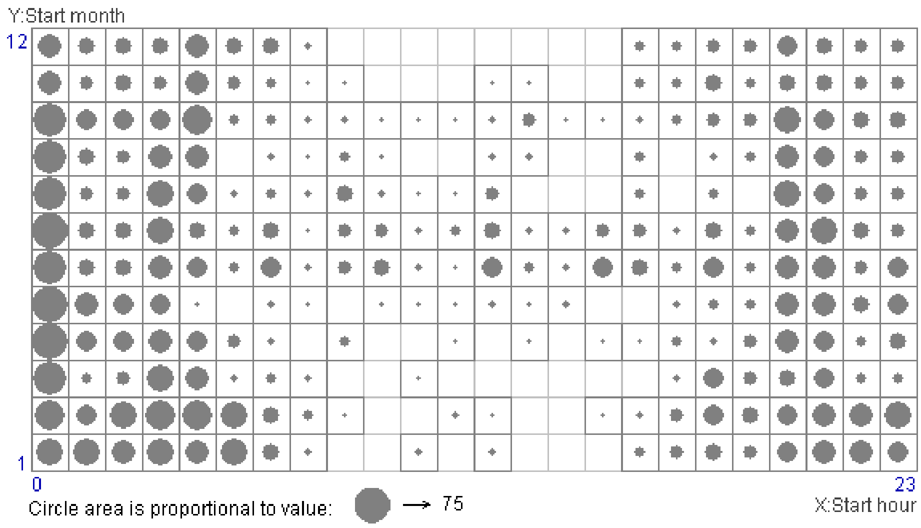

Figure 7: The open area events that occurred in 50m or less from built areas are grouped by the hours of the day (X-axis) and the months of the year (Y-axis). The event frequencies are represented by the sizes of the circles.

The histogram shows us that the event frequencies are higher in all months in early and late hours of the day. However, the intervals of decreased event frequencies start later and end earlier in the winter and late autumn months (1-2 and 11-12) than in the spring and summer months. Generally, we can conclude that the roe deer tend to appear in open areas near villages in dark hours, depending on the season. However, we notice that the event frequencies in the day time are somewhat higher in June and July and, to a lesser degree, in August (months 6-8) than in the other months.

Domain expert’s comment: This is explainable by the roe deer biology. First, female animals have a high energy demand after giving birth (between mid-May and mid-June), so they tend to go for browse in the meadows around villages also in the day. Second, roe deer have their rutting period in July-August and also tend to be more active in the day.

Another interesting observation is that event frequencies get lower in the hours 1-2 and 22-23 compared to the hours before and after that.

Domain expert’s comment: Roe deer feed throughout the 24 hours, but long periods may be spent “lying up” between feeding bouts.

We also extracted the events of appearing in the open areas around the villages from the trajectories of the lynxes. There were only two such events; both occurred when it was dark. Hence, the data tell us that the lynxes tend to avoid open areas close to people but may occasionally enter such areas in dark time.

6.3 Analyzing relations among movers

We have data about two types of movers, roe deer and lynxes. The former are a prey for the latter. Our next task is to detect and investigate their probable encounters, keeping in mind that the data refer only to small samples of the populations of roe deer and lynxes inhabiting the forest.

Among the variables that can be computed and represented in the temporal view is the spatial distance to selected trajectories. We are interested in the distances from the trajectories of the roe deer to the trajectories of the lynxes. For computing the distances, we need to specify the temporal tolerance, i.e., the maximum distance in time between points from two trajectories when it is still meaningful to compute the spatial distance. The temporal tolerance is needed for dealing with data where positions of different movers are measured at diverse time moments and the time intervals between the measurements are unequal.

We choose the temporal tolerance of one hour, taking into account that the data are sparse in time. The computations are done in two temporal views, one for the roe deer (distances to the lynxes) and the other for the lynxes (distances to the roe deer). We set the segment filters in both views to the value interval from 0 to 1km and commit event extraction. Thereby, we extract 39 events of spatial proximity to lynxes from the trajectories of the roe deer and 26 events of spatial proximity to roe deer from the trajectories of the lynxes. Apparently, in some cases a lynx approached a group of two or more roe deer. The events of proximity to lynxes occurred in the trajectories of 16 roe deer, and the events of proximity to roe deer occurred in the trajectory of one lynx, named Nora.

Figure 8 illustrates the events that we have extracted. At the bottom, there are two temporal views representing the trajectories of the lynxes (upper display) and the roe deer (lower display). The upper display shows the distances of the lynxes to the nearest roe deer and the lower display shows the distances of the roe deer to the nearest lynxes. In both displays, the segment filters select the trajectory segments with the distances up to 1km. The map (upper left) and the space-time cube (upper right) show the extracted proximity events. The yellow circles represent the events of the roe deer and the pink circles – the events of the lynxes. The mouse cursor is positioned on one of the segments in the temporal view of the trajectories of the roe deer. The corresponding temporal position is marked in the two temporal views by yellow vertical lines. The corresponding spatial position is marked in the map by the intersection of the black horizontal and vertical lines and in the space-time cube by the red vertical line.

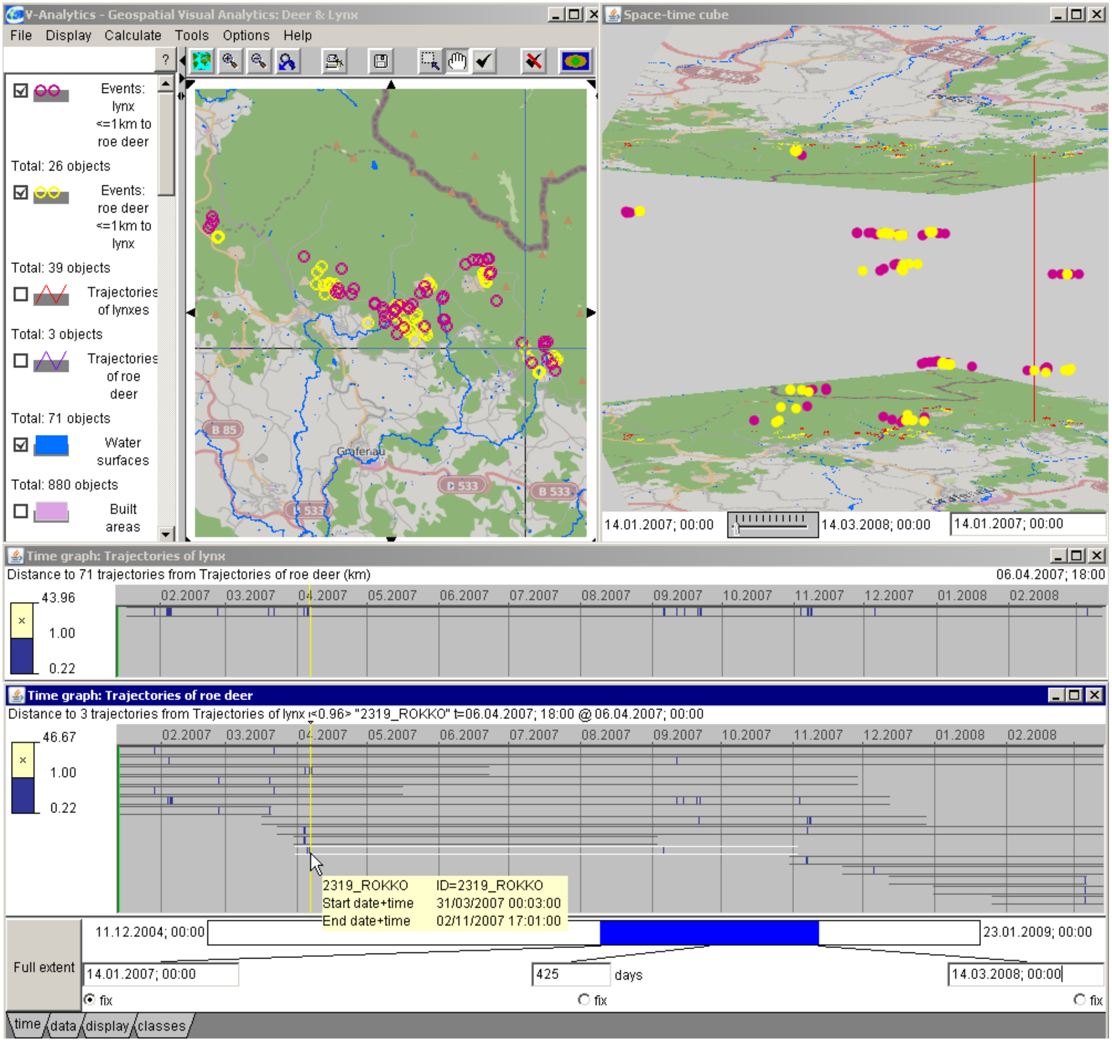

Figure 8: The events of spatial proximity between roe deer and lynxes are visualized in four linked displays: map (upper left), space-time cube (upper right), and temporal views of the trajectories of the lynxes (middle) and roe deer (bottom).

The next question is whether any of the detected approaches of the lynxes to the roe deer resulted in killing the roe deer. We look for the events of spatial proximity to lynxes that occurred shortly before the end times of the trajectories of the roe deer. To extract these events, we open another temporal view of the trajectories of the roe deer and visualize the variable “temporal distance to a selected time moment”; the chosen time moment is the end time of each trajectory. Using the segment filter, we select only the segments with the temporal distances from -24 to 0 hours to the trajectory ends. Simultaneously, the filter in the first temporal view selects the segments with the distances to lynxes not exceeding 1km. By combining the two filters, we find two events of spatial proximity to lynxes that occurred in the last 24 hours of the trajectories of two roe deer, Harald and Heiner.

Among the data received from Bavarian Forest, there is a lookup table with general information about the tracked animals, in particular, their fates. The record about Harald says that it was killed. Now we can say with a high degree of certainty that Harald was killed by Nora. For Heiner, the lookup table says that he died in a traffic accident. We guess that Heiner might occasionally run on a road when trying to escape from Nora and was killed there by a moving vehicle. We project the spatial position of the proximity event between Heiner and Nora on a satellite image from Google Maps and see that the event occurred very close to a forest road. This gives support to our hypothesis but does not exclude other possible reasons for the accident.

6.4 Analyzing relations to events

Events may influence the behaviours of movers. When events are few, the analyst can investigate the possible impacts solely by means of visual and interactive techniques. The temporal filter is used for focusing on time intervals before and after the events and the spatial filter and object filter are used for selecting the movers that were present in the vicinity of the events when they occurred. In this way, we could trace, for example, the movements of the lynx Nora after killing the roe deer Harald. During the following four days, Nora moved several times forth and back between the place of the event and another place located in about 2km north of the first place.

Domain expert's comment: This behaviour is typical for lynxes. A lynx moves to its kill normally in the evening. After feeding, the lynx leaves the kill to a place called daytime resting area. We suppose that if the kill is in a risky environment (for example, close to human infrastructure or outside of the National Park), the lynx moves a farther distance from the kill to find a secure area. If the kill is in a secure place, the lynx might rest close to it.

Purely visual and interactive exploration may be effective in case of few events and few movers involved but not when events and/or movers are more numerous. In the latter case, we suggest extraction of event-related statistics from the trajectories. We shall apply this approach to explore how roe deer behave when being approached by a lynx.

Domain expert's comment: One hypothesis is that roe deer will go to more open areas, were the lynxes cannot ambush them. Another hypothesis is that roe deer will shift their activity more to the daylight, when lynxes are inactive. The open issue is how roe deer recognize lynxes and whether they communicate this to other roe deer. One possibility is that one roe deer senses a lynx and changes its movement behaviour while others that do not sense the lynx perform their normal movement. Another possibility is that the roe deer sensing a lynx warns the others that a lynx is nearby, and the others react by changing their behaviours. Roe deer have a bark which they cry out when they are scared. By following a collared lynx, we have observed that roe deer start to bark when they discover the lynx. It might be possible that they warn others with this bark.

It is quite probable that the available data, being temporally sparse and irregular, may not allow the ecologists to find definite answers to their questions. Still, we want to see what changes of the roe deer's behaviours after probable encounters of lynxes can be detected with our tools. Particularly, we shall try to find out whether the roe deer begin to move more or less actively, whether they tend to move away from the places of the events, whether they tend to come nearer to other roe deer or to move away from them, and whether they tend to go in open areas.

We shall look at the behaviours of the roe deer before and after the 39 events of spatial proximity to the lynxes (further referred to as "encounter events") extracted with the temporal tolerance threshold of 1 hour. The use of a higher threshold would make us less confident that the lynxes were really close to the roe deer and less certain about the times of the possible encounters. In the temporal view of the trajectories of the roe deer, we visualize successively the following variables: distance to the place of the nearest encounter event in the trajectory, movement speed, distance to other roe deer, and distance to the nearest open area. For each attribute, we obtain the statistics (minimum, maximum, median, mean, and standard deviation) of the values separately for 1 day intervals before the starts of the encounter events and for 1 day intervals after the starts of the events. For each event, the statistics are derived only from the trajectory from which the event was earlier extracted.

After obtaining the statistics, we compute the differences between the values after and before the events. The differences are expressed in percentages to the earlier values. Figure 9 presents a display of the table describing the events. The background colouring of the rows corresponds to the cross-classification of the events according to the values of the attributes "% change of the maximum spatial distance to the encounter event" and "% change of the mean speed". The selected value intervals for both attributes are below -10% (large decrease), from -10 to 10% (small change), and over 10% (large increase). The legend explaining the colours is on the right of the table. Light yellow corresponds to large decreases of both the maximum spatial distance to the event location and the mean speed; 12 out of 39 events belong to this class. Greenish brown corresponds to large increases of both attributes; 10 out of 39 events belong to this class. The remaining classes contain from 1 to 4 events. The lengths of the coloured bars in the table cells represent the relative positions of the respective values between the minimum and the maximum values in the columns.

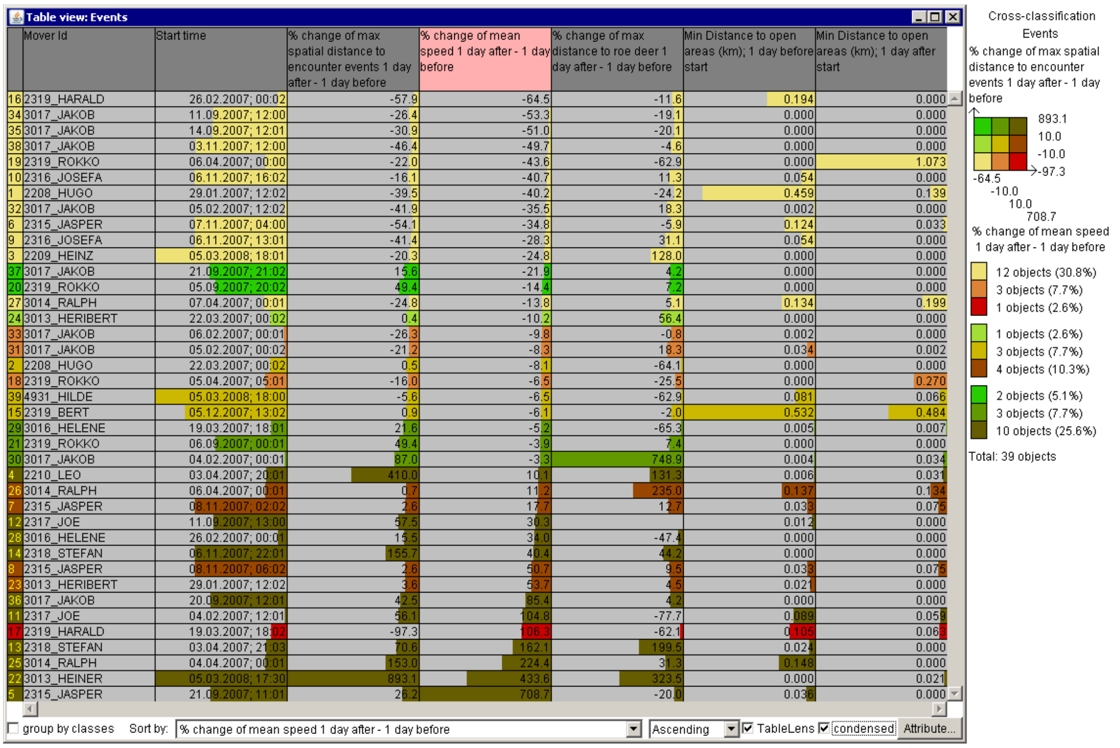
Table view: Events

	Mover Id	Start time	% change of max spatial distance to encounter events 1 day after - 1 day before	% change of mean speed 1 day after - 1 day before	% change of max distance to roe deer 1 day after - 1 day before	Min Distance to open areas (km); 1 day before start	Min Distance to open areas (km); 1 day after start
16	2319_HARALD	26.02.2007; 00:02	-57.9	-64.5	-11.6	0.194	0.000
34	3017_JAKOB	11.09.2007; 12:00	-26.4	-53.3	-19.1	0.000	0.000
35	3017_JAKOB	14.09.2007; 12:01	-30.9	-51.0	-20.1	0.000	0.000
38	3017_JAKOB	03.11.2007; 12:00	-46.4	-49.7	-4.6	0.000	0.000
19	2319_ROKKO	06.04.2007; 00:00	-22.0	-43.6	-62.9	0.000	1.073
10	2316_JOSEFA	06.11.2007; 16:02	-16.1	-40.7	11.3	0.054	0.000
1	2208_HUGO	29.01.2007; 12:02	-39.5	-40.2	-24.2	0.459	0.139
32	3017_JAKOB	05.02.2007; 12:02	-41.9	-35.5	18.3	0.002	0.000
6	2315_JASPER	07.11.2007; 04:00	-54.1	-34.8	-5.9	0.124	0.033
9	2316_JOSEFA	06.11.2007; 13:01	-41.4	-28.3	31.1	0.054	0.000
3	2209_HEINZ	05.03.2008; 18:01	-20.3	-24.8	128.0	0.000	0.000
37	3017_JAKOB	21.09.2007; 21:02	15.6	-21.9	4.2	0.000	0.000
20	2319_ROKKO	05.09.2007; 20:02	49.4	-14.4	7.2	0.000	0.000
27	3014_RALPH	07.04.2007; 00:01	-24.8	-13.8	5.1	0.134	0.199
24	3013_HERIBERT	22.03.2007; 00:02	0.4	-10.2	56.4	0.000	0.000
33	3017_JAKOB	06.02.2007; 00:01	-26.3	-9.8	-0.8	0.002	0.000
31	3017_JAKOB	05.02.2007; 00:02	-21.2	-8.3	18.3	0.034	0.002
2	2208_HUGO	22.03.2007; 00:02	0.5	-8.1	-64.1	0.000	0.000
18	2319_ROKKO	05.04.2007; 05:01	-16.0	-6.5	-25.5	0.000	0.270
39	4931_HILDE	05.03.2008; 18:00	-5.6	-6.5	-62.9	0.081	0.066
15	2319_BERT	05.12.2007; 13:02	0.9	-6.1	-2.0	0.532	0.484
29	3016_HELENE	19.03.2007; 18:01	21.6	-5.2	-65.3	0.005	0.007
21	2319_ROKKO	06.09.2007; 00:01	49.4	-3.9	7.4	0.000	0.000
30	3017_JAKOB	04.02.2007; 00:01	87.0	-3.3	748.9	0.004	0.034
4	2210_LEO	03.04.2007; 20:01	410.0	10.1	131.3	0.006	0.031
26	3014_RALPH	06.04.2007; 00:01	0.7	11.2	235.0	0.137	0.134
7	2315_JASPER	08.11.2007; 02:02	2.6	17.7	12.7	0.033	0.075
12	2317_JOE	11.09.2007; 13:00	57.5	30.3		0.012	0.000
28	3016_HELENE	26.02.2007; 00:01	15.5	34.0	-47.4	0.000	0.000
14	2318_STEFAN	06.11.2007; 22:01	155.7	40.4	44.2	0.000	0.000
8	2315_JASPER	08.11.2007; 06:02	2.6	50.7	9.5	0.033	0.075
23	3013_HERIBERT	29.01.2007; 12:02	3.6	53.7	4.5	0.021	0.000
36	3017_JAKOB	20.09.2007; 12:01	42.5	85.4	4.2	0.000	0.000
11	2317_JOE	04.02.2007; 12:01	56.1	104.8	-77.7	0.089	0.059
17	2319_HARALD	19.03.2007; 18:02	-97.3	106.3	-62.1	0.105	0.063
13	2318_STEFAN	03.04.2007; 21:03	70.6	162.1	199.5	0.024	0.000
25	3014_RALPH	04.04.2007; 00:01	153.0	224.4	31.3	0.148	0.000
22	3013_HEINER	05.03.2008; 17:30	893.1	433.6	323.5	0.000	0.021
5	2315_JASPER	21.09.2007; 11:01	26.2	708.7	-20.0	0.036	0.000

Figure 9: The event-related statistics represent the changes of the roe deer's behaviours after encountering lynxes.

The largest class (light yellow) corresponds to reduced activity of roe deer after the encounter events. The roe deer decreased their speeds and did not try to move away from the places where the events occurred. The changes of the maximum distances to other roe deer greatly vary, which means that there was no clear tendency in the relations with the other roe deer. The second largest class (greenish brown) consists of the events after which the roe deer became more active, i.e., their speeds and the maximum distances to the event locations increased. Like for the reduced activity class, no consistent changes of the distances to other roe deer can be seen. When the events are classified only according to the changes of the speed, both the reduced speed class (below -10% change) and the increased speed class (over 10% change) consist of 15 events.

Hence, the frequencies of the reduced and increased activities of roe deer after being approached by lynxes are very close. It is possible that the change of the movement behaviour reflects the character of the interaction between the roe deer and the lynx. An increase of the movement activity may mean that the lynx chased the roe deer and a decrease may mean that the roe deer just sensed the presence of the predator and tried to hide and stay still, to avoid attracting lynx's attention. Another possible explanation is that the roe deer that decreased their activeness did not sense the lynxes by themselves but were warned by barks of other roe deer while the roe deer that moved more actively did this after sensing the lynxes by themselves. The data do not allow us to find out which explanation is more plausible.

Concerning the behaviours in relation to open areas, there are eight encounter events after which the roe deer entered open areas, i.e., the minimal distances to open areas were positive before the events and zero after them. In 12 cases, the minimal distances to open areas were zeros both before and after the events. Only in three cases the roe deer moved from open areas to forest after the events. Hence, there is a higher tendency towards moving to or staying in open areas after encountering lynxes than towards moving from open areas to forest. There is no correlation between moving from/to open areas and increasing or decreasing the movement activity.

We have seen that our tools can support the investigation of the impact of events on movement behaviours. However, finding clearer answers to the questions of the Bavarian Forest scientists requires data with much finer temporal resolution. It would also be good to increase the sample of tracked animals. Hopefully, the technical problems involved in tracking wild animals will be solved in the near future.

7 Results

We suggest a general approach to accounting for the spatio-temporal context in analyzing movement data. The approach involves extracting interesting movement events from trajectories and analyzing these events as independent spatio-temporal objects. Particularly, the analyst extracts the movement events (parts of the trajectories) having specific spatial and/or temporal relations to selected elements of the context in order to investigate the occurrences of these kinds of relations.

To test the approach, we implemented an interactive event extraction tool and applied it to real data about wild animals. We could detect and extract occurrences of several kinds of relations between the movers and different elements of the context:

- being far from habitual places;
- being in open areas and being in open areas close to built areas;
- being close to other movers of the same or other class;
- being in a certain temporal distance and temporal order (before or after) to selected time moments (ends of the trajectories);
- being in a certain temporal distance and temporal order to selected events.

We were able to analyze the spatial and temporal distributions of the extracted relation occurrences and investigate how these events affect the movement.

We have implemented the tools within an existing system, in which a number of visual and computational tools for exploration and analysis of spatial and temporal data were available before. These tools could be immediately applied to the events and event-related statistics extracted from the movement data by means of the new tools. The whole combination of tools supports sophisticated analyses in which results of earlier phases can be used for obtaining new knowledge in further steps.

The testing has confirmed the soundness of our approach. Despite the flaws in the data caused by the technical difficulties involved in tracking wild animals, we have uncovered a number of behavioural patterns that agree with the existing domain knowledge and could be interpreted by specialists. The domain experts admitted that such a deep investigation of movement behaviours of wild animals would not be possible with the tools they knew before. The experts appreciated our system as a very good instrument for visualization and interactive exploration of movement data, which is capable to support hypothesis building in ecology.

In this experiment, the domain experts did not use the tools by themselves. They posed questions to the tool developers, who did the analysis. The experts then reviewed the reports about the findings and the analysis process and provided their opinions. The collaboration was remote. Now the experts want to start using the tools by themselves. This requires a training session, which is planned for the near future.

8 Conclusion

Our main innovation is that we offer a general approach to extracting and analyzing relations between movement and its spatio-temporal context. The approach is based on treating movement as a composition of spatial events, i.e., objects localized in space and time. The main idea is to supply the analyst with an interactive query tool for extracting movement events based on their relations to selected context elements. The extracted events are treated as independent spatio-temporal objects and may be analyzed using various existing methods suitable for spatial, temporal, and spatio-temporal data. In particular, the events can be computationally combined with other data for deriving new information.

We have tested the approach on a real dataset obtained by tracking movements of wild animals. Despite the real-life complexities pertaining to the data (temporal sparseness, irregularity, and lacunae in the observations), we have been able to uncover a number of interesting facts and behavioural patterns. The process of analysis and its outcomes have been reviewed by domain experts and obtained their positive feedback. In the future, we plan to work on supporting joint analysis of movement data and activity data, which are produced by sensors measuring the acceleration of the collar. Unlike GPS positions, activity data are not transmitted by radio and become available only when the collar is taken back from the animal that wore it. The activity data have much finer temporal resolution and might fill the gaps between the GPS position records. The task of combining GPS tracks with activity data poses new challenges and requires further research and development.

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