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Topologically Characterized Movement Patterns: A Cognitive Assessment

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Abstract

In this paper, we discuss the role of topology as a predictor for the conceptualization of dynamically changing spatial configurations (referred to as movement patterns). We define meaningful units of movement patterns as paths through a topologically defined conceptual neighborhood graph. Topology plays a central role in formal approaches to human cognition and in predicting cognitive similarity ratings—although primarily for static spatial configurations. Formal specifications of the role of topology for characterizing movement patterns do exist, yet there is paucity of behavioral validation. To bridge this gap, we conducted an experiment based on the grouping paradigm to assess factors that underlie conceptualizations of movement patterns. The experiment was designed such that paths through the conceptual neighborhood graph were distinguished by topologically differentiated ending relations. We believe topology can make an important contribution in explaining movement conceptualizations. One recently formulated topology-based contribution is the *endpoint hypothesis*, asserting that a cognitive focus is placed on event ending relations. We discuss the results of our experiment in relation to previous experiments targeted toward a framework for modeling the cognitive conceptualization of dynamically changing spatial relations.

Topologically Characterized Movement Patterns: A Cognitive Assessment

Introduction

Understanding time and movement patterns has developed into a key research area in several sciences. In spatial sciences, for example, driven by the necessity to extend current spatial technology to be able to handle temporal aspect (Laube, Imfeld, & Weibel, 2005; Adrienko, Adrienko, Dykes, Fabrikant, & Wachowicz, 2008; Stewart Hornsby & Cole, 2007; Peuquet & Duan, 1995; Galton, 2004; Goodchild, 2004; Worboys, 2005), several approaches have been suggested to integrate space and time into formal frameworks. The focus on events and movement patterns—compared to earlier models only representing snapshots in time—can also be explained by a strong focus in spatial sciences on cognitive and linguistic aspects of geographic space and endeavors to integrate these aspects into formal characterizations (Mark & Frank, 1991). Time is an essential aspect of how we understand spatial environments as it is intimately linked to causation (Wolff, 2008).

Paralleling these developments, research on temporal aspects in other disciplines, such as philosophy (Casati & Varzi, 1996; Casati & Varzi, 2008) and particularly cognitive psychology (Zacks & Tversky, 2001; Hard, Tversky, & Lang, 2006; Shipley & Zacks, 2008; Wolff, 2008) has increased and led to a better cognitive understanding of: a) event boundaries, that is, how a potentially continuous stream of information is segmented into meaningful units (Newtson, 1976; Zacks, Tversky, & Iyer, 2001; Shipley & Maguire, 2008); b) factors that influence setting event boundaries (Hard et al., 2006; Zacks et al., 2001); c) causal relationships that explain underlying processes and contribute to the conceptualization of events (Wolff, 2008); d) specific parts/aspects of events, such as their endpoints (Regier & Zheng, 2007); and, e) the linguistic aspects of events (Folli & Harley, 2006); to name just a few.

While cognitive aspects of static spatial relations have been researched in the spatial sciences with a special focus on requirements of spatial information technology such as the formal characterization of spatial relations and their constituents (Mark & Egenhofer, 1994b; Xu, 2007; Nedas, Egenhofer, & Wilmsen, 2007; Riedemann, 2005; Matsakis & Sztandera, 2002), movement patterns have not yet been given the same attention, at least not from a cognitive behavioral perspective. We do not lack suggestions for conceptual temporal models (Peuquet, 1994; Mennis, Peuquet, & Qian, 2000; Galton, 2004; Hornsby & Egenhofer, 2000). We lack, however, behavioral research on movement patterns on the geographic scale and an understanding of how formal characterizations of movement patterns relate to cognitive conceptualizations thereof (Worboys & Duckham, 2006; see Lu and Harter 2006 and Klippel et al. 2008 for work in this area). This research is necessary to keep up with the greatly increasing number of investigations on formal aspects of spatio-temporal characterizations and also to advance the cognitive-theoretical basis of geographic information science (GIScience) (Renz, 2002; Montello & Freundschuh, 2004; Schuurman, 2006). The research question addressed in this paper can be condensed to: *Are qualitative calculi cognitively adequate to model cognitive conceptualizations of movement patterns*?

The remainder of this paper is structured as follows: The next Section provides a brief overview of research on the conceptualization of movement patterns as well as a discussion of the research literature on the role of topology for static spatial relations. The following Section details the experiments we conducted to evaluate aspects of conceptualizing movement patterns:

First, we discuss the results of previous experiments (Klippel et al., 2008) within the context of this paper; second, we describe a follow up experiment in which we tackled the question of whether a modification of the ending relation of movement pattern, distinguished by different topological relations, can be the basis for modeling the cognitive conceptualization of movement patterns. In other words, we evaluated a variation of the *endpoint hypothesis* postulated by Regier (2007) for (spatial) movement patterns. The following Section discusses our experimental results and the last Section places these results into a broader scientific context and offers conclusions and suggestions for future research.

Background

Conceptualization of Geographic Scale Movement Patterns

Research on the cognitive conceptualization of movement patterns has a long history within several sciences as a subcomponent of research on events (for an overview see Casati & Varzi, 1996; Shipley & Zacks, 2008; Zacks & Tversky, 2001). The cognitive-behavioral basis of movement patterns on the geographic scale is addressed in some of these research approaches, such as work on the linguistic description of causation by Wolff and collaborators (Song & Wolff, 2005; Wolff, 2008). Within spatial sciences, however, behavioral research on spatio-temporal movement patterns is still an exception, partially due to the complex nature of many geographic scale phenomena (Yuan, 2001). Despite the lack of behavioral research, the spatial sciences have contributed many detailed models of spatio-temporal information. Examples include the extensive work by Peuquet and collaborators (Peuquet, 2001; Mennis et al., 2000), the conceptual work on complex events by Yuan and colleagues (Yuan, 2001; McIntosh & Yuan, 2005), and others (Worboys, 2005; Hornsby & Egenhofer, 2000; Laube et al., 2005). Most of these approaches take into account aspects of human cognition to model spatio-temporal information. The cognitive focus of these models is, however, on general cognitive principles of spatio-temporal knowledge organization; they are not primarily built on behavioral research conducted within geography or checked against behavioral data.

Topology

One important characteristic of pairs of dynamic, spatially extended entities is that they can change their topological relations gradually, a concept discussed as *conceptual neighborhoods* (Freksa, 1992; Egenhofer & Al-Taha, 1992, see Figure 1). A geographic example of interpreting Figure 1 would be a hurricane crossing a peninsula. The idea of conceptual neighborhoods is based on Allen's temporal intervals (Allen, 1983) and has been extended to spatial relations employing the two most prominent frameworks for characterizing topological information in spatial sciences, that is, the region connection calculus (RCC) (Randell, Cui, & Cohn, 1992), and the 9-Intersection model (Egenhofer & Franzosa, 1991).

For example, RCC (following Galton, 2000) is build on a mereotopological connection relation C and $C(x, y)$ meaning that region x is connected to region y. Relation C is both reflexive and symmetric. A part relation P can be defined in terms of C as follows: $P(x, y) \equiv \forall z(C(z, x) \rightarrow C(z, x))$. Meaning that x is a part of y as long as anything connected to x is connected to y. By defining two further relations, a proper part relation, $PP(x, y) \equiv P(x, y) \wedge \neg P(y, x)$ and the overlap relation, $O(x, y) \equiv \exists z(P(z, x) \wedge P(z, y))$, the eight relations between spatially extended entities (see Figure 1) can be formally characterized using the connection relation as a primitive. The abbreviations for these relations are DC (disconnected), EC (externally connected), PO (partial overlap), EQ (coincides), TPP (tangential proper part), NTPP (non-tangential proper part), TPPi (tangential proper part inverse), and NTPPi (non-tangential proper part inverse).

This formal, qualitative characterization—if used to model paths through the conceptual neighborhood graph—can underlie scenarios as diverse as the path of a hurricane across a peninsula, or a lake extending its borders and thereby 'swallowing' a house on its shores, or a terrorist boat entering a harbor (Stewart Hornsby & Cole, 2007; Egenhofer & Al-Taha, 1992; Worboys & Duckham, 2006).

Figure 1 about here

While recent research has investigated the conceptualization of movement patterns (events) (e.g., Zacks et al., 2001) and how perceptual characteristics of movement patterns may induce the conceptualization of their boundaries, a contrasting approach is to start with the presumption (hypothesis) that movement pattern boundaries are based on formal characterizations, as introduced above (see also, Knauff, Rauh, & Renz, 1997; Knauff, Strube, Jola, Rauh, & Schlieder, 2004; Renz, 2002). Behavioral studies are employed as a means of validation by which the cognitive adequacy of formal characterizations of movement patterns is assessed.

An example for this approach is provided by Lu and Harter (2006), using behavioral research to address the question of whether all of Allen's intervals (Allen, 1983) are equally salient in the cognitive conceptualization of movement patterns (in their experiments, fish swimming in a tank). Specifically, their results indicate that relations that describe some kind of overlap (START, DURING, FINISHES, EQUAL) are distinguished from those relations that do not (BEFORE, MEET). Lu and colleagues interpret these results as a challenge to the hypothesis by Regier (2007) that perception and conceptualization of events (movement patterns) is endpoint focused (i.e., that the human cognitive system pays more attention to the endpoints of events rather than, for example, the start points).

The endpoint hypothesis is of central importance to the research reported here on the conceptualization of movement patterns, too. We will be examining the saliency of topologically distinguished endpoints of movement patterns (see Figure 1).

Assumptions of super-classes of topological relations in the characterization of movement patterns are also made in formal approaches. A recent proposal in the spatio-temporal domain by Camara and Jungert (2007) groups the eight topological relations between two spatially extended entities (cf. Figure 1) into two categories: *distance* and *proximity*. Their grouping does not correspond to the findings of Lu and Harter (2006). Camara and Jungert (2007) subsume all but the topological relation disconnected (DC) into the *proximity* category. While they provide arguments for their categorization, this example stresses the need for cognitive-behavioral validation of the relation between formal and cognitive conceptualizations.

Our own behavioral research (Klippel et al., 2008) involving two simple and spatially extended entities has shown that the role of topology in characterizing movement patterns from a cognitive perspective is less clear than in the case of static spatial relations. While Mark and Egenhofer (e.g., Mark & Egenhofer, 1994a, Mark & Egenhofer, 1994b, and Renz, 2002) found that topological equivalent classes are at least not separated by participants similarity ratings, we did not find the same clarity in the case of topologically distinguished dynamic patterns. It is important to note, however, that our previous research did not target ending (or start) relations, but paths through a conceptual neighborhood graph distinguished by identity and size differences. We regard the focus on ending relations an essential gap in our knowledge on how topological relations might be able to contribute to a formal characterization of cognitive conceptualizations of movement patterns.

Category construction

When people encounter sets of new or known entities (or movement patterns / events), they are able to categorize them spontaneously into groups. Given the continuous stream of information people encounter, categorization is an efficient way to reduce the amount of information a cognitive system has to deal with, as it establishes equivalent classes (or categories). Entities within a category are treated as similar to one another, but different from entities in other categories. Directional information, one of the core aspects of spatial knowledge about moving entities, is a geographic example (Golledge, Marsh, & Battersby, 2008). While a digital compass allows for the differentiation of an unlimited number of directions or direction changes (e.g., 36.239 degrees), humans naturally divide directional information into much coarser categories. From an egocentric perspective, a person might refer to their surrounding space as: front, left, right, and back. From the perspective of characterizing movement patterns that occur during wayfinding, a person might distinguish among straight, bear [left,right], left, right, or sharp [left,right] (Klippel & Montello, 2007; Vorwerg, 2003).

A distinction is made between the case where participants learn category structures, that is, placing entities into predefined categories through feedback, and the case where participants are asked to spontaneously divide a given set of entities into groups without feedback. Given the omnipresence of categorization, feedback is regarded as an artificial influence (Milton & Wills, 2004). Several studies have excluded feedback by allowing participants to categorize presented entities in a way they think is most natural (Pothos & Chater, 2002; Milton & Wills, 2004) without providing any a priori information on the number or characteristics of the groupings. The key element of this approach is that no feedback is provided to the participants concerning the agreement of their groupings to previously established category structures. Several names have been used for this approach, including unsupervised human categorization (Pothos & Chater, 2002), free sorting (Billman & Davies, 2005), category construction (Medin, Wattenmaker, & Hampson, 1987), and free classification (Handel & Imai, 1972). We will refer to this approach (that we employ here) as *conceptualization* or *category construction*.

Event Experiments

To shed more light on the question to which extent topology can be used as a predictor for conceptual knowledge expressed through similarity ratings, we first re-evaluated data from previous experiments. We did so with this new question in mind to focus on the strategies participants employed during the creation of similarity ratings. Subsequently, we conducted a new experiment that focuses on a different aspect of topology: topologically distinguished ending relations. This experiment extends the potential framework for *topologically explained* *similarity ratings*. The ideas behind the previous experiments are briefly summarized and then juxtaposed to the new experiment to provide context for this article.

From experiments on the role of static spatial relations, we know that topology plays a central role in human reasoning and in rating the similarity of spatial relations between extended entities (Mark & Egenhofer, 1994a; Knauff et al., 1997; Renz, 2002). We also know that it is necessary to add specific metric details to the description of a static configuration to fully capture situations that are considered similar to each other (Mark, Comas, & Egenhofer, 1995; Nedas et al., 2007; Xu, 2007; Zhan, 2002).

For the dynamic case, topology can play different roles such as the number of topological relations involved or specifying the ending relation of a movement pattern. A topological baseline has not yet been established for use in capturing cognitive conceptualization processes of movement patterns. Several formal treatments and results from psychological studies exist, but these experiments do not specifically target formal characterizations of dynamically changing spatial relations (excepting the few that have been discussed in the previous Section).

The rationale of our experiments was to establish the extent to which topology is able to explain cognitive conceptualizations of movement patterns, or, to be more precise, the scope to which topology explains the similarity ratings of participants that they create for movement patterns involving two spatially extended entities. We wanted to establish where topology matters and where metric (or other) refinement is needed. We based our considerations on earlier work by Egenhofer and Al-Taha (1992, from now on referred to as E&A92), who developed several scenarios using the set of eight topological relations (see previous Section).

E&A92 describe various scenarios, distinguished by the applied topological transformation to two spatially extended entities (e.g., translation, rotation, scaling) and the size ratios and/or movement specifications of the two entities. Unique transformation and specification pairings result in different paths through the conceptual neighborhood graph (see Figure 1). In related work (Klippel et al., 2008), we focused only on those scenarios that use translation and added several factors for the design of the experimental setup. In the case of translation, three scenarios can be distinguished that result in three different paths through the conceptual neighborhood graph (see Figure 1).

The hypothesis for the experiments (Klippel et al., 2008) was that different paths through the conceptual neighborhood graph are a predictor for the similarity ratings by participants for a set of movement patterns.

This means that the scenarios distinguished by E&A92, which are based on different paths through the conceptual neighborhood graph (i.e., a topologically distinguishing factor), should allow for an explanation of the similarity ratings created by participants. The results, however, showed that this is only partially the case and that other factors, such as different size ratios and dynamics (whether one spatial entity is moving or both), had a stronger appeal to participants rating the similarity of the movement patterns. In other words, we *rejected* the hypothesis that paths through the conceptual neighborhood graph (to be more precise: the three paths we used the previous studies, which are the results of a translation transformation) are the best predictor of participants similarity ratings (i.e., the conceptualizations of movement patterns).

However, different paths through the conceptual neighborhood graph are only one possible mechanism for topology to explain similarity ratings. Topology can play a variety of roles in a dynamic scenario, and it is worthwhile to look for other possibilities for topology to act as a predictor of participant similarity ratings and hence reveal the cognitive conceptual basis of movement patterns.

To simplify things, let us stay for the time being with the topological transformation of translation. In the original scenarios by E&A92, the path characteristics created by their translation scenarios were such that the start and ending relation were always the DC (disconnected) relation (see Figure 1). Hence, there was no variation in the relation in which an event would end (or start). A look in the literature shows however that this might be a critical aspect of conceptualizing movement patterns (Lu & Harter, 2006; Camara & Jungert, 2007; Regier & Zheng, 2007). The next section describes our new experiment designed to shed light on the role of ending relations in conceptualizing movement patterns.

Experimental setup

Given the results we have discussed on the importance of endpoints in event conceptualization, we extended our previous experimental setting in the following ways. We know from related research (Knauff et al., 1997) that participants conceptually distinguish the basic eight topological relations (through rating the similarity of spatial scenes). Additionally, we know that not all topological relations (or their ‘corresponding’ temporal relations) administer the same conceptual saliency in behavioral experiments (and in more formal considerations) (Lu & Harter, 2006; Camara & Jungert, 2007). Hence, topology in form of characterizing different ending relations of movement patterns can be assumed to have an influence on the similarity ratings participants create. Therefore, we have the following hypothesis for the experiment reported in this paper:

Movement patterns involving two spatially extended entities (modeled as path through the conceptual neighborhood graph) are conceptually distinguished on the basis of their topological ending relation. This aspect is reflected in participants' similarity ratings.

General setting

The methodology described here is the same as used in previous experiments (Klippel et al., 2008). We used a grouping task, which has long been an important method in psychology for investigating conceptual knowledge and category construction (Medin, 1989; Cooke, 1999; Pothos & Chater, 2002). The motivation behind grouping tasks is that people primarily use conceptual knowledge to determine the similarity of given stimuli. Stimuli are placed into the same group if they are regarded as similar (i.e., as instances of the same concepts); they are placed into different groups if they are regarded as dissimilar (i.e., as instances of different concepts).

The Grouping Tool

We developed and have continuously refined a grouping tool (Knauff et al., 1997; Klippel & Montello, 2007) that allows for the presentation of dynamic (animated) icons (Klippel et al., 2008). The grouping tool partitions the screen into two parts (see Figure 2). The left side of the screen shows the stimulus material (the animated icons). It was necessary to implement a scrolling function due to the large number of tested icons; no problems were observed with this approach, as scrolling is a common procedure in current interface technology. The right side of the screen was empty at the start (no predefined number of groups was provided). Participants created empty boxes, much like an empty folder in Windows, into which the animated icons had to be placed. The interface was kept very simple and other than the drag and drop operation only three buttons were available: New group, Delete group, and Finish. The Finish button only became active upon completing the grouping task (i.e., after all icons from the left side had been placed into groups on the right side).

Figure 2 about here

Participants

19 participants (6 female) took part in the experiment. They were Penn State undergraduate Geography students (average age: 21.7) and received course credit for their participation. All participants were native English speakers and none of them had knowledge about topology, which was tested by a) asking them whether they had heard about topology (18 negative answers), and b) to name any topological relations (no participant named a topological relation correctly).

Procedure

The experiment took place in a GIScience laboratory at the Geography Department at Penn State. Participants were tested in groups (8, 6, 5). The computers (Dell, Pentium D, 3 GHz, 2 GB RAM) in the lab have 20’’ wide screen Dell monitors, suitable for a grouping task. The lab was prepared with view blocks and computers were arranged such that participants could not see the screens of other participants to ensure individuality of the results.

Participants were asked to first give consent. This was followed by an introduction to the experiment and a short biographical survey requesting the aforementioned personal information. Instructions for the grouping tool were then provided: participants were explicitly advised to *imagine something geographic* that the animated icons could represent. An example grouping task using animal icons was then performed to familiarize the participants with the grouping tool and to give them an example of creating similarity ratings from a different domain. After the warm-up task, participants were shown 150 animated icons on the left side of the screen that they had to group according to their similarity (on the right side of the screen). They were explicitly advised that there is no right or wrong way of grouping the icons.

After the main task, participants performed a second task in which they a) had to label the groups they created and detail which geographic scenario they were thinking of and b) draw a symbol for each group. The groups the participants created were shown to them one at the time. The results of this part of the experiment are not discussed in detail in this paper.

Materials

We used 150 animated icons. All icons showed two circles; one light gray circle and one dark gray circle (see, for example, Figure 3). Both circles were partially transparent, each using a different alpha value so when the circles overlapped, the shared space appeared darker but both circles were still identifiable. The icon design was guided by the following criteria: We used the nine cases we employed previously (Klippel et al., 2008) that were derived and extended based on the formal characterization of E&A92 (for extended details, please refer to Klippel et al. 2008). These nine cases are organized into three scenarios, each distinguished by the path through the conceptual neighborhood graph that it elicited.

Scenario 1:

1. Spatially extended entity A is smaller than B and A is moving over B.
2. A is smaller than B and B is moving over A.
3. A is smaller than B and both are moving toward each other.

Scenario 2:

1. A is larger than B and A is moving over B.
2. A is larger than B and B is moving over A.
3. A is larger than B and both are moving toward each other.

Scenario 3:

1. A and B have the same size and A is moving over B.
2. A and B have the same size and B is moving over A.
3. A and B have the same size and both are moving toward each other.

Taking these nine scenarios as a basis, a range of animated icons was created. In addition to these nine cases, we defined two size ratios (while still maintaining the scenario dictated setting, i.e. whether A or B is larger): one ratio with a large size difference between entities and one ratio with a small size difference between entities. These size differences were not fixed but were generated within a range using a random number generator from random.org. For this purpose, random numbers for the ranges given below were generated for the radius of each circle (i.e., the spatially extended entity).

The range for the diameter (in pixels) for the large size difference:

- Small spatial entity: 10-15
- Large spatial entity: 30-35

The range for the diameter (in pixels) for the small size difference

- Small spatial entity: 16-21
- Large spatial entity: 24-29

The last and most important variation we introduced in this experimental setup were the different ending relations. Orthogonal to the two criteria introduced above, a path through the conceptual neighborhood graph can end in nine (or seven) topological relations discussed in previous Sections. That means, if we have a translation movement and start with two spatial entities that are disconnected (DC), we can have the following ending relations in the three scenarios:

- Scenario 1 (see also Figure 1 and 3):

    - DC (the two spatial entities never connected), EC, PO, TPP, PP, TPP-2, PO-2, EC-2, DC-2
- Scenario 2
    - DC, EC, PO, TPPi, PP, TPPi-2, PO-2, EC-2, DC-2
- Scenario 3
    - DC, EC, PO, EQ, PO-2, EC-2, DC-2

Hence, we have nine ending relations for each of the three cases in Scenario 1 times the two different size ratios (54 possibilities). We have the same setting for Scenario 2 (54 possibilities), and we have seven ending relations for each of the three cases in Scenario 3 (were both spatial entities have the same size), again times the two size ratios (42 possibilities). This results in 150 animated icons overall.

Figure 3 about here

Each icon was square and 100×100 pixels in size. At the start of each animation, the pair spatial entities A and B were positioned near opposite borders of the icon. In our previous experiment, we found that the direction of movement (i.e., from which opposite borders the movement starts) had no influence. Here we used only left-right/east-west movements. The initial horizontal distance from the border to the center of each region was set to 15-45 pixels; this adaptation was necessary to accommodate the different ending relations. For example, for the relation DC-2, one spatial entity moved through/across the other; this required some space ‘behind’ the second spatial entity (in case it did not move). The vertical starting position of each of the two spatial entities along the icon boundary was offset using a random number, generated using the website random.org. Each moving spatial entity then moved on a straight line from its starting location to the starting location of its pair. As a result, although spatial entities moved across the icon from one border to the opposite border, the direction of movement was randomized. Note that this experimental design only considers animations with spatial entity trajectories that are at 180° to each other. The more general cases of trajectories at other angles were excluded in the interests of a manageable experimental setup and because the inclusion of additional trajectories did not increase the possible range of topological changes exhibited by the animations. The ending relation PO used the radius of the smaller entity to determine the overlap of the two entities. Figure 4 summarizes the dimensions and construction of one animated icon for B bigger than A, where B is moving over A starting from the left hand boundary of the icon. The dashed arrow in Figure 4 represents the movement vector of B, while “rnd(60/50)” represents a random integer number of pixels used to calculate the starting positions.

Figure 4 about here

We used Macromedia Flash to create the animations, which were subsequently exported as animated GIF icons. A further modification to the animations occurred at this stage. The total number of frames in each animation was varied slightly, from 55 to 70 frames. This ensured that relative speeds of the animations were slightly different, avoiding any possible perceptual effects from synchronous movement. In the customized grouping tool, the animations were tuned to take approximately three to four seconds to complete. At the end of each animation, 15 additional frames were added to indicate perceptually the endpoint of this movement (i.e., the animation stopped at the end position for about 2 seconds, longer than in the previous experiments). Afterwards, the animation loops back to the original starting point and plays again.

Results

Each participants' grouping results in a 150 x 150 similarity matrix. The matrix columns and rows correspond to the number of icons used in this experiment. This matrix encodes all possible similarity ratings between two icons, producing a symmetric matrix of 22,500 cells. Similarity is binary encoded; a pair of icons is coded as '0' if its two items are not placed in the same group and '1' if its two items are placed in the same group. The overall similarity of two items across all participants is obtained by summing over all the similarity matrices of individual participants. For example, if two icons (called A and B) were placed into the same group by all 19 participants, we add 19 individual '1's to obtain an overall score of 19 in the respective cells for matrix position AB and BA, that is, 19 is the highest similarity rating that can be obtained. Please note that the general advice for grouping experiments is to use at least 15 participants (Tullis & Wood, 2004). Yet, we did not rely on this theoretical statement alone and cross validated our results by splitting the pool of participants into two random groups and thereby internally validated that the number of participants was sufficient (as the results were similar, see below).

To analyze the categorical grouping data, we subjected the overall similarity matrix to a hierarchical cluster analysis. Aldenderfer and Blashfield (1984) recommend reporting cluster analysis results together with the following five criteria: *Software*: CLUSTAN™; *Similarity measure*: Squared Euclidean distance; *Clustering method*: Several clustering methods to cross validate the findings: Ward’s method, average linkage, nearest, and furthest neighbor methods. *Number of clusters*: We not only used cluster analysis and the validation techniques discussed below, but additionally show results of a multidimensional scaling (MDS) analysis; *Validation*: Comparison of different clustering methods (see Section Validation), random selection of two sub-groups with a cluster analysis on both groups to compare the results, MDS.

Figure 5 shows a dendrogram generated using Ward’s methods. A six cluster solution seems to be the most valid interpretation; we find two clusters for each of the three scenarios discussed by E&A92. Even more strikingly, the clear distinction we found previously between the number of spatial entities moving in the animation (either one or both) does not appear to be a distinguishing criterion for creating groups, that is, for establishing similarity of animated icons.

Figure 5 about here

We turn now to our main hypothesis that the ending relation of a dynamic geographic phenomenon has great appeal for conceptualizing a dynamic phenomenon and that topology, in the form of defining the ending relation of a movement pattern, can be used as a predictor for the similarity rating of participants. We find that the distinction of the basic scenarios seems to have a great appeal in predicting similarity ratings in this setting, however, the different ending relations are buried deep in the clusters themselves. There is no identifiable consistency that ending relations might play a role across different clusters. It sometimes seems to be the case that the ending relations DC and EC individually form more distinct sub parts in their corresponding clusters, but this could not be confirmed by the KlipArt analysis (see below).

We were, however, intrigued by the results obtained by the cluster analysis, which show that the main grouping criterion was the size difference between the icons and not the movement patterns characteristics (i.e., the different topologically distinguished ending relations). To better understand these results, we used a tool called KlipArt (Klippel, Hardisty, & Weaver, 2009). This tool allows for looking into the grouping behavior of individual participants and/or icons pairings. An example analysis using KlipArt is provided in Figure 6. The Figure shows the grouping behavior for all icons that have the relationship: A is the same size as B and both are small in size and B is moving toward A. Figure 6 clearly demonstrates that size was the major criterion for grouping these icons. About half of the participants (numbers in yellow boxes) placed all icons with this characteristic into the same group (upper right corner) and another three participants placed all but one icon (146) into the same group (lower left corner). An analysis of why icon 146 was placed in a group with other icons showed that size once again was the most important factor as icon number 146 is the smallest of this group and was placed together with other very small icons into the same group.

We performed this kind of analysis for relations defined by the discussed formalisms that guided the design of this experiment. We found that some participants did make grouping distinctions on the basis of topologically distinguished movement patterns. In cases where the topological relation disconnected (DC) was singled out, we found for example, linguistic descriptions such as *species range -- each species (circle) has their own territory but will not* *cross to the other side* (participants 53 in Figure 6). Overall we found two participants who grouped together all icons with the relation disconnect. Other topologically distinguished ending relations yielded similarly low participant numbers.

Figure 6 about here

Validation

First, we validated the interpretation that six is the most sensible interpretation of the number of clusters. We started with analyzing the data using multi-dimensional scaling (MDS) (see Figure 7). MDS, like cluster analysis, is based on similarities, with the difference from cluster analysis that the similarity between entities is used to create a map-like representation that shows the best possible fit for all similarity ratings in two dimensions. The MDS results indicate a clear six cluster structure (CLUSTAN_MDS, minimum stress = 1.7313%, fit is excellent). The gray tones (colors) indicate the groups identified in the cluster analysis in the next Section. The few ‘outliers’ can be explained by the fact that random size ratios sometimes produce ratios close to other size ratios and therefore animated icons seem to have been placed into different groups (see below).

Figure 7 about here

Kos and Psenicka (Kos & Psenicka, 2000) and Clatworthy et al. (2005) suggest examining cluster stability across different clustering methods and across different subsets of participant responses. A comparison across different clustering methods (Ward's method, average-, complete, and single-linkage) showed the same cluster structure for the first three methods and only single linkage, which is prone to chaining, did not exactly show the same results (which we expected). The cluster structure at the cut-off point for the six-cluster solution (shaded areas) is shown in Figure 5 using Ward's method. The dendrogram is scaled to fit the page. As an example, some icons from each cluster—statically showing the DC starting relation—were chosen to provide a better impression of the grouping strategies the participants applied.

Again following Kos and Psenicka (2000), we validated the six cluster interpretation across subsets of participants. Participants were split into two groups using random numbers from the website random.org. We performed Ward's method on both groups and the results show that both sub-groups exhibited nearly identical cluster structures. In both groups a total of 5 (4 different, 1 same) icons (or 3.3%) deviated from the suggested six cluster solution.

The average number of groups that participants created was 8.4, ranging from 2 to 18. Although the number of participants is rather small, we performed an independent t-test on the number of groups male (13) and female (6) participants created. Women created significantly more groups than men ($t=-3.279$, $df=17$, $p=.004$, two-tailed). At this point, this is a result that may be indicative of sex differences (Coluccia & Louse, 2004), but will not be discussed further as our previous results did not indicate significant sex differences.

Discussion

The results show that overall the ending relations in our experimental setup have little effect on the grouping behavior of the participants. This is somewhat unexpected as several related experiments (Regier & Zheng, 2007; Lu & Harter, 2006) did find that the ending relations are important and that certain ending relations are conceptually more similar than others. We expected the need to weight the edges in the conceptual neighborhood graph to better reflect cognitive conceptualization processes according to the ending relation of an event. Because this was found to not be the case, we have to reject our main hypothesis (see Section Experimental Setup).

While the experiment (at large) failed to exhibit similarity ratings influenced by ending relations, it did confirm the importance of size differences for explaining participants' similarity ratings. Size is a perceptually (as well as a conceptually) important classification criterion (Wolff, 2008; Lockhead & Pomerantz, 1991). An outlook on how the size factor can be conceptually explained is given in the conclusion, focusing upon aspects of causality (i.e., making the point that perceptual characteristics are related to conceptual ones). It is important to note that participants did choose, out of a large set of possible semantic and perceptual grouping criteria, size as the best structuring information. Hence, it is not the case that simply each participant picked her or his own criteria.

Additionally, it is important to note that size differences are also a reflection of topologically distinct paths (i.e., whether we go down the left or the right side of the conceptual neighborhood graph), a distinction made in the original classification by E&A92 (see Figure 1 and compare the three basic scenarios described in Section Materials). This is, however, only true for the lower level of the dendrogram, the level with the first clearly distinguished clusters (see Figure 5). Other factors take over if we follow the grouping behavior through the dendrogram; in the case of the experiments reported here, size again, but this time not in favor of topology; it separates large from small size differences, which is topologically not distinguished. This has been the case in the current experiment as well as in our previous work (Klippel et al., 2008). We therefore would need to reverse the statement that topology matters and other aspects refine the conceptualization of movement patterns. It seems to be that *other factors matter and topology refines*. What we do not know yet is how much and in which way other factors matter, and when topology is responsible for rendering distinctions more precise.

Conclusions and Outlook

Topology (and Allen's temporal intervals that both can be characterized by conceptual neighborhood graphs) plays a central role in characterizing movement patterns formally (e.g., Worboys & Duckham, 2006). We have discussed work that makes assumptions on formal grounds on how basic topological relations can be employed to characterize movement patterns and, to provide an additional focus, how the basic eight topological relations are suggested to be grouped together. One discussed proposal is put forth by Camara and Jungert (2007), who suggest the following distinction: DC (disconnected) is in a group of its own and all other topological relations are grouped together. This proposal results in only two superordinate categories for topological relations in characterizing movement patterns.

A behaviorally validated approach is discussed by Lu and Harter (Lu & Harter, 2006). They approached this question from the same general perspective that we took in this article: Are qualitative formal characterizations cognitively adequate? In their experiments they found that temporal relations (that can be mapped onto the topological relations characterized by the conceptual neighborhood graph we used) are grouped together, but differently than suggested by Camara and Jungert. Their two group solution places disconnected (DC) and externally connected (EC) together into a first group and partial overlap (PO), tangential proper part (TPP), and non-tangential proper part (NTPP) together into a second group.

While we set out to add to this research and to resolve the discrepancies between these characterizations, ending relations in our experiments were not the main criterion for conceptualizing movement patterns. One distinction that surfaced in the cluster and MDS analysis we presented is indeed a distinction made topologically but independent of ending relations: The two sides of the conceptual neighborhood graph (paths going down the left side or the right side) are distinguished, which is primarily a reflection of size differences (discussed below). Yet, this is not the dominant criterion of distinction, as again size but this time different size ratios are the most pertinent grouping criterion. To reflect this finding we would need to reverse the statement by Mark and Egenhofer (Topology matters and metric refines) into: Something matters (in this case the size ratios) and topology refines.

Size differences, as they surfaced as a guiding principle for the conceptualization of movement patterns in our experiments, are an example of how perceptual and conceptual aspects of cognition may work in unison. The discussion by Goldstone (1994) on the importance of perceptually induced similarity ratings and the theory of perceptual symbol systems proposed by Barsalou (1999) represent two strong advocates for the perceptual basis of our category system. How is it, then, that size differences could be considered as being such an important factor in conceptualizing movement patterns? Just as a reminder, the two different size ratios were actually randomized size ratios within two distinct size-ratio-ranges, not simply two fixed ratios. Additionally, in the second experiment in Klippel et al. (2008), we also found a tendency to use size differences despite the fact that size was completely randomized (no predefined size ratios). It is certainly the case that we can relate size, or from a geographic perspective, scale, to many important aspects in perceiving and conceptualizing environmental information. Freundschuh and Egenhofer (1997) as well as Montello (1993) have proposed typologies of spaces at different scales to create an awareness of the differences in cognitive processes across different scales. Size differences do not necessarily mean scale differences, but a combination certainly might influence conceptualization processes. Some examples might make this point clearer: It is an important distinction whether a large or a small hurricane crosses a peninsula, whether a small or a large oil slick hits a coast, whether a single buffalo or a herd crosses a corn field, etc. Hence, the size of the entities involved in movement patterns does matter and is not only an aspect of the perceptual characteristics of the stimulus.

Chater (Chater, 1996, Chater, 1999), in several articles, and more recently Pothos (Pothos, 2005; Pothos & Close, 2008), discuss the *simplicity principle* that potentially explains both perceptual organization and conceptual aspects of categorization. Build on the observation that it is crucial for the cognitive systems to find patterns in the world, it is evident that patterns are not randomly defined. Instead, there are guiding principles from both perception and conception that allow for (or favor) certain patterns over others. Without the ability to identify patterns, or, from the perspective of categorization, to classify, the human mind would not be able to understand, explain, or predict anything. Chater and Pothos propose one principle that the human mind employs to find patterns: the pattern that offers the simplest explanation for the available stimulus is chosen. This idea that simplicity is a crucial aspect of cognition manifest itself in manifold research approaches and findings, from Occam's Razor to work on geographic primitives by Brunet (Brunet, 1987).

The interesting question is: *what defines the simplest pattern?* In other words, what is the simplest dimension along which a set of stimuli can be organized into a pattern? In the case of our experimental setup, we can make the observation that topologically distinguished ending relations, while a valid theoretical prediction for human conceptualization (Knauff et al., 1997), is not the simplest distinguishing criterion, neither by itself, nor in combination with other potential factors. Topologically, we would have to distinguish at least nine different categories. Adding any other dimension that potentially could be used—whether topology (here identity that is responsible for whether the path through the conceptual neighborhood graph goes down the left side or the right side), or the dynamics (whether one or both entities are moving), or the size differences—many distinctions (one may say, too many) would be necessary. No doubt that an explicit instruction would allow participants to adhere to these dimensions and would allow them to group the stimulus accordingly. However, in the light of the results of Pothos and colleagues (Pothos & Close, 2008) it seems to be more natural for a perceptual-cognitive agent to select the simplest dimension.

On the other hand, the clustering structure reveals that the groups are not created on singling out one dimension alone! The main grouping structure is indeed a combination of size differences and identity. This finding is very much in line with work on similarity by Goldstone (1994), who asserts that humans are not confined to a single dimension in making similarity judgments, but that they very well may use the combination of two factors.

From a certain perspective, objects and events (e.g., movement patterns) share characteristics. Zacks and Tversky (2001) make a strong point in listing the similarities of objects and events. For example, events and objects are comparable in that they formally can be characterized by partonomies and taxonomies. They also may share a convergence of perceptual and conceptual features at the basic-level of their respective category structure. From another perspective, though, objects and events are dissimilar. Gentner and Boroditsky (Gentner & Boroditsky, 2001) (based on previous work by Genter) point out the difficulties children have with learning verbs compared to naming objects. Gentner and Boroditsky use these findings to revise the view that both, nouns and verbs belong to open-class words but instead, propose a continuum in which verbs are placed between open-class (nouns) and closed-class (prepositions and determines) words. This continuum is referred to as the division of dominance.

The aspect important for the interpretation of our experimental results is that from the latter perspective (objects are conceptually easier than verbs), we could make an additional point as to why the non-changing relation between the entities in our experiment (size ratios) dominated the dynamic aspects. How far this might be related to linguistic influences is beyond the scope of the current article, but it would make an interesting experimental setup to analyze linguistic influences on the conceptualization of movement patterns (Boroditsky, 2001).

The last aspect we would like to briefly mention is work on event segmentation based on shape characteristics of the trajectory of a movement pattern (Shipley & Maguire, 2008). We deliberately did not introduce variations in the trajectories to avoid this aspect in our experimental setup. However, as Shipley and colleagues demonstrate through their theoretical work on object perception and the importance of shape (Biederman, 1987; Singh & Hoffman, 2001), the characteristics of trajectories are an important aspect for the conceptualization of movement patterns. Work toward a more general framework on event conceptualization involving single entities, therefore, would need to incorporate several aspects: the conceptual changes of an entity (although they did not surface in our experiment), the object characteristics of entities involved (that did surface in our experiments), and the shape characteristics of the trajectories.

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Figure Captions

Figure 1. Topological relations as identified by Egenhofer’s (Egenhofer & Franzosa, 1991) 9-intersection model and RCC-8 (Randell et al., 1992) between two spatially extended entities (A and B) arranged as a conceptual neighborhood graph (Freksa 1992, modified). Labels are taken from the RCC terminology: DC – disconnected, EC – externally connected, PO – partial overlap, TPP – tangential proper part, NTPP – non tangential proper part, ‘i’ indicates inverse relations).

Figure 2. Screenshot of an ongoing grouping experiment. The icons are animated in the actual experiment.

Figure 3. Examples of ending relations. All ‘events’ had the same starting condition, i.e. DC. In general, all relations to the left of one of the ending relations have to be passed through, the same relations but with different preceding relations are indicated by ‘-2’ (Note: transparency values have been adapted for printing).

Figure 4. The construction of one icon.

Figure 7. Cluster analysis using Ward’s method. The icons depicted are exemplars to show general size differences the guided the grouping behavior of participants. In each of the created clusters we find different ending relations as well as different dynamic characteristics, i.e. whether one or both entities are moving.

Figure 5. The KlipArt tool. Example analysis of grouping behaviors for subsets of icons.

Figure 6. Multidimensional scaling results. Squares represent animated icons. Coloring (gray tones) is done on the basis of a 6 cluster solution.

Figure 1

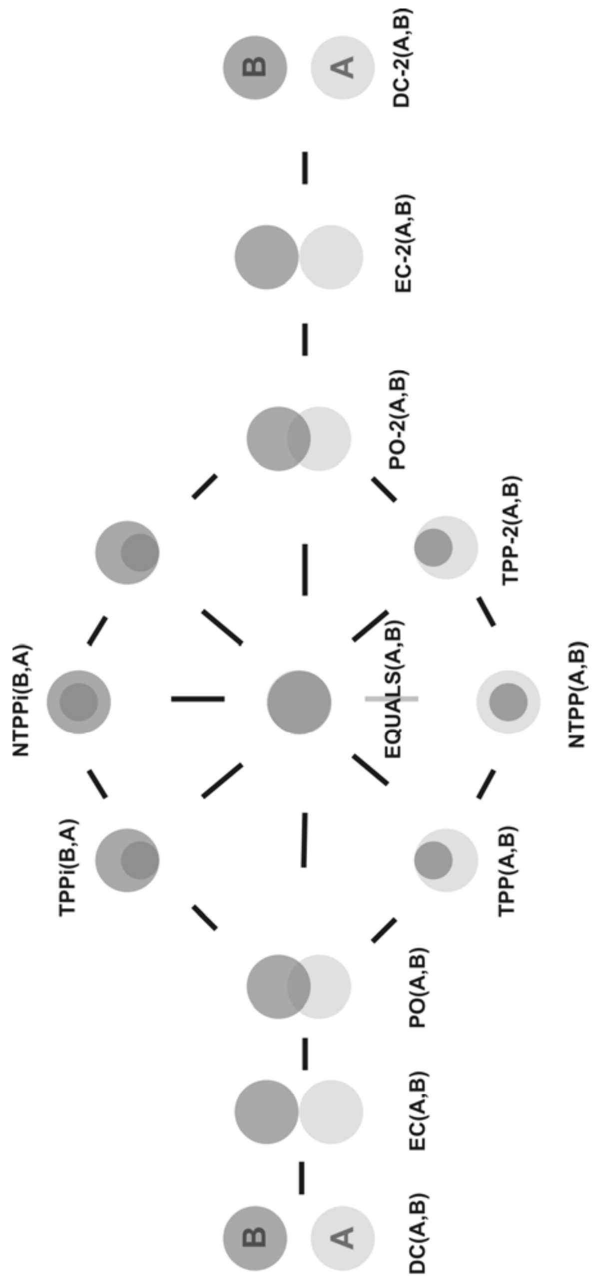
DC-2(A,B)
EC-2(A,B)
PO-2(A,B)
TPP-2(A,B)
NTPPi(B,A)
EQUALS(A,B)
NTPP(A,B)
TPPi(B,A)
TPP(A,B)
PO(A,B)
EC(A,B)
DC(A,B)
B
A
B
A

Figure 2

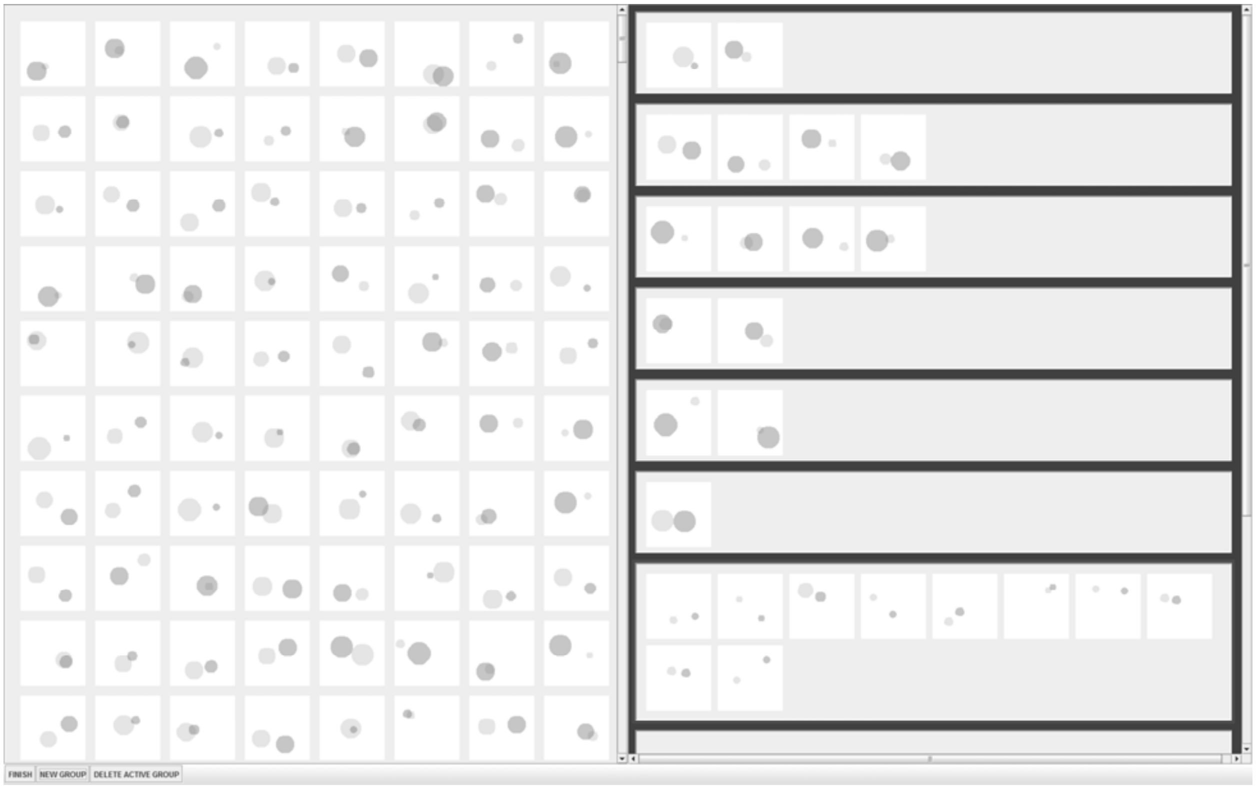

Figure 3

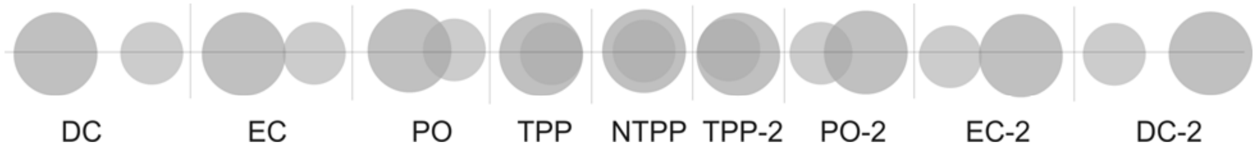

Figure 4

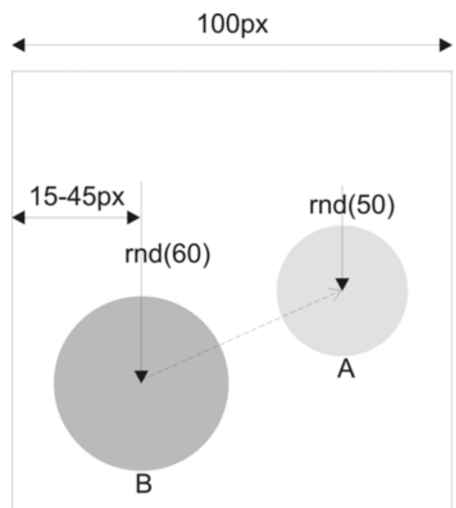

Figure 5

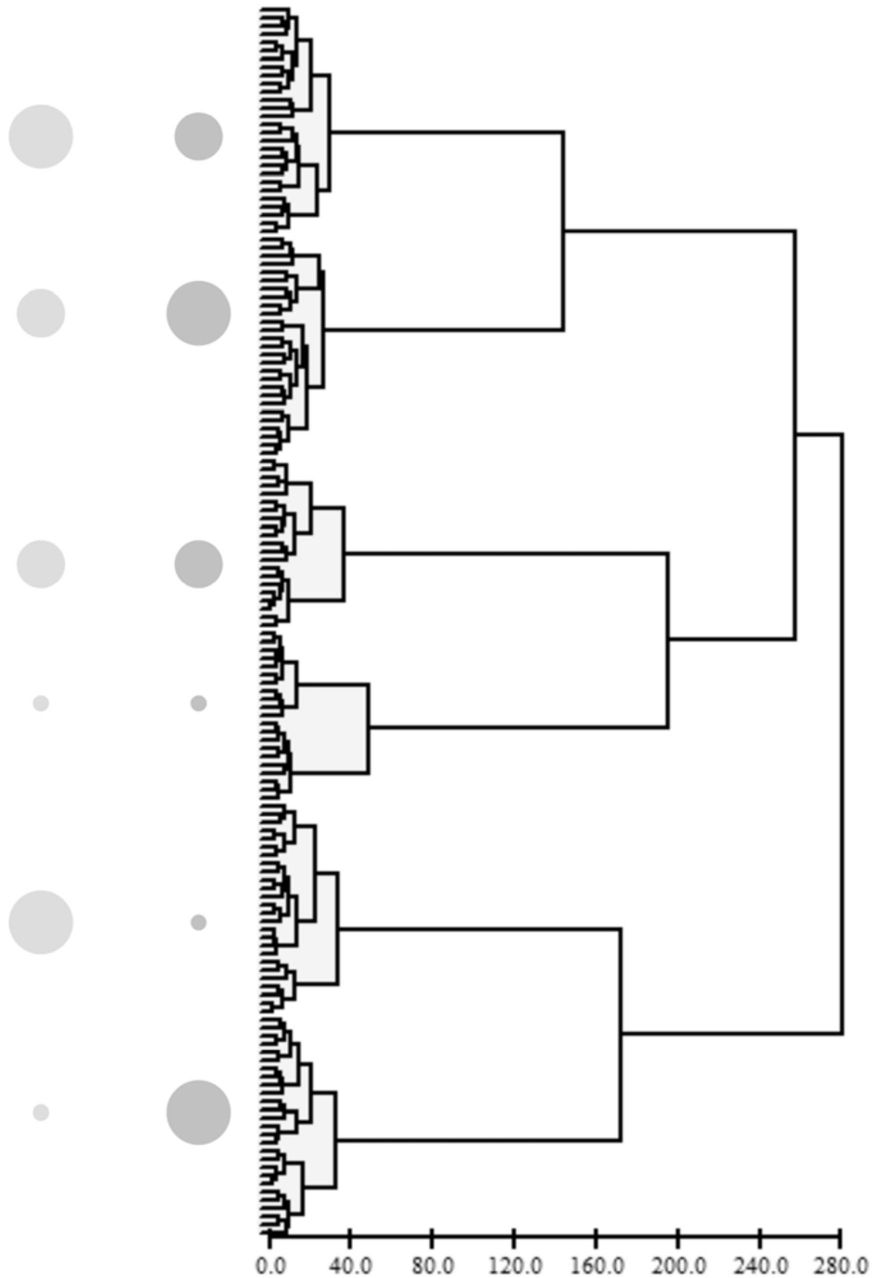

Figure 6

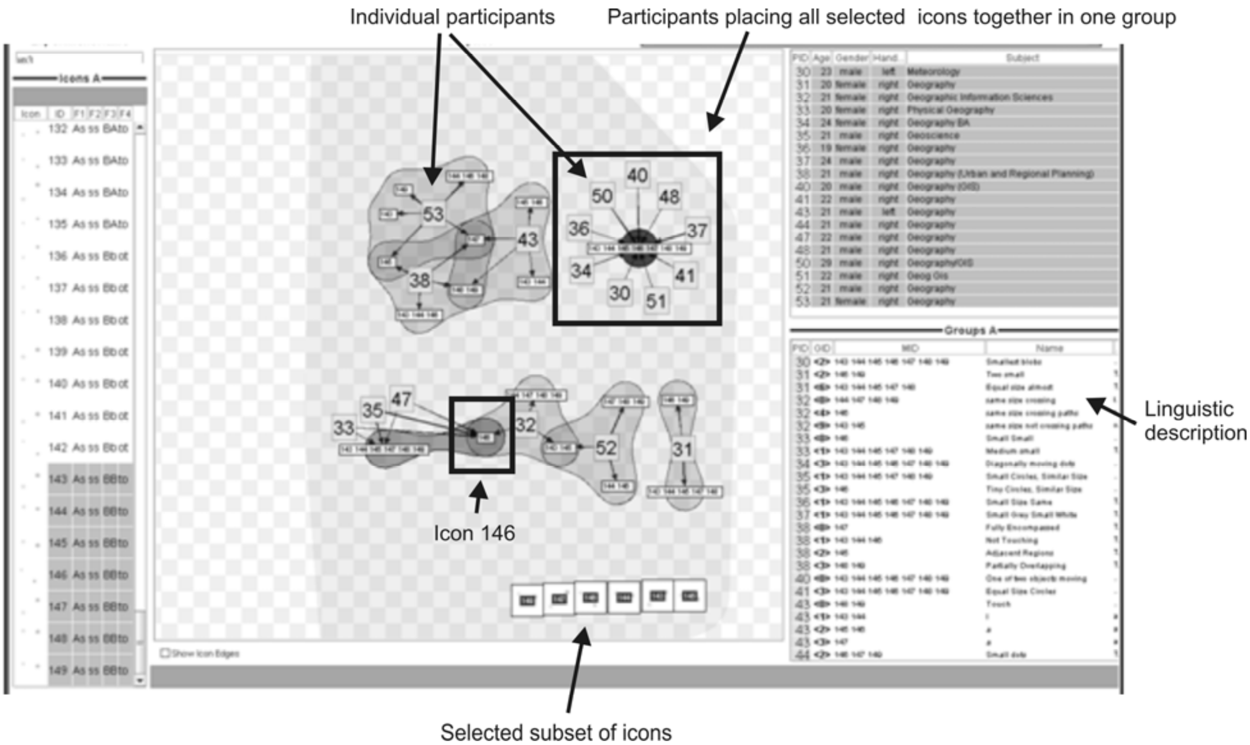
Individual participants
Participants placing all selected icons together in one group
Linguistic description
Icon 146
Selected subset of icons

Figure 7