Analyzing Cognitive Conceptualizations Using Interactive Visual Environments

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ABSTRACT. The conceptualization of spatio-temporal information is an interdisciplinary research area. The focus of this article is on human conceptualizations of spatio-temporal geographic phenomena (also referred to as events). Identifying and understanding human conceptualizations is a crucial component in defining the semantics of spatio-temporal information. However, most research focuses primarily on how humans imbue dynamic phenomena with meaning on a general level. In contrast, this article is concerned with contextual factors (specifically: individual differences) that are too often neglected in general theories and in the analysis of behavioral data. In other words, we are interested in individual or group strategies of participants that are not detected by classical analysis methods. Research on individual difference is gaining widespread attention in cognitive and spatial sciences and it is time to consider individual differences in the area of conceptualizing spatio-temporal information. To be able to shed light on individual differences in behavioral data on how people conceptualize events, we have developed software solutions and combined them with established similarity measures. These software solutions allow analysts to effectively explore individual differences. We demonstrate the feasibility of our approach, its usefulness in analyzing behavioral data, and results that can be obtained through this individualized analysis by reanalyzing four sets of experimental data we previously collected.

Introduction

The most widely used definition of an ontology is that it is *a specification of a conceptualization* (Gruber, 1993). That means that on the one hand a decision has to be made what a *specification* is and how formal this specification should be (e.g., Smith, 1998). On the other hand, and of great interest to a multidisciplinary research community, the focus lies on revealing *conceptualizations*. With respect to the latter and in the case of spatial information we can ask the question: How is the (spatial) world—and in the context of the current article, dynamic spatial phenomena—conceptualized by humans? That is, how do humans divide potentially continuous spatio-temporal information into meaningful units and how does a cognitive system organize these units into categories?

Long before the hype surrounding ontologies (Winter, 2001) and current developments such as the semantic web fostered the prominence of research on conceptualization, researchers from literally every discipline addressed this topic. We often find that the terms 'classification' and 'categorization' are used to capture a similar semantic scope. For example, Abel and collaborators wrote: "If every object and event in the world were taken as distinct and unique—a thing in itself unrelated to anything else—our perception of the world would disintegrate into complete meaninglessness. The purpose of classification is to give order to the things we experience." (Abler et al., 1971, p. 149) Establishing a system that allows us to classify (and from a cognitive perspective, to categorize) is the act of conceptualization. In this generality conceptualization is most likely the most universal transdisciplinary topic there is.

Each discipline has developed its own approaches and methodologies to address the topic of conceptualization and classification. Examples focusing on (cognitive) spatial questions include: linguists who employ the ‘(spatial) language as window to (spatial) cognition’ metaphor to learn about the conceptualization of spatial information through the analysis of linguistic expressions and language use (Lakoff, 1987; Talmy, 1983); psychologists who designed controlled experiments to shed light on questions such as the validity of qualitative spatial calculi (Knauff et al., 1997). The spatial sciences, including geographical information science, address the human understanding of conceptualizations of spatio-temporal information through the development of formal models inspired by cognitive models (Galton, 2000; Hornsby & Egenhofer, 1997; Peuquet, 2001; Worboys, 2005).

An emerging topic of interest is the influence of contextual factors on conceptualization processes (e.g., Keßler, 2010). Rather than assuming that there is a single true structure that can be discovered (which may be true in some sense) it has been acknowledged that the conceptualization of a given set of entities or events can change depending on contextual factors, including individual differences (Mark, 1993).

Especially qualitative research has acknowledge the plurality of conceptualizations through the development of approaches such as discourse theory (Lakshman, 2010); cross-cultural and cross-linguistic research has contributed to the theoretical understanding that, rather than assuming an objective reality, conceptualizations exist in human minds and may be only shared by certain cultural groups. In response to these findings, researchers started to develop concepts theories that incorporate context. For example, Gabora and collaborators (Gabora et al., 2008) are developing an *ecological theory of concepts* to account for contextual effects employing ideas from quantum mechanics. In a complementary direction, researchers interested in scientific aspects of classification and conceptualization incorporate context dependent factors (situatedness) to account for alternative conceptualizations of the same part of the world (Brodaric & Gahegan, 2007).

The focus of this article is a synthesis of these themes. We discuss our methodological contribution that employs an interactive visual environment to analyze context specific conceptualizations elicited in behavioral experiments. The context in our experiments (so far) are individual differences that fall through the cracks of many of the analysis methods that are classically applied to behavioral data (for example, cluster analysis Everitt, 2001). The visual methods we developed allow for revealing cross-cultural and cross-linguistic but also on simple individual differences that occur in many behavioral experiments. While individual differences have become a prominent research topic in psychology and the cognitive sciences, current approaches relevant to spatial cognition focus primarily on differences in spatial abilities (for example measured through the water level test Piaget & Inhelder, 1948/56/67) or general restrictions in working memory capacity. Our research fills this gap by creating tools that allow for the analysis of conceptualizations of participants at the group as well as at the individual level. We consider this research critical due to the omnipresence of contextual factors and the requirements of, for example, information systems to account for individual differences; we need to advance methodological capabilities to understand conceptualization in different contexts whether they are based on individual preferences, cultural influences, or external factors. As Mojsilovic and colleagues state for the area of database design: "… we need tools to construct a semantic bridge between the user [one might say: different users] and the database." Our goal is to help building this bridge.

The reminder of this article is structured as follows: Section 2 focuses on the (re-) analysis of behavioral data using the special perspective of context and individual differences: after a short introduction to the behavioral research methodology, we discuss the tools we developed. Their applicability and value is demonstrated using data we collected over the last three years of research. Conclusions and outlook put the results into perspective and lay out future avenues of research.

Analyzing behavioral data to reveal individual differences

In the following sections, we discuss several aspects of individual differences by reanalyzing data from experiments that we have conducted to elicit conceptual knowledge on the basis of similarity ratings. These experiments probe the conceptualization of geographic scale movement patterns using a grouping paradigm, that is, asking participants to create groups out of a set of animated icons. Additionally, the similarity data (icons placed into the same group) is amended by collecting linguistic descriptions for the groups that participants created in the experiments. This information is valuable in that language works as a window to cognition (Osherson et al., 1990) and can provide critical insights into conceptualization processes. We have collected this kind of data in a variety of domains such as direction concepts (how many direction concepts do humans distinguish and does it matter whether they think about them linguistically as compared to non-linguistically, Klippel & Montello, 2007), the influence of salient shape characteristics of multivariate point symbols on classifying semantically different objects (Klippel, Hardisty, & Weaver, 2009), and, most importantly for this article, the conceptualization of dynamic scenes or events (Klippel et al., 2008; Klippel & Li, 2009). While the focus of the reanalysis using visual analysis tools is here on event conceptualization, we hope that the research methodology we introduce will find wider applicability in various fields (e.g., cross linguistic / cultural studies, expert versus novice assessments) as the grouping paradigm is a widely used method (Medin et al., 1987; Pothos, 2005; Wood & Wood, 2008).

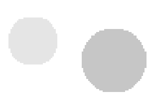
In the following sections we provide a brief description of the research methodology, but try to balance the level of detail so as to not distract from the main focus of the article—our study on individual differences.

Methodology

In the present investigation on individual differences, we are using data from four experiments that all addressed the question of the role that topology plays in conceptualizing geographic events. All of our experiments use a grouping paradigm to elicit conceptual knowledge, specifically, the conceptualization of events. The grouping paradigm is well known in psychology and has also been used in behavioral spatial information science (Knauff et al., 1997; Mark & Egenhofer, 1994; Renz, 2002). The experiments we are discussing here use animated stimuli to address questions of *event conceptualization*. Table 1 gives an overview of research questions and some statistics of experimental designs. It also shows an example of what the stimulus looked like. This work is built on topologically distinguished spatial relations (Egenhofer & Franzosa, 1991; Randell et al., 1992) and the notion of *conceptual neighborhood graphs* (Egenhofer & Al-Taha, 1992; Freksa, 1992). These experiments extend research on the cognitive adequacy of topological calculi from the static domain (Knauff et al., 1997; Mark & Egenhofer, 1994) into the domain of spatio-temporal phenomena[1]. It is important to note that individual differences were not the focus in any of the previous publications.

Figure 1 shows two screen shots from the experiment tool to provide a general idea of the participants' task. The top part shows the initial screen a participant sees (icons are animated in the experiments). A participant's task is to place icons from the left side of the screen into groups on the right side. The number of groups, and which icons to put in each group, is a decision for each participant to make. This procedure is referred to as free classification (Billman & Davies, 2005), unsupervised human categorization (Pothos & Chater, 2002), or category construction (Medin et al., 1987). The bottom part of Figure 1 provides an impression of an ongoing experiment in which the participant has created a handful of groups and is placing icons into these groups. In cases in which the stimulus consisted of geometric figures, participants were encouraged to think about geographic examples[2].

Table 1. Details of the reanalyzed experiments.

Experiment	Icon example (these are animated in the actual experiments)	Central question	#icons, #participants
XP1		Are (left side / right side) paths through the conceptual neighborhood graph the predominant factor for conceptualizing movement patterns?	I: 144 P: 19
XP2		Same as for XP1, except that the icon size was randomized.	I: 144 P: 20
XP3		Are topologically distinguished ending relations the dominant factor for conceptualizing movement patterns?	I: 150 P: 19

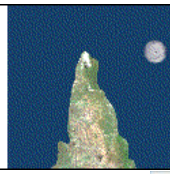
XP4		Same as for XP3.	I: 54 P: 26

Figure 1. Two screenshots of the experimental setup using the grouping paradigm. The top half shows the initial screen that participants see (here from experiment XP4). The bottom half shows a mimicked ongoing experiment.

The animated icons are designed such that they potentially can be distinguished on the basis of the spatial, topologically defined relations that the movement patterns end in. For clarification refer to Figure 2. In Experiment 4, for example, we used a hurricane peninsula scenario. The end position of the hurricanes was varied on the basis of eight topological relations differentiated by Egenhofer's intersection models and RCC8 (Egenhofer & Franzosa, 1991; Randell et al., 1992). For example, a hurricane that does not make landfall can be characterized by a short path through the conceptual neighborhood graph as only the disconnected (DC) relationship holds between the two entities. In contrast, a hurricane that crosses the entire peninsula would have a long path through the conceptual neighborhood graph, i.e., DC-EC-PO-TPP-NTPP-TPP-PO-EC-DC.

In our experiments we included additional factors in the design of the animated icons such as using geometric figures versus real world scenarios, size differences, whether one or both entities are moving, and directions of movement.

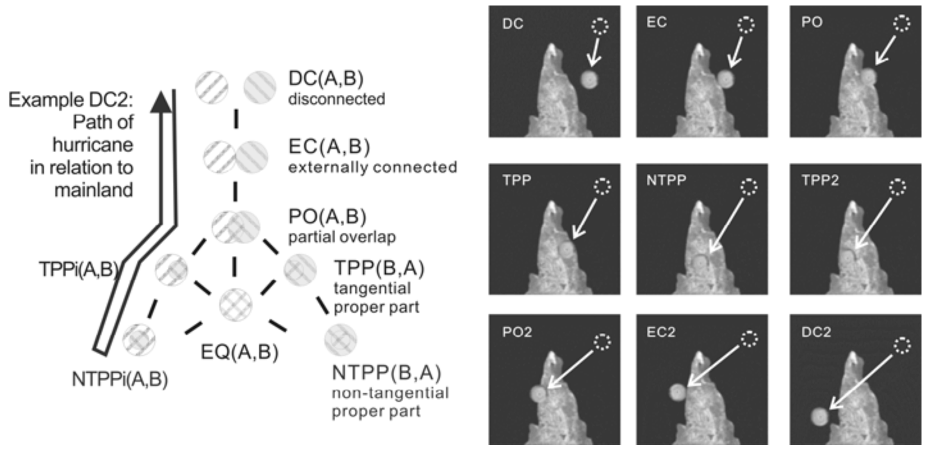


Figure 2. Left: Conceptual neighborhood graph (Egenhofer & Al-Taha, 1992; Freksa, 1992). Right: Different paths of hurricanes distinguished by ending relations. Depicted is the ending relation of the hurricane movement (solid disk) and the start relation (dashed circle). The actual start and ending relations are randomized within their topologically defined equivalence class (from Klippel & Li, 2009).

(Re-) Analysis of the data

The ‘usual’ analysis of grouping data is straightforward. The grouping of each participant results in a similarity matrix that encodes similarity as a binary value: 0 if two animated icons are not in the same group, 1 if two animated icons are in the same group. Summing over the individual similarity matrices of all participants results in an overall similarity matrix that can be evaluated with clustering or multidimensional scaling algorithms to reveal natural groupings.

However, what we are interested in here are not the overall results of cluster analysis but methods that allow us to shed light on individual differences in the conceptualization of movement patterns and category construction/conceptualization. To this end, we have developed interactive visualization software for exploration and analysis of individual differences in grouping data (that is indicative of different conceptualizations of events). Using Improvise, an integrated environment for developing highly interactive visual analysis tools (Weaver, 2004), we have so far built two tools that display similarity matrix data sets in matrix and graph form. Improvise supports the rapid, data-driven and analysis-driven development of visual analysis tools that provide multiple interactively coupled ("coordinated") views onto multivariate data. While other matrix-similarity visualization approaches exist (Ahlqvist, 2010), we custom made our two matrix visualization tools specifically for analysis of behavioral data. The tools were developed over several versions in close collaboration between the authors, and reflect iterative refinement to tailor methods and interactions to reveal insights from experiment data on individual differences.

MatrixVisualizer

The first visual tool, shown in Figure 3, displays two half matrices (here taken from experiment 4, a hurricane approaching/crossing a peninsula). These half matrices provide different perspective on the grouping behavior of participants. While the upper left matrix is a direct visualization of similarities between icons, the lower right matrix visualizes results of additional similarity assessments. We discuss and explain both matrices in the following.

Each cell in the upper left matrix encodes, in color and optional text, the number of times that participants placed the icon for that row and the icon for that column into the same group. The abbreviations/names of rows and columns (i.e., the icons) are topological relations that the movement patterns end in (taken from XP4, see Figure 2). This matrix can be optionally filtered to show counts for an arbitrary subset of participants by way of interactive selection from miniature icon co-occurrence matrices along the bottom and right sides of the lower right matrix.

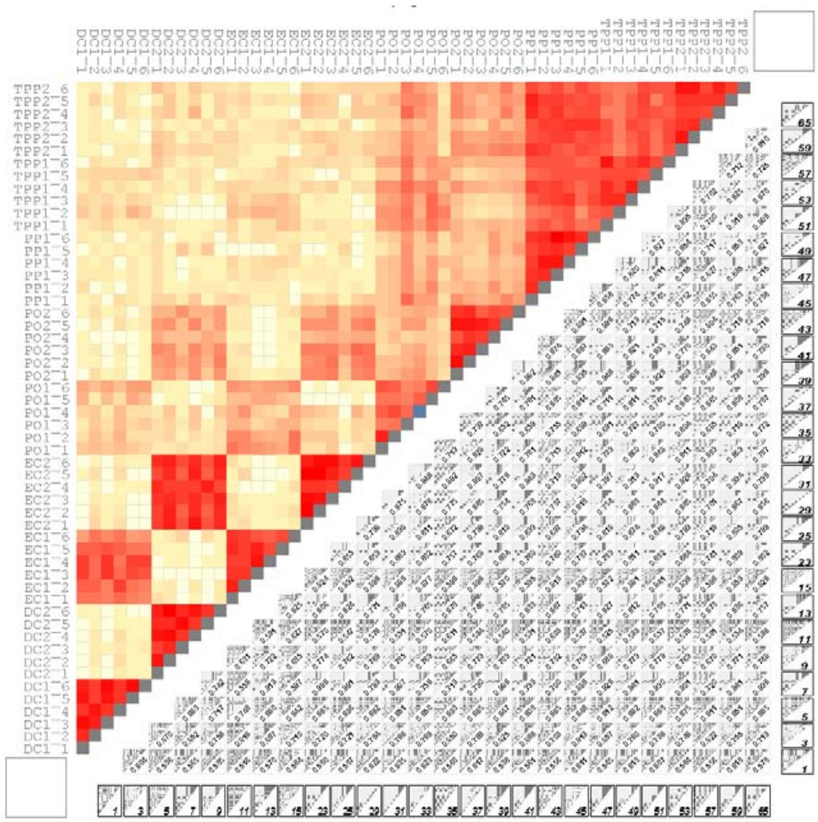


Figure 3. Analysis of individual differences of the conceptualization of movement patterns (i.e. grouping behavior / similarity ratings), for XP4. Patterns emerged on the basis of actual grouping behavior of participants. The upper left part shows a matrix that visualizes the similarity of animated icons directly, that is, the darker red a grid cell is, the more similar are two icons rated to each other. The lower right, in contrast, shows a visual representation of the Levenshtein distance comparing the grouping behavior of all participants with each other. Black grid cells indicate different grouping behavior; white grid cells indicate identical grouping behavior[3].

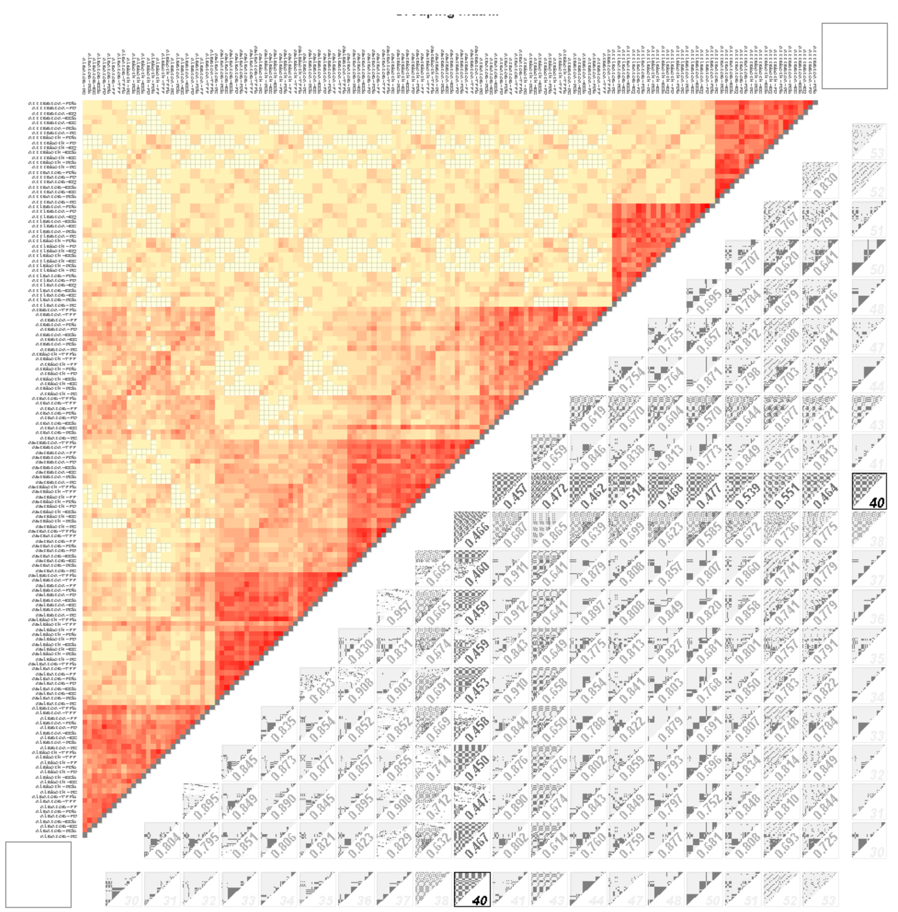


Figure 4. A screenshot from the MatrixVisualizer for XP3. Participant 40 is highlighted. Visual inspection of Levenshtein distances in the lower right matrix reveals that participant 40 adopted a different strategy than most other participants. Likewise, other participants form groups that are revealed by comparison of salient patterns in the pairwise Levenshtein matrices.

In contrast, cells in the lower right matrix contain miniature *binary difference matrices* for each row-column pair of participants. Each of these matrices is accompanied by a binary similarity measure, calculated as a "simple Levenshtein distance" of $\mathbf{1\text{-}(cells_{different}\ /\ cells_{total})}$. The Levenshtein distance (Levenshtein, 1966) allows for comparing participants with each other to reveal individual differences. While the Levenshtein distance (also called edit distance) in general allows for three operations (insert, delete, and replace), we only need the replace function as all matrices have the same length (i.e., number of cells, which technically can be captured by the Hamming distance (e.g., Gusfield, 1997). With the result of this analysis it becomes possible to compare individual differences (between participants).

The following example demonstrates the application of this similarity assessment to shed light on individual differences. For demonstration purposes assume we are having only three participants (p1, p2, p3) who create groups out of a set of 5 animated icons showing, for example, geographic events (cp. Figure 2). The grouping behavior is binary encoded as '0' or '1' in a similarity matrix for each participant. Instead of summing over all matrices to perform, for example, cluster analysis (or multidimensional scaling) to reveal the 'natural' grouping structure, we can use individual matrices and compare them directly with each other visually (and numerically). To do so, we calculate the Levenshtein distance between each pair of matrices, that is, between matrix_p1 and matrix_p2, matrix_p2 and matrix_p3, and matrix_p1 and matrix_p3. Figure 5 shows the visual matrix comparison between participant 1 and 2 and reveals that they performed the grouping task in exactly the same way; this results in a Levenshtein distance of 0. Participant 3, however, seems to have adopted a different strategy and created groups differently from participant 1 and 2. A comparison of the matrices reveals this difference; the Levenshtein distances between participant 3 and 1 and participant 3 and 2 is 4 (in both cases).

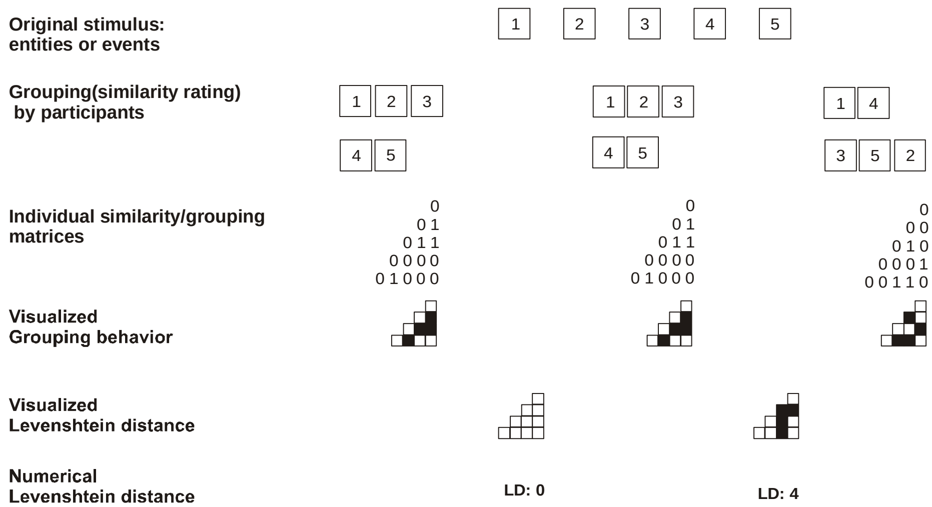


Figure 5. Demonstrates the calculation of the Levenshtein distance to evaluate the differences in event conceptualization between participants. Individual similarity matrices that encode the grouping behavior (as a reflection of the conceptualization of the stimulus material) are compared directly with one another visually and numerically.

In our experiments we have more than three participants and more than five icons, and therefore both visual and statistical approaches can be applied to detect differences between participants. Inspecting the visualized Levenshtein matrices allows for identifying outliers and/or similar groups, that is, participants who created matrices that are different from other participants' grouping behavior. These differences may occur on the level of individuals or groups of individuals.

The tremendous advantage that the visual Levenshtein approach has over the pure numerical one is that we build on the pattern detecting power of the human perceptual systems (Ware, 2004). The interactivity of the MatrixVisualizer allows for following up on any differences that are detected by deliberately focusing (through selection) on particular participants and icons. This coupling of visual pattern detection with the support of computational techniques and interactive interfaces is the essence of visual analysis approaches.

Additionally, the same (numerical) Levenshtein distance could be produced by two very different similarity matrices. The Levenshtein distance only takes into account the number of edits, independent of *where* the edits have to be made. In contrast, using the matrix visualization of Levenshtein distances as shown in Figure 5 reveals overall patterns that can be used to visually inspect differences to a) immediately detect which icons are treated differently by participants, as revealed by the location of required edits in the matrix (black grid cells), and/or b) use the general pattern to single out individual participants or groups of participants. While it might be possible to create a version of the numerical Levenshtein distance that focuses on subparts of strings (or matrices), the visual analysis approach we adopted here provides this information efficiently to a researcher.

In the two examples provided in Figures 3 and 4 we can easily detect differences, both on the group and individual level[4]. These two experiments are also the extremes regarding the number of animated icons used. While XP3 uses 150 animated icons, resulting in a similarity matrix of 22,500 cells, XP4 uses only 54 animated icons (2,916 cells). With an increased number of icons we also detect a larger variety of individual differences and strategies that surface more clearly. Nonetheless, in both examples we can identify visual patterns in the visualized Levenshtein distance. In Figure 3 we find, for example, patterns that ultimately lead to high similarity (dark red, upper right corner) between the following ending relations (TPP1, NTPP (PP), and TPP2). This is indicated by the dark red part of the right corner of the upper left matrix in Figure 3. Several participants seem to have adopted this strategy as it surfaces in their individual matrices—the right and bottom edge matrices in the lower right part—too. What we also find is that participant 11 sticks out somewhat from other participants. We will come back to this observation in the next section (KlipArt).

Figure 4 provides another demonstration of individual differences and visually salient patterns that identify groups of participants. In this case, participant 40 behaves differently from the rest of the participants as clearly indicated by the black spots on his/her matrices in comparison with all other participants. The low similarity values (the index discussed above that compares his/her matrix with the matrices of all other participants) confirm this observation. We dive deeper into these results in the next section.

Other participants form groups which are revealed by the pattern their individual matrices show, as well as the pattern that the pairwise comparison reveals. If we look at the individual matrices both in Figure 3 and 4 (the ones on the outside indicating each individual participant's grouping behavior), we can compare these patterns to the overall similarity matrix in the upper left matrix. Several participants adhere to this mainstream pattern and we can quickly identify the participants who do so. Consequently, the intersection of columns and rows of participants with similar grouping patterns is showing fewer black grid cells and smaller simple Levenshtein indices. In contrast, participants who have different grouping patterns show more black grid cells (and larger Levenshtein distances) in the column-row comparison.

Calculating the Levenshtein distances for all participant pairs also creates a proximity matrix for comparing all participants with each other on the basis of their grouping behavior. This proximity—the Levenshtein distance, as another window on similarities and/or dissimilarities between participants—can be used as input to cluster analysis or multidimensional scaling procedures to augment the visualized similarity analysis discussed above (see Figure 5). For example, Figure 6 shows multidimensional scaling maps for experiment XP3 with an outlier participant (left) and after removing that participant (right). It is obvious that participant 40 is different from all other participants. Removing participant 40 from the analysis allows for properly visualizing the similarity between participants, that is, their grouping behavior using multidimensional scaling. We will come back to participant 40 in the next section.

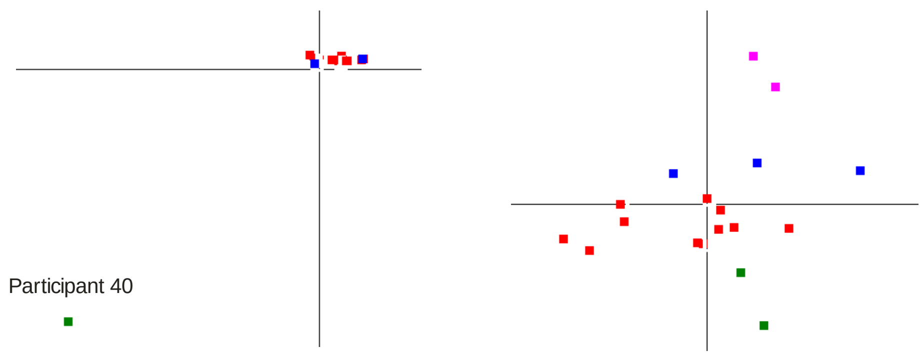


Figure 6. Two MDS plots of XP3, on the left using the calculated Levenshtein distances as proximities, and on the right the same analysis after removing the outlier (participant 40).

KlipArt

We now have demonstrated an efficient way of getting an idea of differences on the individual or group level. What we do not know yet is, what are these differences and how are they related to the original data (stimulus) characteristics? So far we simply have identified those participants (or groups of participants) who overall behave similar to one another and different to others.

To better serve our interest in revealing and explaining individual differences in the conceptualization of movement patterns, we implemented a second visual analysis tool called KlipArt. The first version of KlipArt has been used to analyze the influence of shape characteristics of star plot glyphs on classification (Klippel et al., 2009) and has been iteratively improved; we are currently using version 4. Figure 7 shows an example, again of XP4, that is, the same data set as we used in Figure 3. The KlipArt user interface displays a graph consisting of a node (yellow square) for each participant plus a node for each unique grouping of icons produced by at least one participant. Edges connect each participant to the groups that they (and potentially others) created. Bubble-like 'packs' encompass the grouping nodes of each participant. The graph supports dragging of any visual element (nodes, edges, and packs) as well as toggling of an iterative force-directed (spring-based) layout algorithm, allowing the experimenter to interactively manipulate the graph in order to tease apart even complex many-to-many grouping relationships.

Subsets of visual elements can be flexibly selected for inclusion in the graph in order to reveal individual differences in conceptualizing movement patterns. This analysis can be done from two perspectives: Either from the perspective of icons that have been treated differently by different participants (for example, those with particular high or particular low similarity ratings), or from the perspective of individual participants or groups of participants (for example, those discussed in the previous section or, say, age/gender differences).

For an example of the first stimulus-centered perspective, consider Figure 3. It shows that not all topologically distinguished ending relations (in case of a hurricane moving across a peninsula, XP4) are equally salient from a cognitive conceptual perspective. The darker red colors in the top right part indicate that relations of inclusion (TPP1 and PP (which is NTPP), and TPP2) are often grouped together. Likewise, relations that do not show any kind of overlap are often grouped together, too. These differences are reflected, for example, in differentiating RCC-8 from RCC-5 and different levels of granularity in Egenhofer's intersection models, and can contribute to answering the question of which granularity of topological calculi is cognitively more adequate to allow for formalizing cognitive conceptualizations (as an essential step in designing natural interfaces). The question we are addressing here, however, is whether we also find individual differences between participants with respect to these salient patterns of conceptualizing movement patterns.

As an example, we selected non-overlapping ending relations, DC and EC (12 animated icons in total), in XP4 as an interesting subgroup of all possible ending relations. Together as a group, they received high similarity ratings. For these ending relations we now assess the grouping behavior (and linguistic labels) of all participants. Figure 7 shows several patterns: There are several participants who placed all 12 selected icons (6 DC and 6 EC) together in one group (P: 35, 29, 39, 23, 7); there are participants who created two distinct groups (P: 25, 37, 31, 41) separating DC and EC; there are participants who created one or two groups but also singled out one extra animated icon (e.g. P: 47, 33), and there are participants who created a variety of groups such as participant 45. As indicated earlier, in the "regular" analysis of this data (i.e. cluster analysis, see Klippel and Li 2009), these differences are purposefully ignored. The design of KlipArt allows for following up on them and separating those that are 'mistakes' (identified through analyzing linguistic labels, see below) from those that reveal *potentially different conceptualizations*. Again, this approach embodies a key goal of visual analysis—to leverage the best of human and computational capabilities through the use of dynamic visual interfaces.

We also collect linguistic labels for the groups that participants generate (both a short label, maximum of five words, and a long label, more like a description). These labels are shown in the KlipArt interface, too (see Figure 7, bottom right). For the two largest sub-groups, of participants who placed all 12 icons into one group and participants who separated DC and EC, we find that participants make spatial distinctions of the movement patterns but each does so with a different focus. While the participants who created only one group used criteria such as 'the path is not crossing' or 'the hurricane stops on the right side', the participants who created two groups and distinguished DC from EC focus on the ending relation.

Inspecting further grouping behaviors we find that some participants simply made a 'mistake' or were lazy with some icons. They simply did not attend to the animation to the end. The current implementation of KlipArt separates all individually created groups and does not allow for fuzzy criteria such as 'all but one'. Hence, participant 33 and 47 can be identified as belonging to the two previous groups (i.e., those who created one group out of DC/EC and those who created two groups) on the basis of the verbal descriptions that they provided for the icons they singled out. That is, it became apparent they simply placed one icon in the 'wrong' group but did not mean to do so. In contrast, the in-depth analysis of participant 45 and participant 11, who were identified as outliers previously on the basis of the Levenshtein distance analysis (see Figures 3 and 4), revealed that they applied different grouping strategies than most other participants. As they obviously applied different grouping criteria, we selected them individually but also selected all icons to reveal and examine their grouping strategy across the entire dataset (keep in mind both participants are from XP4). Figure 8 shows the grouping behavior of these two participants for all icons, again accessible with just a click or two in the KlipArt interface. Participant 11 adopted a mixed strategy in which s/he differentiated locations where the hurricane hit the peninsula, such as hurricanes that hit the tip or the bottom of the peninsula, from hurricanes that moved across the land. Likewise, participant

45 adopted a strategy in which s/he started to separate hurricanes on the basis of the location where they made landfall and less so on the basis of topological relations. Yet, in analyzing their grouping behavior it would be fair to say that there was also some impatience in watching the animations to the very end (which was not the case for most other participants). The participant failed to "correctly" (according to their own category system) classify several movement patterns (icons).

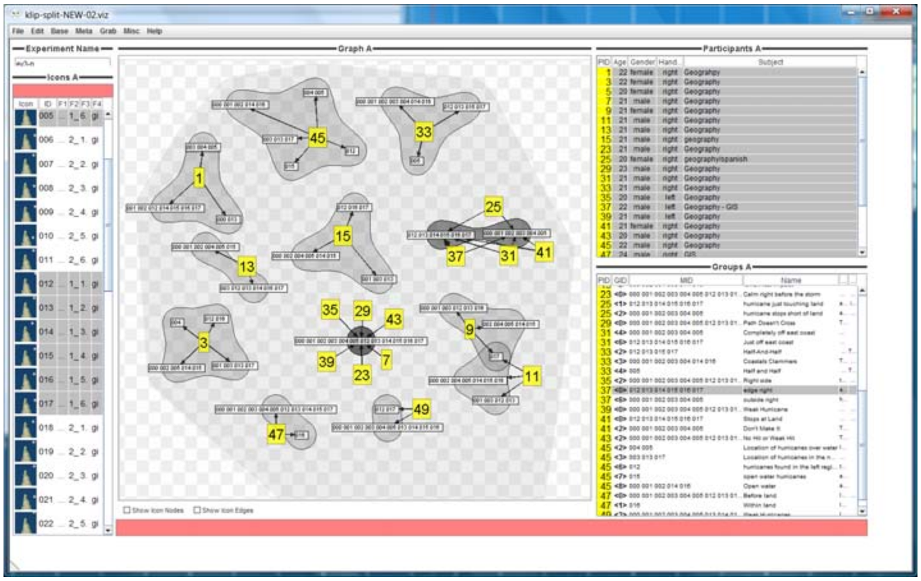


Figure 7. The grouping behavior of all XP4 participants for hurricanes that end in the relation DC (do not make landfall) and EC (just bump into the peninsula).

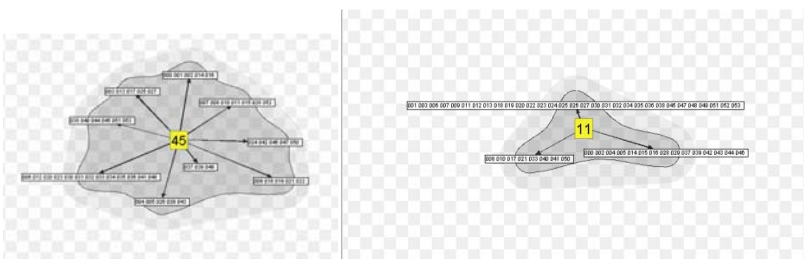


Figure 8. Grouping behavior of XP4 participants 11 and 45 for all (54) animated icons.

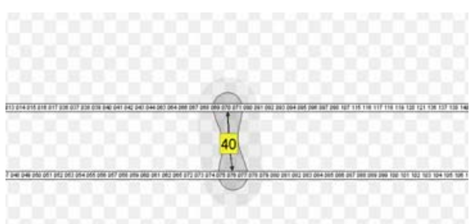


Figure 9. Grouping behavior of XP3 participant 40. This participant clearly stood out from all other participants in grouping behavior. It turns out that the participant created only 2 groups by distinguishing those events in which one entity is moving from those in which both entities are moving, despite there being a large number (150) of animated icons.

A last example is taken again from XP3 and the previously identified visually salient participant 40 (Figure 9). In trying to answer the question why this participant shows such a different pattern in the visualized Levenshtein distance from the others, we again used the KlipArt tool. This analysis revealed that participant 40 only created two groups distinguishing movement patterns in which one or two entities are moving. The majority of participants settled on a strategy to classify the movement patterns by size differences in this experiment. Interestingly, none of these strategies is topologically grounded.

Conclusions and outlook

The majority of behavioral research on cognitive conceptualization (category construction) in the spatial sciences that uses similarity measures as a methodology to reveal conceptual knowledge dismisses context as a within experiment factor. The type of context we focused on in this article addressed individual differences in how a set of stimuli displaying spatio-temporal information is conceptualized, that is, how a category structure is established (constructed). This approach to individual differences is different from a classical perspective on individual differences that addresses and distinguishes factors such as high or low spatial abilities. The individual differences in our experiments arise from different criteria/strategies that participants adopt to make sense of (conceptualize) a set of stimuli (movement patterns) that they are presented with. It is important to note that the way that participants (humans) create order (groups/categories) out of chaos (the whole set of stimuli) is by no means arbitrary or unconstrained, neither in the event experiments in which we used geometric entities as moving entities (XP1-3) nor in the event experiments in which we used real world scenarios. Apart from some glitches—"mistakes" and/or obvious laziness—in the grouping behavior, the strategies that participants adopted are sensible criteria that they chose based on salient characteristics found in the stimulus.

In our previous research, classical, yet off-the-shelf, analysis methods such as cluster analysis helped us to reveal natural groupings (conceptualizations) based on the predominant criterion participants (overall) selected for constructing categories. In contrast, the work presented in this article allowed us to shed light on individual strategies participants adopted, through the use of visual analysis tools. Context, and individual differences as one aspect of context, is already a central research topic. We have added to this research a critical component that allows for identifying individual differences in behavioral data on the conceptualization of spatio-temporal information. To the best of our knowledge, tools that allow for an in-depth analysis of individual differences in conceptualization do not exist and most classical statistical approaches are not well suited to perform these kinds of analysis. While it is possible to have predefined hypotheses about individual differences such as male/female or high/low spatial abilities, our approach and the analysis we demonstrated allows for an efficient post hoc analysis of different strategies that participants have adopted that researches may, or may not, have been aware of in designing their experiments. In addition we showed the importance of combining different tools: MatrixVisualizer to detect patterns and KlipArt to follow up on these patterns with an in-depth analysis.

Why should we be concerned with context and individual differences in conceptualizing spatio-temporal information? There are many possible answers to this question and we would like to point out two and subsequently discuss future lines of research. The first is to bring research in the spatial sciences that deals with behavioral assessments of conceptualizations in line with research directions in cognitive sciences (Montello, 2009). Many inspirations for this work come from the groundbreaking research that David Mark and collaborators conducted over the last two decades (Mark, 1999; Mark & Egenhofer, 1995). Mark pointed out early the cultural and linguistic differences (as aspects of context) that exist in conceptualizing spatial entities. Results of this research culminated in a theory referred to as ethnophysiography (Mark & Turk, 2003) addressing the different ways that landscapes are conceptualized in different cultural contexts. Our goal is to add to this research by developing methods that are better tailored to reveal contextual differences. As even the cognitive sciences have yet to develop a consistent approach on how context is integrated into concept theories (e.g., Coventry & Garrod, 2004) we regard it as crucial to make tools available to researchers to shed light on contextual factors that influence conceptualization processes. Even in recent theories in cognitive sciences that develop sophisticated mathematical approaches to handle contextual factors the need exists to identify “a well-defined set of the most relevant contexts” (Gabora et al., 2008, p. 102). Our research provides a means, tailored to the analysis of behavioral data, to identify the range of relevant contexts that participants apply to construct categories.

Second, in the age of technological developments that allow for tailoring information toward user needs, we consider it crucial to develop research methodologies that allow for revealing individual differences rather than choosing a one-size-fits all approach (see Raubal, 2005). For instance, if we think of the design of natural language interfaces, one problem that has been identified is the naming problem (Furnas et al., 1987). This problem boils down to the fact that users are creative with respect to names they give to entities, which poses challenges for designing natural data base query languages. This problem has been addressed for static spatial relations based on topological distinctions that are central to many spatial information science (Riedemann, 2005). Given again research in the cognitive sciences that asserts that naming events is more complicated than naming objects and static spatial relations (Gentner & Boroditsky, 2001), it is not surprising that linguistically referring to spatio-temporal information poses additional challenges and offers even more degrees of freedom, that is, the same (from a formal point of view) event can be referred to using a plethora of linguistic constructs. We have many more options to conceptualize events than objects, starting from deciding where to segment potentially continuous flows of information, focusing (and changing) reference objects, focusing on the location of the endpoint of an event or characterizing paths (or path segments), and last but not least using non-spatial language to encode spatial information (see also Klippel & Li, 2009). The research on individual differences that we present here, especially in case of the fourth experiment (hurricane/peninsula), reveals a first systematic approach on how events at the geographic scale may be a) conceptualized and b) linguistically labeled. KlipArt, through its ability to access both category construction behavior and linguistic labels in the same interactive environment, makes linguistic analysis at this level of detail possible. This research is an important step to extend the solutions that have been proposed for disambiguating and improving natural language interactions at the human-computer interface for objects to events. Especially the grounding of our experiments in established formal frameworks of spatial information science (Egenhofer & Franzosa, 1991; Freksa, 1992; Randell et al., 1992) allows for deepening the understanding between conceptualization, linguistic externalization, formal representation, and individual differences (context). The combination of formal characterizations—topology and conceptual neighborhood graphs—with behavioral evaluations is an important step to cognitively and formally ground ontological approaches to human centered computing (Knauff et al., 1997; Mark & Egenhofer, 1994). While such past research has been fruitfully conducted in the static domain, technical development is starting to allow for applying it to the conceptualization of geographic events and, as discussed in this article, individual differences (Klippel & Li, 2009; Wolff, 2008).

A second aspect of how our research contributes to technological developments with a focus on human-computer interaction resides in the central role that ontologies play in bridging the semantic gap (e.g., Fonseca & Egenhofer, 1999). Approaches to create ontologies are manifold and existing ontology editors make it easy for everyone to create his or her own ontology. This may be a good thing as ontologies offer a possibility to capture different perspectives or contexts on the same data set. However, current research on ontologies shows a strong interest in grounded ontologies; Scheider et al. (2009) write: “One would prefer a method for grounding ontological primitives in observation procedures in order to support more general ontology mappings.” Referring back to the quote above by Gabora et al. (Gabora et al., 2008), establishing relevant contexts relates to grounded ontologies in that we can claim that salient characteristics of events lend themselves to anchor observation procedures that Scheider et al. call for. To establish the set of salient characteristics (relevant contexts) needs the approach that we laid out in this paper: a research methodology that allows for an in-depth analysis of the individual (or group) strategies that are used in parallel to conceptualize the same spatio-temporal information.

While our work has primarily addressed the role of topology (the calculi Scheider et al. and many others have used) for characterizing movement patterns, the methodology we developed is widely applicable to research on the conceptualization of spatial and temporal information from a cognitive perspective with a particular focus in revealing contextual (e.g., individual) differences. In all areas where ontologies are used to facilitate the interaction between humans and machines it is essential to validate the formal characterization through behavioral experiments. While most experiments aim for revealing the “most appropriate” solution, using the best ordering of a given part of the world, and applying methods such as cluster analysis to reveal the “natural grouping” that participants prefer, our research adds a new perspective. Instead of one solution, we are able to reveal multiple, individualized solutions. This multiplicity of solutions that can co-exist (and potentially could be weighted) represents an essential step toward increasing the flexibility of information systems in understanding human conceptualizations. The methodology thus also tries to encourage a positive rather than normative analytic outlook.

The visual tools shown here are prototypes, built as a part of our initial exploration of potential applications of visual analysis techniques to the exploration and analysis of behavioral data on the conceptualization of movement patterns. In future work, we anticipate further improvements to the visual representation, interaction, and analytic capability of both KlipArt and the MatrixVisualizer. For example, the text nodes that visually represent icon groupings could be replaced with the icons themselves, thereby providing a way to examine the breakdown of spatial categories within and between participants more directly. Similarly, the linguistic labels given to each icon group could be used to label the graph edges that connect participant nodes to icon grouping nodes, resulting in a small ‘cloud’ of labels for each group. As we have seen, the grouping criterion is a strict one in that it requires an exact match for all participants connected to that group. As we have seen in the analysis, however, often only one or occasionally two icons are wrongly categorized by a participant which makes them appear different from their peers. Two possibilities are currently under consideration to reduce and/or post-process the data. First, we are considering relaxing the grouping constraint and allowing for displaying groups that are nearly identical; for example, all but one icon have to match across participants connected to that group. Second, it would be possible to change the similarity matrix of participants temporarily after inspecting their grouping choices in order to enhance the visual analysis of the grouping behavior. Icons that are left out by mistake could be reclassified by hand. This latter option should be strengthened by other analytical and statistical approaches to prevent data manipulation.

Finally, enhanced filter capabilities would allow the experimenter to iteratively select arbitrary subsets of participants, icons, groups, and labels for precise drill-down in both tools, enabling the exploration of idiosyncratic patterns of spatial conceptualization in terms of both the primary grouping data and any available secondary demographic data describing the participants themselves. Interactive mixed-type, multi-dimensional filtering and dissection capability is well established for data sets from a variety of domains (Weaver, 2008, 2010), and appears readily adaptable for use with matrix-based similarity data of the sort considered here. Extensions that support not only disjunction but also negation and conjunction in interactive visual queries (Weaver, 2009) promise to further significantly expand the space of questions that experimenters can pose in order to probe individual differences.

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Footnotes:
1 For extensive details on the experiments, refer to (Klippel et al., 2008; Klippel, 2009; Klippel & Li, 2009).
2 This procedure is common practice. However, some recent results from our lab (Klippel, 2010) have shown that the semantic context is essential for the conceptualization process. This fact does not change the usefulness and effectiveness of the tools we discuss in this article.
3 Please note that this pattern is "reversed" for the individual participant matrices along the right and bottom edge, in which black indicates that two icons are placed into the same group.
4 Please note the limitation of presenting this information in this ‘tiny’ visual format. These tools are meant to be used on large screen and unfold their full potential through their interactive capabilities. We provide information and screenshots in high resolution on the following website: http://cognitivegiscience.psu.edu/software.html

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