Cognitive Invariants of Geographic Event Conceptualization: What Matters and What Refines?

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Abstract. Behavioral experiments addressing the conceptualization of geographic events are few and far between. Our research seeks to address this deficiency by developing an experimental framework on the conceptualization of movement patterns. In this paper, we report on a critical experiment that is designed to shed light on the question of cognitively salient invariants in such conceptualization. Invariants have been identified as being critical to human information processing, particularly for the processing of dynamic information. In our experiment, we systematically address cognitive invariants of one class of geographic events: single entity movement patterns. To this end, we designed 72 animated icons that depict the movement patterns of hurricanes around two invariants: size difference and topological equivalence class movement patterns endpoints. While the endpoint hypothesis, put forth by Regier (2007), claims a particular focus of human cognition to ending relations of events, other research suggests that simplicity principles guide categorization and, additionally, that static information is easier to process than dynamic information. Our experiments show a clear picture: Size matters. Nonetheless, we also find categorization behaviors consistent with experiments in both the spatial and temporal domain, namely that topology refines these behaviors and that topological equivalence classes are categorized consistently. These results are critical steppingstones in validating spatial formalism from a cognitive perspective and cognitively grounding work on ontologies.

Keywords: Geographic event conceptualization, topology, similarity, spatial cognition.

1. Introduction

The world is dynamic. The embodied human mind possesses evolved cognitive mechanisms that allow it to effectively process dynamic information. We can, for example, maintain a consistent identification of objects even though they change during optical flow (Gibson, 1979), or segment continuous information into meaningful units (e.g., Tversky, Zacks, & Hard, 2008). Without the capacity to make sense of dynamic information, humans would be unable to survive.

Recent progress in computer technology allows us to tailor behavioral experiments to deliver results that help to create a better understanding of how the human mind understands dynamic information (events). Shipley (2008) writes: “The advent of computers allows us to control events with greater flexibility than ever before. It is time to seriously consider the appropriate place for events in our science. At the risk of being overly polemical, events appear to be a fundamental unit of experience, perhaps even the atoms of consciousness, and thus should be the natural unit of analysis for most psychological domains.” (p. 5)

We tailor our experiments to establish frameworks of movement/event characterization with the goal of improving the cognitive adequacy (Strube, 1991) of spatial formalisms (e.g. Freksa, 1991). Formalisms are at the heart of many theories in geographic information science. Behaviorally validating these formalisms has long been recognized as a crucial step to envision the next generation of theories and applications in spatial sciences (Montello, 2009).

We focus in particular on event conceptualization. We define event conceptualization as category construction (Medin, Wattenmaker, & Hampson, 1987), meaning that we are interested in how humans naturally categorize geographic events. We seek to identify, from a cognitive perspective, factors that are used to distinguish various events. More specifically, movement patterns of individual entities. One way to distinguish these movement patterns and create meaningful units is through the identification of transformational or structural invariants (Gibson, 1979; Shaw, McIntyre, & Mace, 1974; Egenhofer & Al-Taha, 1992).

Researchers in most scientific fields have addressed the topic of invariants’ importance to the cognitive systems. Klix (1992) refers to Descartes as maybe the first to make this point: „Das Menschliche Denkvermögen bleibt immer ein und dasselbe, wenn es sich auch den verschiedensten Gegenständen zuwendet, und es erfährt durch ihre Verschiedenartigkeit ebenso wenig eine Veränderung wie das Sonnenlicht durch die Mannigfaltigkeit der Gegenstände, die es bestrahlt.“ [The human mind stays the same even though it may turn to different objects. In this sense it is like sunlight that does not change either although it shines on many different objects.]

While this argument may be a bit too strong, in a similar vein we find researchers such as Robert Shaw (1974) and J. J. Gibson (1979), both of whom make strong arguments for invariants in the perception of objects and events. Shaw refers to properties that do not change as *transformationally invariant*; Gibson refers to a temporally constant characteristic of the environment as a *structural invariant* (see also Shipley, 2008). The importance of identifying invariants of events is also noted by Galton (2000), who speaks of our ability to intersubjectively identify invariants of time that allow us to construct a shared understanding of our physical (and social) environments. Without this agreement on certain characteristics of spatial environments that ground our meaningful understanding of spatial environments (Scheider, Janowicz, & Kuhn, 2009), the concept of a shared reality and our ability to communicate about this reality would not be possible.

But how can we characterize invariants in dynamic spatial environments? In the qualitative research community, topology has been identified as a way to define invariants (topological equivalence) in order to characterize spatial information in such a way that it becomes possible to model commonsense representations and reasoning. Topology, unquestionably, is playing a central role in characterizing movement patterns and in bridging the (semantic) gap between a formal characterization of movement patterns and the human understanding of movement patterns (e.g., Kurata & Egenhofer, 2009). Numerous research papers address the characterization of the movement patterns of particularly individual agents (whether they are people, vehicles, or hurricanes) using topological characterization (e.g., Stewart Hornsby & Li, 2009). The motivation to focus on topological characterization stems from the importance that topology plays in a) efficiently representing spatial information, b) in the cognitive understanding of spatial environments, and c) linguistic distinction of spatial relations that are reflected by topological equivalence classes (Cohn, 1997). Yet, while static spatial relations have long been of interest and have been addressed from both the formal and the cognitive behavioral side, movement patterns (events)—while being the focus of formal characterization—have not seen the same attention from a cognitive behavioral perspective. Shipley, as mentioned above, points out that the advent of computers allows us now to control events and event characteristics with unprecedented detail. This control is necessary to deepen our understanding of the cognitive processes underlying the perception and cognition of events.

The reminder of this article is structured as follows. We start by describing an experiment designed to answer a crucial question about the dominance of potentially competing invariants, namely the effects of size differences and topologically defined ending relations of movement patterns. In the discussion and conclusion section, we show how the results of the experiment advance knowledge on cognitive conceptualization of movement patterns, how they help to close the semantic gap between formalism and a cognitive understanding of events, and how they can be applied to increase the cognitive adequacy of similarity ratings.

2. Event experiments

In our previous experiments (Klippel, Worboys, & Duckham, 2008; Klippel, 2009; Klippel & Li, 2009), we analyzed the role that topology plays in the conceptualization of geographic movement patterns. These experiments differ from those of other researchers, such as the numerous experiments by Mark and Egenhofer (e.g., 1994) or Xu (2007), in that we use animated stimuli. Such ongoing experimental development is considered essential for research on the cognitive understanding of events (Shipley, 2008). While some researchers conducting similar experiments in the static domain have found topology to be the most important invariant for distinguishing spatial relations, our results were different in two important ways. First, in experiments with competing invariants such as size differences or different dynamic characteristics (whether one entity is moving or both), we found that it was necessary to reverse the famous statement by Mark and Egenhofer that *topology matters and metric refines*. We found that other characteristics mattered and that topological distinctions were used as refinements. For example, participants first distinguished between one entity moving or both, and afterwards made some topologically induced distinctions. Second, in experiments in which we employed real world scenarios (e.g., a hurricane crossing a peninsula), participants did use topologically defined ending relations as the main cognitive invariant. Two important aspects are worth keeping in mind, however. First, we did not introduce many alternative factors; it would, for example, not make sense to have the peninsula moving rather than the hurricane. Second, even though topological distinctions were used as the main criterion for categorizing movement patterns, we found that not all topological relations are equally salient from a cognitive perspective. Most strikingly, we found similarities to work by Lu and Harter (Lu & Harter, 2006), who employed Allen's intervals as a hypothesis for participants and cognitively salient ending relations. Their findings indicate that participants group together temporal relations that show some kind of overlap and distinguish them from those relations that do not overlap.

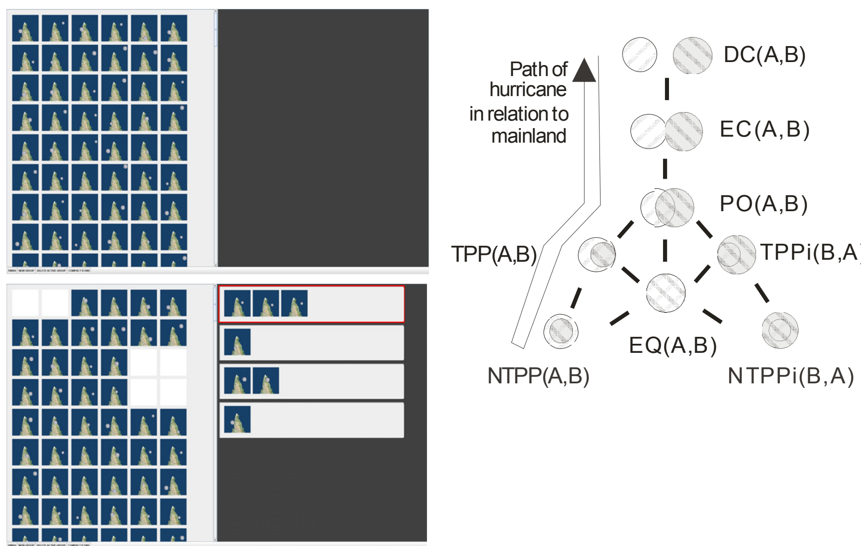

Figure 1. Screenshot of the experiment interface. Top: Initial screen; bottom: mimicked ongoing experiment. On the right side a conceptual neighborhood graph is depicted.

We set up an experiment to shed more light on the question of the dominance of invariants in constructing categories of geographic events. We are interested in two aspects that result from previous experiments, but have not been answered before together: Are topologically distinguished ending relations the cognitively most salient invariant in the category construction of movement patterns? If not, do we still find the different saliencies for individual topologically distinguished ending relations that we find in the absence of size differences? We thus used a real world scenario—a hurricane crossing a peninsula (Klippel & Li, 2009)—but introduced the previously influential factor of size as an additional factor.

Participants. 20 Penn State undergraduate students took part in the experiment; eight were male, the average age was 20.85. Participants were recruited from both Geography and Information Sciences & Technology. They were reimbursed US$10.

Material. We created 72 animated icons, each 120x120 pixels in size. The icons show a peninsula surrounded by water and a hurricane moving toward the peninsula from the top-right corner. Adobe Flash CS4 was used to create the animations and export them in animated GIF format. The animations were further smoothed and enhanced in appearance using the Easy GIF Animator software. Variation was introduced by randomizing both the start and end coordinates of the hurricanes. Start coordinates are all located near the top-right corner. End coordinates were chosen according to one of nine topological equivalence classes (see below and Figure 1).

Given the importance of ending relations for the conceptualization and understanding of events (Regier, 1996; Regier & Zheng, 2007), we selected the end coordinates randomly such that they would fall into one of the topological equivalence classes specified by the conceptual neighborhood graph in Figure 1 on the basis of RCC-8 (Randell, Cui, & Cohn, 1992) or the 9-intersection model (Egenhofer & Franzosa, 1991). Hence, the following ending relations were realized (see also Figure 1): DC1 – the hurricane does not make landfall; EC1 – the hurricane kind of bumps into the peninsula; PO1 – the hurricane just reaches land such that half of the hurricane is on land and the other half is over water; TPP1 – the hurricane makes landfall but is still 'connected' to the water; NTPP – the hurricane makes landfall and is completely over land; TPP2 – same as TPP1 but the hurricane nearly made it out to the water again; PO2 – same as PO1 but on the other side of the peninsula; EC2 – same as EC1 but on the other side of the Peninsula; DC2 – same as DC1 but has crossed the peninsula completely.

For each of these topological equivalence classes, we created eight animated icons that differed in the actual starting and ending coordinates but not the topologically characterized path of the movement through the conceptual neighborhood. Of these eight animations, four showed a large hurricane and four showed a small hurricane. Adding this latter aspect extends previous research in order to answer the question of dominant cognitive invariants in the conceptualization of movement patterns.

Procedure. The experiments took place as a group experiment. For this purpose, we equipped a GIS lab in the Department of Geography at Penn State with view blocks such that up to 16 participants could partake in the experiment at the same time but not see each other's screens. The lab is equipped with 24'' Dell wide screen monitors providing excellent conditions for performing a grouping experiment on a screen. The software we used in previous experiments was improved such that at the beginning of the main experiment all animated icons would appear on the left side of the screen (all at the same time) but that moving one icon from the left side into a group (category) on the right side would leave the spot empty (see Figure 1). Otherwise the experiment followed established and tested experimental paradigms.

The participants were randomly assigned to computers, provided consent, and entered anonymous personal data such as age and field of study. They received a short introduction detailing the scenario and the course of the experiment. This text explicitly referred to the stimulus as hurricane and peninsula. It also made clear that there are no right or wrong ways to creates group (categories), and that it is up to the participants themselves to select criteria and the number of appropriate groups (categories). To make this point even clearer, participants were provided with a warm up task and were asked to group animals such as dogs, cats, and camels. The grouping software does not allow for ending a task before all icons are placed into groups, whether in the warm up task or in the main experiment.

In the main experiment, participants were presented with the 72 animated icons. In the first part of the main experiments they created as many groups (categories) as they deemed appropriate. Participants had to explicitly create all groups, that is, there are no groups depicted or implied on the right side of the experimental software user interface (see Figure 1). Participants can create and delete groups, move animated icons into and out of groups, or move icons between groups. This procedure is referred to alternately as category construction (Medin et al., 1987), free classification, or unsupervised learning (Pothos & Chater, 2002).

After placing all icons into groups, participants entered the second part of the main experiment. In this part, participants were presented again with the groups that they had created in the first part. The groups were presented one at the time, and the participants asked to linguistically label them and to draw a sketch map, a graphic symbol that represents the group. The linguistic labeling task has two parts: to provide a short description of no more than 5 words, and to provide a more detailed explanation of the rationale upon which a particular group was created.

3. Results

We first analyze the category construction behavior of the participants. To this end, we first calculate individual grouping matrices for each participant. Individual matrices encode the grouping behavior for all possible (72 x 72 = 5184) icon pairings as binary values. A '0' in a matrix indicates two icons are not placed into the same category and a '1' indicates that two icons are placed into the same category. We then calculate an overall similarity matrix (OSM) by summing over all individual matrices. An OSM thus encodes similarities on the basis of grouping behavior: the least similarity, '0', indicates that two icons were never placed into the same group; the highest similarity, '20', indicates that the corresponding pair of icons were placed into the same group by all participants.

The OSM is the basis for both the cluster analysis methods and the multidimensional scaling (MDS) that we discuss in the following sections. We validate cluster results using approved and recommended methods (Kos & Psenicka, 2000; Clatworthy, Buick, Hankins, Weinman, & Horne, 2005): a) the comparison of different clustering methods and b) splitting the participant pool randomly in half and comparing the result (that we will not discuss in detail here but that showed similar results).

We compared three clustering methods: Ward's method (or increase sum of squares), average linkage, and complete linkage. Ward's method is often preferred for its use of a statistical measure, that is, minimizing the increase of the sum of squared differences from the group mean. In contrast, average and complete linkage use arithmetic calculations to analyze the similarity structure. Hence, in case these different methods indicate similar clustering structures such as the inferred number of clusters, they can be used as validation.

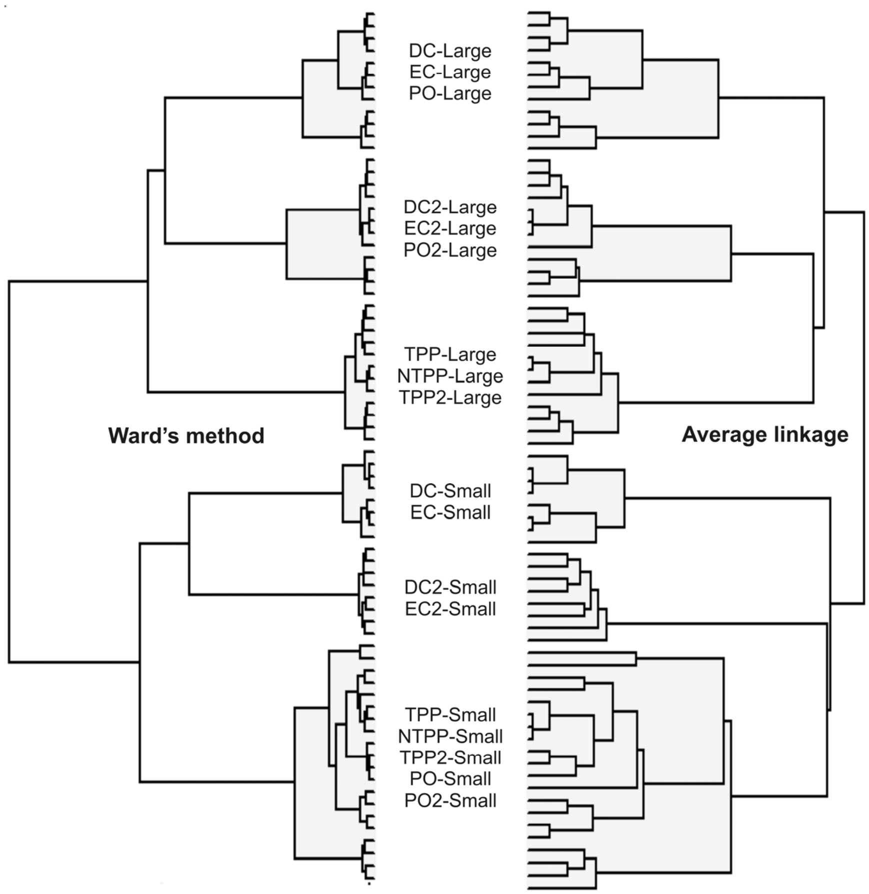

Figure 2. Depicted are two clustering method: Ward's method and average linkage (the original three cluster analyses can be found at: http://www.cognitivegiscience.psu.edu/cluster-analysis.jpg). The comparison of the different clustering methods shows basically the same results indicating the validity of the interpretation.

Figure 2 shows the results of two (out of three) cluster analyses (as mentioned above). The dendrograms reveal that size is the dominating factor. This is shown in both dendrograms (Ward's method and average linkage); they both show that participants used size to create two distinct groups. While complete linkage (see website) does not show the same bifurcated structure on the basis of size, but size is still clearly used to distinguish (cut through) each topologically defined equivalence class. The saliency of topologically defined ending relations thus functions as a refinement. While size is the primary criterion that participants use to differentiate the hurricane movement patterns, the further differentiation based on topologically defined ending relations gives a similar picture to previous experimental results within each size category. Most importantly, we again were not able to replicated findings from static experiments that hint at equal saliency of all topologically defined ending relations (see Knauff, Rauh, & Renz, 1997). In other words, we again find that certain topological relations are conceptually closer together than others, in a pattern that is similar to those of previous experiments (see Klippel & Li, 2009): Ending relations that do not show some kind of overlap (DC and EC) are separated from those that do show some kind of overlap (TPP and NTPP). The exception to this pattern is that the ending relation partial overlap (PO) that has been identified in previous experiments as a "flip-flop" relation is not as clearly conceptualized as other ending relations. The changing character of the PO relation becomes particularly apparent in the case of small hurricanes. This deviation from the pattern is most likely related to perceptual characteristics, that is, this relation becomes harder to identify properly in cases in which the hurricane is small.

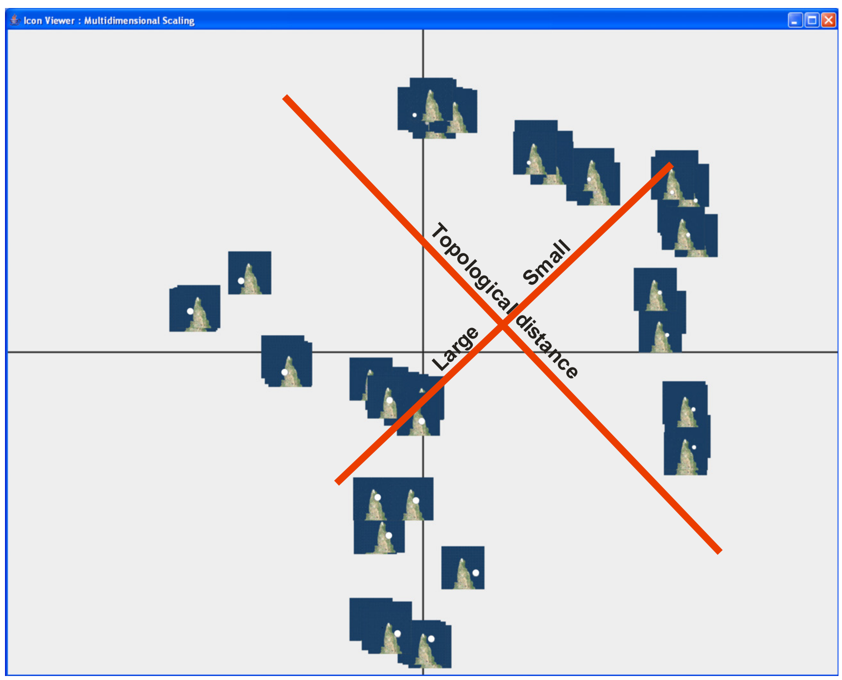

Figure 3. MDS analysis of the category construction behavior. In the ideal case, MDS analysis allows for labeling the axis of the plot. In our case, this can be nicely done as participants clearly distinguished size differences as well as topologically defined ending relations.

For an additional perspective on the category construction behavior of the participants, we also subjected the OSM directly to a multidimensional scaling algorithm using Clustan™. The results of this analysis are shown in Figure 3. We used a custom-made software tool to visualize MDS results, that is, to place a picture showing only the ending relation of the hurricane movement. The pictures are reduced in size, but with a total of 72 pictures some overlap (which actually indicates high similarity) was unavoidable. One ideal outcome of MDS is to identify axes and label those axes. In our case this is nicely possible. The first axis (see Figure 3) is making the distinction between small and large hurricanes. This axis clearly confirms the analysis that we obtained from the cluster analysis in Figure 2 that size matters. The second axis reflects the conceptual distance between different topologically defined ending relations of movement patterns. This axis reveals that certain topologically defined ending relations—the ones found grouped close together in the dendrograms— are conceptually closer together than others.

To further confirm these results, we used KlipArt (Klippel, Hardisty, & Weaver, 2009) to analyze the category construction behavior together with the linguistic descriptions that participants provided. Figure 4 shows an example of the grouping behavior for hurricane movement patterns that do not make landfall. In this case the conceptual neighborhood path is very short because peninsula and hurricane are always disconnected (DC). It is clear that most participants (14 out of 20) separated the animated icons on the basis of the size of the icons, compared to 2 participants who place all icons in the same category. The linguistic analysis allowed us to shed more light on the rationale of the category construction behavior. It also revealed that participant 7 made a ‘mistake’ and meant to classify the icons into two categories, participant 2 meant to group all icons into one group, and that participants 8 and 21 did use size as a criterion but made finer distinctions based on where the hurricanes made landfall.

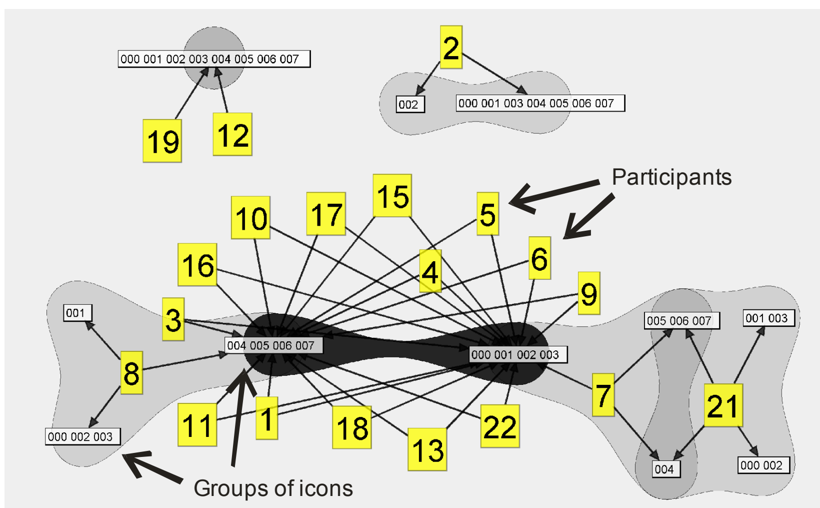

Figure 4. KlipArt analysis. An in depth analysis reveals the category construction behavior and allows for linking linguistic descriptions with category construction behavior. The Figure clearly shows that, for the movement patterns characterized as DC, most participants (14 out of 20) used size as the main distinguishing criterion (in which icons 000, 001, 002, and 003 show a large hurricane and icons 004, 005, 006, and 007 show a small one). Additional linguistic analysis reveals that 17 out of 20 participants used size in the category construction process.

We now turn to the analysis of the linguistic descriptions that the participants created. We focus here primarily on the short descriptions that participants provided for the groups that they created. Participants created a total of 140 groups, hence we had 140 labels with an average length of 3.5 words. The aspect we focused on is the question whether the size of the hurricanes was mentioned either directly, such as '*large* hurricane' or '*small* storm', or indirectly, such as '*weak* hurricane' or '*strong* hurricane'. In 86% of the labels, we find either a direct or indirect reference to the size of the hurricanes.

4. Discussion

The results of our experiment add to the understanding of how events in geographic space are conceptualized. Previous experiments provided insufficient evidence about the salience of topologically defined ending relations of movement patterns compared to other factors such as size differences. Our experiment closes this gap in our knowledge.

We analyzed different types of data with the intention to cross-validate experimental results. To this end, we collected category construction information (similarity assessments) and linguistic labels. Combining both data sources offers valuable insights into cognitive processes underlying the category construction of geographic events. Additionally, we cross-validated our findings by employing different analysis methods. We used different types of cluster analysis that we compared against one another, performed the same analysis on random subgroups of participants, used multidimensional scaling to improve the interpretation of the data through spatialization (Skupin & Fabrikant, 2007), and additionally, we used a custom-made software tool, KlipArt, that allows us to analyze the category construction behavior of individual or groups of participants for specific groups of icons. Amazingly, all these analyses converge on the same conclusion: *Size matters and topology refines*.

We now have, however, a conundrum: Given the importance of events exhibited through a strong interest of different research communities in spatio-temporal frameworks, it is amazing that a static aspect dominates that category construction behavior or participants. Could it be that size is a domain-specific concept and factor? We could make the argument that size may be more important in one domain than in another. It makes an important conceptual difference, whether a small hurricane passes over a peninsula or whether a large one does. This distinction may not be as crucial for other domains, for example, whether a big tanker crosses a certain area or a small one. However, our previous experiments, that used geometric form (circles) and in which participants were 'only' asked to imagine something geographic, showed a clear dominance of size differences, too. Hence, unquestionably, size differences are an important factor in perception (Wolff, 2008; Lockhead & Pomerantz, 1991) as well as in conception. We would argue that in most cases size (extent) is an conceptually important piece of information.

Despite the dominance of size as the main criterion for categorization, we must point out that topology also plays a role in refining category construction. Even more importantly, we find a pattern that is consistent with those of our own previous experiments (Klippel & Li, 2009) as well as experiments from the temporal domain

(Lu & Harter, 2006). This consistent pattern has the following characteristics. Unlike the results of the experiments conducted by Knauff and collaborators (Knauff et al., 1997), topologically defined ending relations of movement patterns do not all have the same conceptual salience. Whereas in the static domain all eight topological relations show comparable salience, in the case of events, there is a clear pattern that distinguishes topological relations that overlap (TPP and NTPP) from those that do not (DC and EC). The one somewhat inconsistent exception is the relation partial overlap (PO).

5. Conclusions

Analyzing movement patterns, developing models for event-oriented approaches to spatial information, and developing a theory of how events at the geographic scale are construed and understood by humans, are all prominent research efforts in geographic information science. Our research fills a *critical niche*: We are developing a systematic and extensive research framework for the behavioral exploration, assessment, and validation of the semantics of movement patterns. The key aspects of our research are: a) developing a multi-method and multi-data-type analysis framework that makes it possible to open multiple *windows to cognition* and thereby substantially improve our understanding of cognitive processes underlying the conceptualization of events; b) utilizing computational methods to display events as animations to be used in behavioral experiments; c) cross-validating our research findings to improve the reliability of our interpretations; d) tailoring the research design to bridge the semantic gap between formalisms and their capacity to model the human mind.

We demonstrated that, with these prerequisites, the design and evaluation of qualitative formalisms—critical for geographic information science—becomes feasible and can be conducted in great depth. Additionally, we are able to focus on how events at the geographic scale are conceptualized. Step by step we add to a cognitive theory of geographic event conceptualization that is grounded in the theoretical foundations laid out in spatial information science (e.g., Kurata & Egenhofer, 2009; Stewart Hornsby & Li, 2009) but that also allows for evaluating proposed formalisms. We consider this step by step approach essential, as it basically combines the theory building that we find in psychology and cognitive science with topics relevant to spatial information theory. The fruitfulness of this combination has been explicated in the original work by Mark and Egenhofer (e.g., Mark & Egenhofer, 1994), that many researchers, including us, have adopted.

Our future work in this area includes the following directions. While we have shown now that size matters and that topology refines in the conceptualization of hurricane movement patterns, we are aiming for a theory of conceptualizing movement patterns that is able to explain aspects of movement conceptualization that are universal across different domains and those where the semantic context might be influential. The semantic context can be thought of in two ways. The first is that different domains will emphasize or de-emphasize the cognitive saliency of different topological relations. While we do have cross-validation through the work by Lu and

Harter (Lu & Harter, 2006) that an important distinction has to be made between topological relations that show some kind of overlap and those that do not, there are the open questions of whether this is the case across different domains (hurricanes, tornados, boats, etc.), and why this does not seem to be the case in the static domain. To this end, we have designed scenarios that are taken from different domains and also added a comparison of statically depicted paths of hurricanes.

The second is that the semantics of a domain might be different for experts and non-experts. This is a crucial topic that has received a lot of attention (Bryant, 2000). There very well may be some fine tuning in category construction behavior when comparing experts and non-experts. We share the belief put forth by Goldstone (1994) that even though we could define arbitrary concepts according to theoretical or contextual information, but humans—experts and non-experts—indeed derive most useful information from perceptual input, and this information is valid even in more complex theoretical constructs.

Two more aspects are interesting to us in this regard. First, how may different topological transformations influence the cognitive saliency of topologically defined ending relations? For instance, if we compare translation (such as hurricane movement) with scaling (such as the extension and shrinking of a lake), we can create an identical conceptual path through a conceptual neighborhood graph (Egenhofer & Al-Taha, 1992). However, does this lead to a different assessment of the cognitive salience of topologically defined ending relations?

Second, we are working on extending our research framework to evaluate further different formalisms. So far we have focused on conceptual neighborhood graphs based on topological relations between two extended spatial entities. More recently Kurata (Kurata, 2008) proposed an extension of the 9 intersection model, the 9+-intersection model (last year's best GIScience paper).This framework explicitly addresses the modeling of movement patterns by utilizing the source-path-goal characteristics of every movement. Kurata and Egenhofer (2009) use this approach to model the cognitive understanding of movement patterns. The critical question is whether from a cognitive perspective this framework works as is, or whether it requires cognitive adaptations. We are currently working on experiments that will shed light on the question of whether all 26 primitive relations defined by the 9+ intersection model are equally salient from a cognitive perspective.

A second line of research is to use the results of our experiments to inform similarity assessment of movement patterns. One of the most critical aspects in establishing similarity measures is the specification of weights. If we take the conceptual neighborhood graph that provides the basis for our experiments as an example for topological and—more generally—graph-based similarity measures, we find that most research on similarity is using non-weighted edges (Schwering, 2008). If we change, for instance, the underlying formalism from RCC8 to RCC5 (also possible in Egenhofer's models with some differences in the coarser models), then we will also change the similarity between topological relations. Likewise, while the assumption of equal weights does not seem to contradict results using static spatial relations (Knauff et al., 1997), this assumption contradicts findings in the dynamic domain (Lu & Harter, 2006; Klippel & Li, 2009). Hence, it is essential to a) understand the different roles that topology plays in the static and the dynamic domain, and b) to refine topological similarity ratings that are based on graph structures such as the conceptual neighborhood graph. Our results thus far provide input to such refinements and we are currently working on integrating them into the SIM-DL framework (Janowicz, Keßler, Schwarz, Wilkes, Panov, Espeter et al., 2007). The two possibilities we are exploring are the use of fusion coefficients that can be derived from different clustering algorithms, or, alternatively, we are exploring ways to use the similarity ratings directly. In line with the future research directions specified above, we will derive similarity values for different spatial and semantic contexts with the goal of establishing a universal similarity measure that would generally improve similarity assessments. Nonetheless, we continue working on context-specific tailoring of similarity assessments to non-topological information under different contexts and in different semantic domains.

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