Integrated Visualization of Space and Time: A Distributed Cognition Perspective

Eva Mayr, Günther Schreder, Saminu Salisu, and Florian Windhager

Fig. 1. Integrated spatiotemporal visualization methods.

Abstract—Spatiotemporal visualizations pose certain challenges for comprehension and reasoning processes. This specifically applies to casual users who want to gain an overview of the spatiotemporal origins of large cultural collections in a relatively short time. Based on a distributed cognition approach, we compare four visualization techniques (coordinated multiple views, color coding, animation and space-time cube representations), which offer different solutions to represent spatial and temporal information in an integrated fashion. We firstly assess the strengths and weaknesses of these techniques with regard to existing work. We then complement these findings with a close look at the reasoning processes of 18 casual users. In a mixed methods study, they explored a photo collection from the middle of the 20th century by means of all four spatiotemporal visualization techniques. We investigate and compare the effects of these techniques on processes of internalization, spatiotemporal reasoning and comprehension by analyzing the observed spatial, temporal and spatiotemporal insights and the degree of connectedness of these insights. Our results provide an in-depth look at how each visualization technique supports the construction of coherent internal representations and, together with data on cognitive load and subjective preferences, help to understand for which tasks and users they are suited.

Index Terms—I.6.9.c Information visualization, I.6.9.d Multivariate visualization, H.5.1.d Evaluation/methodology, spatiotemporal data, distributed cognition, insights, image collection, cultural heritage data

1 INTRODUCTION

Various visualization techniques have been developed to represent spatiotemporal data in an integrated fashion: Mostly, such techniques utilize a map to visualize the geographic distribution of objects or events, and encode temporal data by either mapping time to time (animation [1]), mapping time to a retinal variable (color coding [2]), or mapping time to a spatial dimension - which can be done either by utilizing a third display dimension (i.e., space-time cube representation [3]), or by mapping time to a linear timeline representation within a coordinated view [4]. These representations assist users in visual-analytical activities of reasoning, problem-solving and sensemaking with spatiotemporal phenomena, and are of relevance in various areas [5].

A specifically challenging field of application is the area of *cultural heritage collections* (CHC), where an increasing amount of visual interfaces act as mediators between large digital collections and a wide variety of users [6]. Digital CHC come with a multitude of (meta)data dimensions, including *spatial* and *temporal* data, e.g. to document an artifact's place of origin, and the time it was created.

CHC are frequently presented to *casual users* with no expertise on the data dimensions nor on visualizations [7]. Such users have to orient themselves in the CHC first [8], before they can engage in serendipitous browsing or exploratory search [9].

In this paper we explore how non-expert visitors of CHC can actually utilize spatiotemporal visualizations to acquire an overview in a relatively short period of time. To assess how they augment the construction of and reasoning with an internal representation of the CHC in such a casual context, we explore the strengths and limitations of different spatiotemporally integrated visualization techniques¹.

Current evaluations of spatiotemporal visualization techniques fall short because they a) compare only two (or sometimes three) different techniques, b) they primarily use time and errors as indicators, c) they do not necessarily build on tasks that require the identification of multivariate overview patterns, and d) they do not take into account the specifics of casual users. With this paper we report on a comparative study that aims to close this research gap: We a) compare four different techniques in a within-design, namely color coding (CC), animation (ANI) and space-time cube-representation (STC) against a coordinated multiple view system (CMV). We b) pioneer a new methodology to look into the

- Eva Mayr, Günther Schreder, Saminu Salisu, and Florian Windhager are with the Department for Knowledge and Communication Management, Danube University Krems, Austria.

E-mail: firstname.lastname@donau-uni.ac.at

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of

Publication xx xxx. 201x; date of current version xx xxx. 201x.

For information on obtaining reprints of this article, please send

e-mail to: reprints@ieee.org.

Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxx/.

¹ Time-orientation is also essential for many other visualizations of CHC data [10]: “the feedback indicated that [time] is a dimension that could be expanded across all views” (p. 46). Thus the question of how to effectively represent and integrate time is relevant for all CHC data dimensions and visualizations, not only geographic ones.

Fig. 2. A distributed cognition system: Users working with an InfoVis interface as external representation (ER) generate augmented internal representations (IRs) in working memory or also memorize them as specific or generalized IR.

construction of internal representations of these four techniques, c) confront users with tasks that require the integration of spatial and temporal data dimensions from an overview perspective, and d) adapt our research design to the characteristics of casual users. While focusing this study on CHC data, we consider its methods and results to also have relevance for many other data domains, as acquisition of overview and orientation (to guide subsequent exploration) is a substantial task wherever sensemaking with spatiotemporal data plays a role [11].

Against our theoretical background of distributed cognition (sec 2) we discuss the visual-analytical strengths and limitations of different spatiotemporal visualization techniques and review empirical evidence of how they perform in comparison to one another (sec. 3). We present a mixed-methods study (sec.4) and report on our results (sec. 5). In the discussion, we reflect on our findings and derive objectives for future research (sec. 6).

2 INTERNAL REPRESENTATIONS AS COGNITIVE COLLAGES OR MENTAL MODELS

Information visualization (InfoVis) systems aim to amplify and augment human cognition in face of abstract data [12]. They do so by providing external representations (ER) of the data, which serve as the external component for distributed cognition systems, to support and dynamically enhance internal representations (IR) and corresponding reasoning processes (see fig. 2).

2.1 On the Interplay Between External and Internal Representations

The framework of distributed cognition and model-based reasoning [13], [14] declares various cognitive processes to be relevant for the design and evaluation of visual ERs. We enrich their formalization with concepts of other scholars, including [15]–[17].

Internalization: If there is no prior knowledge or existing IR, the process of internalization leads to the construction of a new IR based on a given ER (i.e. acquisition or learning). This process firstly creates an augmented IR in working memory, and (after more thorough exploration) potentially also an instance of a memorized IR in long term memory. Multiple examinations of similar ERs furthermore can lead to the abstraction and generalization of generalized IRs or graph schemata, which guide future processing and sensemaking.

Augmentation: Memorized IRs can be activated and simulated in working memory for visual reasoning operations, but they can also be augmented by an (interactive) ER to work in joint, i.e., as a coupled or distributed system. Augmentation is the standard constellation studied by visualization research: InfoVis systems unburden a cognitive system and its working memory from representing (i.e. reading, synthesizing and imagining) the full complexity of external data on their own. Resulting IRs can remain sketchy, lean and lightweight, but they can also be elaborated later on. Corresponding reasoning processes then can be offloaded to

distributed HCI cycles controlled by visual perception and interaction [16]: Users drive the interactive inspection and reasoning process, while the computer provides the calculation and detailed representation of complex data.

2.2 Cognitive Integration of Multidimensional IRs

Distributed cognition assumes that IRs commonly reproduce the basic design of an ER, but that the utility and quality of the resulting IRs can widely vary [17]. An IR is not only influenced by the specific design of an ER, but also by the internalization and processing on the user’s side. In general, distributed cognition assumes that IRs do not veridically reproduce ERs but act as lightweight ‘models’, which mirror some of their structural and functional features. While Liu and Stasko [13] use the term ‘mental model’ indifferently for all types of IRs, Tversky [15] introduces the term ‘cognitive collages’ to point out essential differences in modelling quality:

- On the one side, *mental models* are defined as more elaborate and internally consistent constructions, which effectively connect and integrate different aspects and perspectives of a complex phenomenon, and “capture the categorical spatial relations among elements coherently, allowing perspective-taking, reorientation, and spatial inferences” [15, p. 15].
- On the other side, *cognitive collages* are sketchy, fragmentary and oftentimes distorted IRs, resulting from quick and superficial internalization processes of a complex stimulus. They merge snippets of partial information, differing perspectives and reference points into rather incoherent or vague IRs, which can be viable and good enough for many situations, but have detrimental effects on more complex processes of visual reasoning and sensemaking.

According to this distinction, coherence and consistency (or degree of integration) are central aspects of an IR. This is especially true for more complex, multi-dimensional representations, as they facilitate distributed multi-dimensional reasoning activities. In contrast to jumbled or distorted collages, mental models enable InfoVis users to better navigate and manipulate their internal information space, to meaningfully connect points of reference, and to conduct visual inferences and novel perspective-taking operations² [17].

In a classical experiment Johnson-Laird [18] showed that an incoherent or discontinuous textual ER impedes the construction of an integrated IR and increases cognitive load. Elaborating an existing IR or building up an IR step by step requires lower cognitive effort

² It is worth noting, that navigation and perspective taking are by far more demanding tasks with regard to InfoVis design spaces, than with regard to the physical or architectural spaces addressed in [15]. In many InfoVis systems, a user’s cognition has to navigate way more than just three data dimensions, which are distributed across multiple views, and encoded due to a variety of different layout and design principles.

than combining multiple existing ones; the error rate of information retrieval decreases, and it can be assumed that understanding of spatiotemporal configurations is more successful [17]. We consider this experiment to point towards severe limitations which users of less integrated InfoVis systems (e.g. with coordinated multiple views) are facing, when they have to synthesize a bigger picture of complex data and reason with it.

Obviously, the design of an ER - and how it connects multiple data aspects and dimensions - matters for the reasoning with an IR. *Therefore, this paper focuses on the question, how visualizations which integrate spatial and temporal data more or less closely affect the construction of more or less integrated IRs, and to what extent they enable coherent reasoning processes.* We contend that holistic design factors like coherence and consistency are important parameters of ERs, which deserve specific attention - especially in casual settings.

2.3 Evaluation of IRs in Casual Settings

How can we evaluate the construction of IR for more complex visualizations in casual settings, with specific regard to multi-dimensional information integration? We consider such a complex question to urge for an extended evaluation approach, which goes beyond the standard task-based and expert-oriented testing of a visualization's efficiency.

1. For all scenarios of reasoning with multidimensional data, the factual design of an ER can lead to more or less integrated IRs - which further support or impede the corresponding visual reasoning processes.

Consequences: The integrational strength of an ER has to be measured via the coherence and consistency of the resulting IRs - which is a non-trivial evaluation challenge of its own [19] - e.g. by analyzing the connectivity of insights.

2. As opposed to visualization experts, casual users might have no specific graph schemata available, which would allow to immediately start reasoning with an augmented IR. "There has been virtually no study on how users understand new external visualizations" [13, p. 1002].

Consequences: Evaluations of ERs have to look into the learning processes and take the cognitive accessibility of ERs and (ease of) their internalization into account, i.e. by interviews, think aloud and questionnaires.

3. Casual users are less performance-oriented [20] and do not follow well-defined tasks [7].

Consequences: Evaluation should look into cognitive processes and how IRs are actually assembled and utilized.

4. To motivate casual users of InfoVis and draw them into the analytical process, user experience plays a central role. *Consequences:* User experience and pleasing aspects [20] should be part of the evaluation - way more than for expert users.

5. Casual users are (per definition) a highly diverse and heterogeneous population.

Consequences: Evaluation should look into the performances and preferences of subgroups.

While we consider these factors to substantially influence the cognitive access to and reasoning with visualizations in a casual context - and thus include them into our study design (see section 4) - the actual design of an ER itself obviously remains central. We took a closer analytical look at four different techniques and complement this analysis with empirical results further down.

3 SEPARATED AND INTEGRATED TECHNIQUES TO REPRESENT SPATIAL AND TEMPORAL DATA ASPECTS

Various visualization methods have been developed to represent spatial and temporal data aspects in an integrated fashion. We take a closer look at three of them, including color coding (CC), animation (ANI) and space-time cube-representation (STC) - and compare them against a system of coordinated multiple views (CMV). First,

we discuss their strengths and weaknesses from a cognitive perspective, to establish a basis against which we can compare our results and findings later on.

3.1 Coordinated Multiple Views

Numerous approaches to spatiotemporal visualization of CHC data combine a geographic map with a time graph, which is most often a linear representation of time [21], [22]. CMV techniques visualize spatial and temporal data aspects with two separated representations, but reconnect these separated views via interaction methods, e.g. via coordinated highlighting or linking and brushing [4], [23].

Strengths & Limitations: CMV representations do not provide a direct spatiotemporal integration, as users cannot give attention to both representations at the same time (split attention effect, [24], [25]). It is likely that users generate two separate internal representations (one for each view), that have to be integrated later on - with additional cognitive load [18]. Depending on the amount of interaction and visual work users invests to bridge this split of attention and to interconnect their corresponding IRs, the degree of integration can be either non-existent or relatively solid..

3.2 Animation

As "dynamic representations" [26, p. 66] ANI techniques map time to the time dimension of a visual representation [1], [27], [28]. As such, they can represent the spatiotemporal origins of CHC objects as events, appearing and disappearing over time. With ANI, spatiotemporal integration is only possible by an observer's memory, which can be easily overloaded. A distinction derives from utilizing a smooth and continuous traversal (i.e., ANI), or a discrete sequence of steps, which we refer to as a *slideshow*. ANI can further be implemented as non-interactive or interactive representation, allowing users to go back and forth in time [29, p. 1588].

Strengths & Limitations: It is well known that ANI can foster the perception of even subtle changes or display dynamics, but also that the user's working memory is easily overwhelmed when too much information changes too fast [28] and that non-salient changes can be easily missed [30]. Also problems of split attention between the map and time information is an unresolved problem in animation - even more so than in CMV, as information on the map is missed during inspection of the timeline [1]. Interaction (like pausing or user control) can help go back and forth in time, but increases interaction costs and comparing frames remains demanding for the working memory. Griffin et al. [30] compared 4 different animation speeds and observed best performance with a moderate speed (1.2 to 1.5 sec per frame - depending on the salience of the cluster).

3.3 Color Coding

CC approaches merge multiple temporal layers into one integrated layer and utilize transparency to see all object or event positions at once [cp. "superimposition", [31]]. Time is mostly encoded with an additional retinal variable, like color (e.g. [2]).

Strengths & Limitations: Interestingly, we did not find any research that studies color coded spatiotemporal visualizations. This might be due to a basic concern whether time encoded by color is visually salient and discriminable enough, and whether it could be appropriately integrated into the representation of geographic coordinates (which utilize *position* as a much stronger visual variable according to [32]). By using a CC technique, users still can build up a spatiotemporally integrated representation of the data, as long as frequent issues caused by visual clutter and occlusion can be solved (see [33] for utilizing non-overlapping glyphs).

3.4 Space-Time Cube

STC representations merge a map and a linear timelines orthogonally, which unfolds a three-dimensional, cubic space [34]. This technique allows to map the spatiotemporal origins of CHC objects as a three-dimensional point cloud [3], [35] and enables a direct (gestalt-perceptual) integration of spatiotemporal origins.

Table 1. A summary of visual-analytical strengths and limitations of spatiotemporal visualization methods.

	Coordinated Multiple Views (CMV)	Animation (ANI)	Color Coding (CC)	Space-Time Cube (STC)
Strengths	<ul style="list-style-type: none"> + plain map + plain timeline, open for additional encoding of information (e.g. histogram) 	<ul style="list-style-type: none"> + salient detection of change + small occupancy of display space + passive perception possible 	<ul style="list-style-type: none"> + direct perceptual spatiotemporal integration + small occupancy of display space 	<ul style="list-style-type: none"> + direct perceptual spatiotemporal integration + time is mapped to the same visual variable as space (position) [32] + attraction power [38] + conceptual mediator [55]
Limitations	<ul style="list-style-type: none"> – no direct spatiotemporal integration – split attention effect [24; 25] – high visual work – high interaction costs (e.g. brushing) – large occupancy of display space 	<ul style="list-style-type: none"> – spatiotemporal integration only via working memory – split attention between map and time slider [1] – memory overload [45] – high interaction costs – occlusion possible [43] 	<ul style="list-style-type: none"> – occlusion possible (2D) [33] – time is mapped to an retinal variable with little discriminability [32] – no empirical data 	<ul style="list-style-type: none"> – occlusion possible (3D) [37] – high interaction costs [36] – high cognitive load [45] – medium occupancy of display space

Strengths & limitations: From a cognitive perspective, STC representations offer one perceptually integrated view in which time is also mapped to space, making temporal and spatial information aspects similarly salient via position [32]. Users thus can easily build up a spatiotemporally integrated “metashape” of a CHC. However, in such a three-dimensional visualization, occlusion—and increased interaction costs—are a constant challenge [36], [37]. Still, evaluations confirm that space–time cube visualizations are easy to use, convey a high user experience [38], and are especially suited for the exploration of spatiotemporal patterns [39], [40]. Furthermore, STC representations can support the navigation and conceptual mediation between different spatiotemporal views [41] (see sec. 7).

3.5 Comparison of Techniques

As for a comparative look at the various strengths and limitations of these representation techniques we sum up major factors in table 1. Furthermore, we summarize results (with specific regard to spatiotemporal integration) from evaluations and studies conducted so far:

Kveladze et al. [42] compared different studies evaluating the STC, contrasting the STC with static maps with or without coordinated timeline and ANI. In a first study, [38] compared a time-labelled map with a STC. Amini et al. [39] replicated the experiment, but tried to hold interaction possibilities constant by having time labels, time slider and animation available in both views. In both studies, users were faster with the STC for describing the overall movement patterns in the data. Users of CMV had to interact more with the time slider to answer these questions resulting in longer time on spatiotemporal tasks. Overall, studies confirm that CMV are better suited for elementary tasks and STC for complex, spatiotemporal tasks [43], [44]. STC representations seem to perform worse if the “metric properties of a visualization” have to be perceived [40, p. 20].

Comparisons of ANI and STC provide contradicting results: In [45] overall performance was best with the STC, whereas in [46] they performed better with ANI. Griffin et al. [30] contrasted animated maps with juxtaposed (small multiple) ones. In ANI trials participants identified spatio-temporal patterns more often and faster.

Comparisons of *cognitive load* showed that CMV are easier to process than ANI and STC [47]. In ANI visual clutter was found to be highest in more complex data sets [45].

Overall, the task performance with different spatiotemporal visualization techniques strongly depends on the tasks and data used [48]. Consequently, a newer group of studies does not study individual spatiotemporal visualizations, but allows users to select

the ones which seem most appropriate for the current task [49] or combines them in a coordinated manner [44], [50]–[52]. Users more often turned to the STC in a complex dataset, and to a static map in a simpler data set [51]. For spatiotemporal overview tasks, non-expert users preferred a STC, because “the time info is embedded into the visualization” [39, p. 12]. But if they have access to CMV and STC, they use univariate (e.g. geographic map) visualizations first and switch to the STC to add temporal information to the spatial patterns in a second step [49]. These studies show that users select an ER that augments their reasoning with an IR in the best way. It also shows that they prefer to build up an IR step-by-step: first one dimension and later integrating the second one. However, in a comparison of expert and non-expert users [49] observed that experts are more inclined to switch between different visualizations whereas non-experts more often rely on one single visualization.

Insofar, it is highly relevant to identify a visualization technique that empowers casual users of CHC to gain a spatiotemporal overview on a CHC - or in cognitive terms: to construct an augmented IR and reason on it in an integrated fashion. The aim of our study is to compare four different spatiotemporal visualization techniques and their effects on IR. The reviewed studies show that CMV, ANI and STC all have their strengths and limitations depending on the complexity of data and tasks. We are not aware of any studies evaluating CC in the spatiotemporal domain. The following study is the first to compare all four spatiotemporal visualization techniques and to evaluate their differential effects on how they augment the construction of an IR by casual users. The connectedness of the insights allowed us to differentiate between more coherent mental models and rather fragmented cognitive collages.

4 METHODOLOGY

To assess and compare the casual accessibility and efficiency of CMV, ANI, CC and STC representations, we tested them as they have been implemented within the “PolyCube” system. [35], [53].

4.1 Implementation

The research project *PolyCube - Towards integrated mental models of cultural heritage data*³ [7], [53] develops an integrated multi-perspective interface for the visual exploration of CHC. In line with the idea of *generous interfaces* [54], it offers multiple spatiotemporal overviews to provide visitors with conceptual orientation on a collection’s structure and content [35]. While the system offers all of

³ URL: <https://www.donau-uni.ac.at/en/polycube>

these views for the user’s choice and connects them with seamless transitions [55], we separated them for the purpose of this study.⁴

4.1.1 Data

We chose the photography collection of Charles W. Cushman⁵ for this study, which has been prepared and geo-referenced by Miriam Posner [56]. Charles W. Cushman was an amateur photographer and alumnus from Indiana University. The collection he bequeathed to the university encompasses 14,500 photographs, which were taken between the years 1938 to 1969, and largely tagged with metadata (such as place, date, or keywords) by himself. This CHC is characterized by its hybrid character between CHC data and movement data: The spatiotemporal origins of pictures always coincide with points on the spatiotemporal movement trajectory of one artist⁶. To make multiple subsets of the data available and to avoid learning effects between visualization techniques, we selected four periods of three years each, which showed unique and notable spatiotemporal dynamics. Segment 1 thus includes 477 photographs from 1938 to 1941, segment 2 comprises 572 pictures from 1942 to 1945, segment 3 comprises 1469 pictures from 1950 to 1952, and segment 4 contains 1134 pictures from 1953 to 1955.

4.1.2 Visualization Prototype

The PolyCube system is developed on a Javascript framework and utilizes D3.js (for data processing) and three.js (for 3D rendering) libraries with no need for server side dependencies. The following design choices were taken for the four visualization techniques (for screenshots see fig. 1 and for interaction options see table 2):

- For the *CMV* perspective we implemented a standard map on the left side, and a ‘dot plot’ on the right, which arranged all objects in the shape of a point-based histogram, with monthly columns.
- For the *ANI* we aggregated objects in 36 frames (according to months, similar to [30]), and offered one complete run during 18 seconds.
- For the *CC* representation we utilized the Viridis color scale to encode temporal origin against a white background to maximize contrast. The color legend was at the timeline widget.
- As for the *STC* representation we introduced two planes above the map (with year labels) to indicate the beginning and ending of years. Additionally an auxiliary line was shown upon object selection, pointing from the object to the place of origin on the geographic data plane.

To ensure comparability across the four different VIS techniques, measures were taken to consistently harmonize design and visual encoding choices across the different views. For all four representations various interaction options were implemented (see table 1): A *zoom* functionality was used to control map size, a *panning* function allowed moving the map across the screen, and a combined *selection* and *preview* functionality enabled selection of individual data points in all visualizations (with an image preview showing the corresponding photos on demand). Furthermore a *brushing* functionality was implemented on a timeline widget, which allowed the selection and isolation of images according to the selected date range. For the *STC rotation* was enabled to allow for a 360 degree spherical inspection.

⁴ For an interactive version of the four views, see: <https://danubevislab.github.io/polycube/ieevis2018/>

⁵ URL: <http://webapp1.dlib.indiana.edu/cushman/index.jsp>

⁶ As such we are showcasing a solo exhibition of a travelling artist, rather than a group or thematic exhibition, which would exhibit clearly different spatiotemporal patterns.

Table 2. Visual encoding and interaction methods across the views

		CMV	ANI	CC	STC
Visual Encoding	CH object	Circle Dot	Circle Dot	Circle Dot	Circle Dot
	Spatial Origin	Spatial position (on a Map)	Spatial position (on a Map)	Spatial position (on a Map)	Spatial position (x & y coordinate)
	Temporal Origin	Dot Plot (+Timeline Widget)	Timeline (+Timeline Widget)	Color Coding (+Timeline Widget)	Spatial position (z-Axis) (+Timeline Widget)
Interactions	Zooming	Yes: On the map	Yes: On the map	Yes: On the map	Yes: On the Cube only
	Panning	Yes: On the map	Yes: On the map	Yes: On the map	Yes: On the Cube only
	Rotation	N/A	N/A	N/A	Yes: On the cube only
	Single Select	Yes: On the map, on the dot plot	Yes: On the map	Yes: On the map	Yes: On the point cloud
	Temporal Brush	Yes: On the timeline widget	Yes: On the timeline widget	Yes: On the timeline widget	Yes: On the timeline widget

One of the major challenges we encountered in visualizing the Cushman collection were identical spatial and temporal coordinates - due to a modest granularity of their spatial and temporal documentation with regard to cities and days. As a result, up to 70 data points were to be drawn in a single point. To manage this issue of *occlusion* we introduced a spatial randomization function (“nooverlap”): This function allowed to display multiple data points that occur in one point easily by just adding a small amount of jitter to the x and y position of each data point representing an image, while keeping them close to their point of origin.

4.2 Study Design

To evaluate the four different spatiotemporal visualizations, a mixed-method design was developed, which integrates task-based evaluation, but also the specific aspects identified as relevant in this casual setting (see section 2.3).

4.2.1 Experimental Design

The four different spatiotemporal visualization techniques (CMV, ANI, CC and STC) were tested as within-variable – each with one of the four three-year segments of Cushman’s collection. The presentation order of the different visualization techniques was permuted and balanced.

As casual users require conceptual orientation before exploring a CHC [8], [9], our focus is solely on spatiotemporal overview tasks like overall movement patterns and temporal differences in movements (like applied in [39], [49]). Similarly [57] promote the use of high-level, insight-based tasks to better understand sensemaking processes with spatiotemporal visualizations.

For each visualization technique participants had to solve three tasks, which required the integration of spatial and temporal data: In task 1, participants were asked to describe the photographer’s movement within the three-year segment. In the subsequent tasks, they should identify the time periods with most (task 2) and least (task 3) travel activity. These tasks correspond to the general space and general time questions in the task taxonomy by [58]. We also pretested more specific (well-defined) spatiotemporal tasks, but decided to focus on these more ill-defined ones, as the corresponding cognitive processes are more elaborated and diverse [59].

Similar to [49], [51] we applied a mixed method approach which provides the opportunity to confirm and enrich quantitative results [57]. Kveladze et al. [49], [51] analyzed think aloud protocols to understand the selection of and interaction with different visualization techniques. We also use think-aloud protocols, but our focus of analyses are insights, which are understood as an indicator of knowledge building [60] and of the construction and spatial reasoning with augmented IR.

4.2.2 Procedure

Overall, 18 participants (27-58 years old, 8 male, 10 female, 10 with and 8 without an academic degree) individually tested the visualization techniques on a 21’’ full screen.

After some demographic questions, the experimenter explained the first visualization and allowed the participants to familiarize themselves with the technique. Afterwards he encouraged the participant to explore the collection while focusing on the general overview and Cushman's movement patterns. After a maximum of five minutes of exploration, the experimenter turned off the screen and interviewed the participants, which major movements or travel patterns (s)he was able to see. After the interview, the experimenter turned on the screen again and the participant had to solve the three tasks. A shorter procedure was used for the other three visualization techniques: Following a short familiarization and exploration phase the participants only solved the three tasks.

After each of the four iterations, the participants answered an adapted German version of the NASA TLX [56]. In a final interview, the participants were asked to rank the visualization techniques on different dimensions and to explain their preferences.

The test session took approximately 1 hour. Participants were encouraged to think-aloud during the whole procedure. Their utterances were audio recorded and interactions with the visualization technique were screen recorded.

For the categorization of the verbal protocols, two authors coded the utterances and resolved inconsistencies in discussions. During the first exploration and interview, we analyzed the integratedness of users' knowledge building insights on a spatial, temporal and spatiotemporal dimension. For the analysis of task performance, we did not use error or time on task, rather we applied qualitative analyses and evaluated the answers' plausibility and spatial and temporal granularity.

5 RESULTS

We will present our analyses of the think aloud protocols during the free exploration and task execution first. Then we will discuss the quantitative results on cognitive load and subjective preferences and amend them with qualitative observations.

5.1 IR Construction during Free Exploration

Comparing the free exploration of the four spatiotemporal visualization techniques (cp. fig. 3), we observed profound differences: As expected, in the less integrated CMV hardly any spatiotemporal insights were observed, in ANI no temporal, and only some spatiotemporal insights were observed. In contrast, for CC and STC participants generated multiple temporal, spatial and spatiotemporal insights, which were also found to be better connected (in the sense of a mental model). In the following, we will describe the performances with augmented IRs for each technique.

Using the *CMV*, the participants were able to generate a lot of spatial insights, but rarely formulated temporal or spatiotemporal insights during the exploration phase. Participant 10 (P10) managed to gain a good overview of the spatial distribution including some assumptions to make sense of the data ("in the bustling areas on the coasts... and in Arizona ...not much to see there...maybe he got some relatives there...New York, Washington DC, Chicago, Miami, all the crowded places... Florida ... perhaps due to the weather..."). At the same time P10 obtained rather little temporal information and was not able to integrate the insights on a spatiotemporal level ("...during different times in different places...two to three months in one place or maybe two and then he moved on...now and then he moved from east to west, but I didn't look closely..."). More spatiotemporal insights were reported during the interview than during the exploration phase. The major drawback of *CMV* was that the insights gained through the histogram or from pictures the participants randomly selected during the exploration was used to fill the knowledge-gaps: participants erroneously assumed that Cushman travelled mostly during the times he took the most pictures (P5 & P9) and that Cushman only travelled in one direction (P8 & P20).

Fig. 3. Knowledge-building insights on spatial (S), temporal (T) and spatiotemporal (ST) dimensions.

Only participants that dug deeper into the data with the timeline widget or which were selecting and comparing individual pictures were able to correctly formulate insights on the spatiotemporal dimension. As this was not done systematically, these insights - though sometimes rather detailed - remained isolated and could not be connected to other insights.

With the *ANI*, participants generated fewer insights in total. This was especially true for the temporal distribution of the data - no insights on this dimension were recorded. According to the verbal protocols, the animation was perceived as too fast and it was very tedious to keep the information in memory. P3 said during the first exposure: "The dots come and go, I couldn't take anything away from it". It can be assumed that the stream of new information constantly replaces the information held in short term memory before it can be transferred to long term memory. While P3 was nevertheless able to reproduce the overall pattern of Cushman's movement, the other participants failed to do so.

The participants who worked with the *CC* had the most connected spatiotemporal insights. Even P2, who did not generate relevant insights during the exploration, was able to correctly describe the major movement pattern during the interview.

The *STC* achieved mixed results: P11 and P13 could not reproduce the overall patterns in the data after interacting with the *STC*. On the other hand P12 and P14 were able to report many details. But whereas P14 generated a fair amount of spatial and spatiotemporal insights, P12 focused solely on temporal patterns and neglected the spatial distribution of the pictures ("1938: pictures in autumn and winter... 1939: first half of the year, then nothing... 1940: he did a lot of pictures during this year, the amount of pictures increased dramatically... 1938 only the second half of the year, maybe the start of his career ...I mainly observed from side view, so I missed out on [locations]...I think west and east..."). We assume that the insights generated by the participants largely depend on the

interaction with the STC, especially which perspectives they chose during the exploration.

5.2 Solving Spatiotemporal Tasks

The think-aloud protocols were analyzed with respect to the plausibility and the granularity on the spatial and temporal data dimension (cp. fig. 4). As the first task - to identify *spatiotemporal movement patterns* - was very open and many different movement patterns could be described, it is not possible to define a single “correct” solution. Thus, we coded whether the think-aloud protocols contained plausible utterances on spatial and temporal patterns (0=wrong, 1=partially plausible, 2=plausible). Additionally, we analyzed on which granularities participants identified patterns in spatial data (0=N/E/S/W, 1=states, 2=places) and in temporal data (0=beginning/end, 1=year, 2=month).

Fig. 4. Spatial and temporal plausibility (left) and granularity (right) of the spatiotemporal movement patterns described.

Overall, users gained a good overview on spatial and temporal patterns with all four visualization techniques. In comparison to CMV, plausibility was higher in spatial patterns for ANI and CC, but not for STC. No differences were found in temporal patterns. The granularity of the described patterns was lower on spatial patterns with the STC and on temporal patterns with ANI. This observation of lower granularities can be explained by some difficulties expressed by users of these visualization techniques: Some STC users had severe problems to relate data points to their spatial position - “I can’t see where the points actually are [rotation] but here I can’t see the map” (P6, f). In the ANI, users reported problems to follow the map and the timeline at the same time - “I’ll ignore the years, because I cannot look at two parts at the same time” (P16, m). Some users developed interaction strategies to solve this problem by panning the map nearer to the timeline and decreasing the visual distance between the visual components.

But what can these findings tell us about the integration of spatial and temporal data? We compared whether the visualization techniques enabled users to identify plausible movement patterns – on both spatial and on temporal data dimensions. Table 3 gives an overview on how many users described only one-dimensional patterns or highly plausible patterns on both data dimensions. This table shows similar results for all visualization techniques, except for ANI: Only partially integrated movement patterns were described – further illustrating the problems ANI users had to follow the spatial and temporal progress at the same time.

Table 3. Level of integration of spatial and temporal patterns.

	none	partial	full
CMV	3	3	7
ANI	3	10	5
CC	1	4	5
STC	2	5	5

As for subsequent tasks, participants were asked to identify the year with most (task 2) or least travel activity (task 3). We evaluated the

plausibility and granularity of their explanations (as for task 1), but only on a temporal level. To solve this task, users had to compare the spatial dispersion of different years.

The temporal granularity of the utterances did not differ, but an effect of visualization technique on plausibility was observed (cp. figure 5): Users of the STC gave more plausible answers than users of the other visualization techniques. This effect can be seen clearly for task 2; in task 3 they still perform best, but similar to when they use CC. In the STC participants could best compare spatiotemporal patterns across time.

What problems occurred with the other visualization techniques? Again, some CMV users mistook the amount of pictures in the histogram for travel activity (P3: “In 1942 there is a gap with less pictures. Always when he took less pictures”). In ANI, users had to keep in mind the different travel activities and compare them virtually - a highly demanding and difficult task.

Fig. 5. Temporal plausibility and granularity for identifying time periods with high (left) or low travel activity (right).

5.3 Cognitive Load

Even though most participants were able to solve the tasks with different visualization techniques, an important question is the amount of cognitive load required to do so. Participants reported slightly higher cognitive load and lower subjective performance when working with STC and ANI in comparison with CMV and CC (see figure 6). The requirements for interaction were perceived as highest in SS and STC; frustration levels were generally quite low, but lowest in CC.

When looking at *gender* differences, women reported much lower cognitive load and higher performance for CC than men. This effect could be explained with higher difficulties of color discrimination with men, for example P16 (m) saw “4 different colors”.

Also, the participants’ *level of education* makes a clear difference: Academic participants did perceive all visualization techniques similarly high in cognitive load. In contrast, participants with a lower level of education rated CC best (on all questions) and reported rather high levels of frustration for CMV and STC.

5.4 Subjective Preferences

In casual settings - where users can normally choose, whether and how long they interact with a visualization system - the perceived attractiveness is an important factor [20]. Overall, participants liked CC best - due to its aesthetic appeal and ease-of-use (see figure 7). Second-best is the STC, which was found least boring and most informative. ANI and CMV were perceived less positive: Both have little aesthetic appeal; ANI was evaluated as least informative and most difficult to use and CMV as most boring.

With respect to *gender*, men liked three visualization techniques similarly (STC as informative, CMV and CC as easy to use), but women are more in favor of CC - on all dimensions.

Differences due to *level of education* are highest in the evaluation of STC: It is more favored by academics than by non-academics (maybe due to a higher perceived ease of use and informative value).

Fig. 6. NASA TLX for the different visualization techniques (a) overall, (b) men, (c) women, (d) academics and (e) non-academics.

Fig. 7. Subjective preferences for the different visualization techniques (a) overall, (b) men, (c) women, (d) academics and (e) non-academics.

6 DISCUSSION

During the *free exploration and interview* we observed pronounced interindividual differences: Participants who used CMV and ANI showed a lack of correct spatiotemporal insights. Nearly no temporal insights were generated when using ANI and only few spatial insights when using STC. The participants achieved the best results with CC - all of them were able to describe the basic spatiotemporal patterns in the exploration phase or the interview.

We rated the connectedness of the insights higher with STC and CC than for CMV and ANI. We argue that the level of perceptual integration of temporal and spatial information is higher with STC and CC and consequently support the construction of a mental model. In contrast, with ANI a user has to hold too much information in memory and thus just catches a glimpse of the overall movement pattern. Similarly with CMV, the participants only explored some details with the timeline widget and mostly missed out on the overall pattern. In both cases the participants generated only singular insights, what we interpret – using Tversky’s definition [15] – as cognitive collages.

Additionally, we observed fewer interindividual differences with CC than with STC. CC supported all participants in the construction of a spatiotemporal mental model, but with STC some participants had difficulties with the interaction (P16: “I felt uncomfortable with 3D, I’m not used to video games, I even have difficulties with google earth.”) or properly reading the spatial information.

Similar to the free exploration and interview, the participants’ answers on task 1 (*describing movement patterns*) showed a lower temporal granularity with ANI and lower spatial granularity with STC. With ANI, participants could not describe both - plausible spatial *and* temporal patterns, whereas with STC they were able to do so (even though on a lower granularity level). Harrower and Fabrikant [2008] assumed a split attention effect in ANI between the map and timeline. Indeed, such an effect was observed in our study as well, resulting in more superficial descriptions of temporal patterns with respect to the granularities used. Even though a split attention effect also occurs in CMV, the effect in ANI is more severe: In CMV the split attention effect results in higher visual work, in ANI users necessarily miss the information that they are not attending to.

The finding that spatial patterns are of lower granularity when using a STC is in accordance with the finding of [40] that the STC is less powerful on metric properties, but further specifies this finding that this is mainly true for spatial details, less for temporal ones. To

improve users’ spatial awareness, [61] compared different STC variations. For the more general tasks they observed higher accuracy and fewer interactions when users are provided a movable map plane or a linked 2D map than a vertical reference line (which was used in this study).

For the *comparison of movement patterns over time*, users performed better with the STC in task 2 and both with CC and STC in task 3. A possible explanation of the STC’s superiority is that users could build up a better mental model of the travel activities over the whole time course whereas later data points occluded earlier ones in the CC and it was less easy to construct a mental model of the whole time period. A different (but bold) hypothesis is, that due to the rotation possibilities STC users had to create a richer IR and memorize more aspects of the CHC than CC users, who had the same representation available all the time. This would surely result in higher cognitive load, but also in a richer IR.

As was found in the study by Willems et al. [45], *cognitive load* was higher when working with STC and ANI than when working with CMV. We tested CC as an additional spatiotemporally integrated visualization technique which is similar low in cognitive load as CMV. Together with the observations that CC supports the construction of a spatiotemporally well-connected IR and performs well on spatiotemporal tasks, this makes this visualization technique a promising one - worth further research. Especially, as men experienced higher cognitive load with this method - maybe due to difficulties in discriminating the colors.

Subjective preferences were highest for the more integrated visualization techniques - CC and STC. But on the STC opinions greatly differ: Women and non-academics clearly prefer CC over the STC and rate the STC as most difficult to use. Furthermore, we collected numerous hints that attraction power and user experience of ER matter to casual users. As opposed to experts, they do not necessarily show intrinsic motivation for data exploration, which is why other factors have to attract them or draw them in. If it is not the content itself, the overall ER design and interaction experience matters. Exemplarily, numerous participants were not enthused by the muted beige in the background (P13: “the color reminds me of my grandma’s pantyhose”) – which was chosen due to its nonintrusive character – and suggested to do something more entertaining with it.

7 CONCLUSION & OUTLOOK

We reported on a study on the cognitive integration of spatial and temporal information when using four different visualization

techniques, which aim to provide casual users with spatiotemporal overview and orientation in the area of CHC data.

For this purpose, we activated a terminological suggestion which we consider as highly relevant in the InfoVis context and pioneered ways to formalize and empirically measure it: Tversky [15] firstly suggested a quality gradient for IRs, which she expected to have notable consequences for complex reasoning processes. To get an empirical grip on this distinction - and to transfer the notion of mental models and cognitive collages to the domain of InfoVis - we analyzed think aloud protocols with the assumption, that knowledge building insights [41] form the basic elements or building blocks of IRs. We rated the connectedness of the observed insights to differentiate between more coherent mental models and rather fragmented cognitive collages. Whereas the latter were considered to consist of one or more singular, unrelated insights, only an aggregation of connected insights was specified as a mental model. We think this approach provides a window into the IR of users, and how they actually integrate spatial and temporal data dimensions. With this study we only conducted a qualitative rating of the connectedness of insights. But as this approach turned out to be quite productive in finding relevant differences regarding the interplay of ER and IR constructions, we can imagine - and want to recommend - further developments in the future. Exemplarily, using a more sophisticated technique like structuring or visualizing the connected insights [62] could help to further advance and improve this novel evaluation perspective.

As for the main results of our comparative evaluation, we found that the best-integrated IRs resulted from interaction with CC and STC, followed by CMV and ANI. As a surprise, color coding - which we found not to be covered by studies so far - had not only similarly integrating effects as STC, but was also lower in cognitive load. We consider this to be a result which invites or even requires further investigation. On the detail level we were able to document a variety of representational strengths and weaknesses for each view - as well as notable differences for various user groups. From a practical design perspective we consider this to be a substantial argument speaking for the combined utilization of multiple spatiotemporal ERs, "to maximise insight, balance the strengths and weaknesses of individual views, and avoid misinterpretation" [63, p. 9].

As for the users' navigation between different views, seamless transitions and operations revolving around STC representations have been described to support cognitive translation processes [35], [41]. We aim to shed light on the effects of this hypothesis during the PolyCube system's ongoing development and investigate how traceable STC operations help to support the maintenance of the users' mental map or model. Furthermore we will work on generalizing all of the spatiotemporal design solutions and put a variety of other, non-geographic visualization methods (see figure 8, bottom half) in the place of the geographic map.

Figure 8. Intended extension of the PolyCube system, integrating not only maps as geotemporal representations (brown), but also various non-geographic mapping techniques (green).

As a next step, we want to evaluate the system on an advanced level of construction (e.g. including time-oriented network or treemap visualizations) and to compare the current results across different InfoVis types and techniques (see Figure 8).

Eventually, it will be interesting to compare the added value of different visualization techniques for different CHC visitors and target groups with more systematic studies, including comparison of applications in digital and traditional CHC institutions, like libraries, archives and museums. In this relatively young field of research, evaluations are needed [6], and will lead the way to the development of more accessible and effective guidance and sensemaking systems.

ACKNOWLEDGMENTS

This work was supported by a grant from the Austrian Science Fund (FWF), project no. P28363-24 and from the NFB, project no. SC16-032.

REFERENCES

- [1] M. Harrower and S. Fabrikant, "The role of map animation for geographic visualization," *Geogr. Vis.*, pp. 49–65, 2008.
- [2] A. Betti, D. H. Gerrits, B. Speckmann, and H. Van den Berg, "GlamMap: visualising library metadata," *Proc. VALA*, 2014.
- [3] M.-J. Kraak, "Timelines, temporal resolution, temporal zoom and time geography," in *Proceedings 22nd International Cartographic Conference, A Coruna Spain*, 2005.
- [4] J. C. Roberts, "Coordinated multiple views for exploratory geovisualization," *Geogr. Vis. Concepts Tools Appl.*, pp. 25–48, 2008.
- [5] C. Zhong, T. Wang, W. Zeng, and S. M. Arisona, "Spatiotemporal visualisation: A survey and outlook," in *Digital Urban Modeling and Simulation*, Springer, 2012, pp. 299–317.
- [6] F. Windhager, "Visualization of Cultural Heritage Collection Data: State of the Art and Future Challenges," *Forthcoming*.
- [7] E. Mayr, P. Federico, S. Miksch, G. Schreder, M. Smuc, and F. Windhager, "Visualization of Cultural Heritage Data for Casual Users," presented at the 2016 Workshop on Visualization for the Digital Humanities, Baltimore, 2016.
- [8] R. Villa, P. D. Clough, M. M. Hall, and S. A. Rutter, "Search or Browse? Casual Information Access to a Cultural Heritage Collection," in *European Workshop on Human-Computer Interaction and Information Retrieval*, 2013, vol. 1033, pp. 19–22.
- [9] M. Dörk, S. Carpendale, and C. Williamson, "The information flaneur: A fresh look at information seeking," in *Proc. of the SIGCHI conf. on human factors in computing systems*, 2011, pp. 1215–1224.
- [10] M. Dörk, C. Pietsch, and G. Credico, "One view is not enough. High-level visualizations of a large cultural collection," *Spec. Issue Inf. Des. J.*, vol. 23:1, pp. 39–47, 2017.
- [11] G. Andrienko, N. Andrienko, J. Dykes, S. I. Fabrikant, and M. Wachowicz, "Geovisualization of Dynamics, Movement and Change: Key Issues and Developing Approaches in Visualization Research," *Inf. Vis.*, vol. 7, no. 3–4, pp. 173–180, Sep. 2008.
- [12] R. Arias-Hernandez, T. M. Green, and B. Fisher, "From cognitive amplifiers to cognitive prostheses: Understandings of the material basis of cognition in visual analytics," *Interdiscip. Sci. Rev.*, vol. 37, no. 1, pp. 4–18, 2012.
- [13] Z. Liu and J. Stasko, "Mental models, visual reasoning and interaction in information visualization: A top-down perspective," *IEEE Trans. Vis. Comput. Graph.*, vol. 16, no. 6, pp. 999–1008, 2010.
- [14] Z. Liu, N. Nersessian, and J. Stasko, "Distributed cognition as a theoretical framework for information visualization," *IEEE Trans. Vis. Comput. Graph.*, vol. 14, no. 6, 2008.
- [15] B. Tversky, "Cognitive maps, cognitive collages, and spatial mental models," *Spat. Inf. Theory Theor. Basis GIS*, pp. 14–24, 1993.
- [16] M. Hegarty, "The cognitive science of visual-spatial displays: Implications for design," *Top. Cogn. Sci.*, vol. 3, pp. 446–474, 2011.
- [17] G. Schreder, F. Windhager, M. Smuc, and E. Mayr, "A Mental Models Perspective on Designing Information Visualizations for Political Communication," *JeDEM*, vol. 8, no. 3, pp. 80–99, 2016.
- [18] P. N. Johnson-Laird, "Mental models in cognitive science," *Cogn. Sci.*, vol. 4, no. 1, pp. 71–115, 1980.
- [19] E. Mayr, G. Schreder, M. Smuc, and F. Windhager, "Looking at the Representations in Our Mind: Measuring Mental Models of

- Information Visualizations,” in *Proceedings of the Beyond Time and Errors on Novel Evaluation Methods for Visualization*, New York, NY, USA, 2016, pp. 96–103.
- [20] Z. Pousman, J. T. Stasko, and M. Mateas, “Casual information visualization: Depictions of data in everyday life,” *Vis. Comput. Graph. IEEE Trans. On*, vol. 13, no. 6, pp. 1145–1152, 2007.
 - [21] S. Jänicke, C. Heine, and G. Scheuermann, “GeoTemCo: Comparative visualization of geospatial-temporal data with clutter removal based on dynamic Delaunay triangulations,” in *Comp. Vision, Imaging and Comp. Graphics. Theory & Application*, Springer, 2013, pp. 160–175.
 - [22] D. Edelstein, P. Findlen, G. Ceserani, C. Winterer, and N. Coleman, “Historical Research in a Digital Age: Reflections from the Mapping the Republic of Letters ProjectHistorical Research in a Digital Age,” *Am. Hist. Rev.*, vol. 122, no. 2, pp. 400–424, 2017.
 - [23] M. Q. Wang Baldonado, A. Woodruff, and A. Kuchinsky, “Guidelines for using multiple views in information visualization,” in *Proc. of the working conference on Advanced visual interfaces*, 2000, pp. 110–119.
 - [24] P. Ayres and J. Sweller, “The split-attention principle in multimedia learning,” *Camb. Handb. Multimed. Learn.*, vol. 2, 2014.
 - [25] P. Chandler and J. Sweller, “The split-attention effect as a factor in the design of instruction,” *Br. J. Educ. Psychol.*, vol. 62, pp. 233–246, 1992.
 - [26] T. A. Slocum *et al.*, “Cognitive and usability issues in geovisualization,” *Cartogr. Geogr. Inf. Sci.*, vol. 28, pp. 61–75, 2001.
 - [27] M. Harrower, “The cognitive limits of animated maps,” *Cartogr. Int. J. Geogr. Inf. Geovisualization*, vol. 42, no. 4, pp. 349–357, 2007.
 - [28] S. Kriglstein, M. Pohl, and M. Smuc, “Pep up your time machine: recommendations for the design of information visualizations of time-dependent data,” in *Handbook of human centric visualization*, Springer, 2014, pp. 203–225.
 - [29] G. Andrienko *et al.*, “Space, time and visual analytics,” *Int. J. Geogr. Inf. Sci.*, vol. 24, no. 10, pp. 1577–1600, 2010.
 - [30] A. L. Griffin, A. M. MacEachren, F. Hardisty, E. Steiner, and B. Li, “A Comparison of Animated Maps with Static Small-Multiple Maps for Visually Identifying Space-Time Clusters,” *Ann. Assoc. Am. Geogr.*, vol. 96, no. 4, pp. 740–753, 2006.
 - [31] W. Javed and N. Elmquist, “Exploring the design space of composite visualization,” in *Pacific Visualization Symposium (PacificVis), 2012 IEEE*, 2012, pp. 1–8.
 - [32] W. S. Cleveland and R. McGill, “Graphical perception: Theory, experimentation, and application to the development of graphical methods,” *J. Am. Stat. Assoc.*, vol. 79, no. 387, pp. 531–554, 1984.
 - [33] R. Scheepens, H. Van De Wetering, and J. J. Van Wijk, “Non-overlapping aggregated multivariate glyphs for moving objects,” in *IEEE Pacific Visualization Symposium (PacificVis)*, 2014, pp. 17–24.
 - [34] P. Gatalaky, N. Andrienko, and G. Andrienko, “Interactive analysis of event data using space-time cube,” in *Information Visualisation, 2004. IV 2004. Proc.. 8th Int. Conference on*, 2004, pp. 145–152.
 - [35] F. Windhager, Schreder, Günther, Salisu, Saminu M., and Mayr, Eva, “Orchestrating overviews: A synoptic approach to the visualization of cultural collections,” *Open Libr. Humanit.*, vol. forthcoming, 2018.
 - [36] T. Munzner, *Visualization analysis and design*. CRC press, 2014.
 - [37] N. Elmquist and P. Tsigas, “A taxonomy of 3d occlusion management for visualization,” *IEEE Trans. Vis. Comput. Graph.*, vol. 14, no. 5, pp. 1095–1109, 2008.
 - [38] P. O. Kristensson *et al.*, “An evaluation of space time cube representation of spatiotemporal patterns,” *IEEE Trans. Vis. Comput. Graph.*, vol. 15, no. 4, pp. 696–702, 2009.
 - [39] F. Amini, S. Rufiange, Z. Hossain, Q. Ventura, P. Irani, and M. J. McGuffin, “The impact of interactivity on comprehending 2D and 3D visualizations of movement data,” *IEEE Trans. Vis. Comput. Graph.*, vol. 21, no. 1, pp. 122–135, 2015.
 - [40] A. Kjellin, L. W. Pettersson, S. Seipel, and M. Lind, “Evaluating 2d and 3d visualizations of spatiotemporal information,” *ACM Trans. Appl. Percept. TAP*, vol. 7, no. 3, p. 19, 2010.
 - [41] B. Bach, P. Dragicevic, D. Archambault, C. Hurter, and S. Carpendale, “A Descriptive Framework for Temporal Data Visualizations Based on Generalized Space-Time Cubes,” in *Computer Graphics Forum*, 2017, vol. 36, pp. 36–61.
 - [42] I. Kveladze, M.-J. Kraak, and C. P. van Elzakker, “A methodological framework for researching the usability of the space-time cube,” *Cartogr. J.*, vol. 50, no. 3, pp. 201–210, 2013.
 - [43] T. Gonçalves, A. P. Afonso, and B. Martins, “Visualizing human trajectories: Comparing space-time cubes and static maps,” in *Proceedings of the 28th International BCS Human Computer Interaction Conference on HCI 2014-Sand, Sea and Sky-Holiday HCI*, 2014, pp. 207–212.
 - [44] T. Gonçalves, A. P. Afonso, and B. Martins, “Why not both?: combining 2D maps and 3D space-time cubes for human trajectory data visualization,” in *Proceedings of the 30th International BCS Human Computer Interaction Conference: Fusion!*, 2016, p. 22.
 - [45] N. Willems, H. Van De Wetering, and J. J. Van Wijk, “Evaluation of the visibility of vessel movement features in trajectory visualizations,” in *Computer Graphics Forum*, 2011, vol. 30, pp. 801–810.
 - [46] E. Kaya, M. T. Eren, C. Doger, and S. Balcişoy, “Do 3D visualizations fail? An empirical discussion on 2D and 3D representations of the spatio-temporal data,” *Proc. EURASIA Graph.*, vol. 2014, 2014.
 - [47] A. Bisantz *et al.*, “Maps, Space-time Cubes, and Meta-Information for Understanding Path Information: A Comparative Analysis,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 2014, vol. 58, pp. 370–374.
 - [48] N. Andrienko, G. Andrienko, and P. Gatalaky, “Impact of data and task characteristics on design of spatio-temporal data visualization tools,” in *Exploring geovisualization*, Elsevier, 2005, pp. 201–222.
 - [49] I. Kveladze, M.-J. Kraak, and C. P. Van Elzakker, “The space-time cube as part of a GeoVisual analytics environment to support the understanding of movement data,” *Int. J. Geogr. Inf. Sci.*, vol. 29, no. 11, pp. 2001–2016, 2015.
 - [50] I. Kveladze and M.-J. Kraak, “What do we know about the space-time cube from cartographic and usability perspective,” *Columb. Ohio USA Proc. Autocarto*, pp. 16–18, 2012.
 - [51] I. Kveladze, M.-J. Kraak, and C. P. van Elzakker, “The Usability of a GeoVisual Analytics Environment for the Exploration and Analysis of Different Datasets,” in *International Cartographic Conference*, 2017, pp. 207–221.
 - [52] T. Gonçalves, A. P. Afonso, B. Martins, and D. Gonçalves, “ST-TrajVis: interacting with trajectory data,” in *Proceedings of the 27th International BCS Human Computer Interaction Conference*, 2013, p. 48.
 - [53] F. Windhager, E. Mayr, G. Schreder, M. Smuc, P. Federico, and S. Miksch, “Reframing Cultural Heritage Collections in a Visualization Framework of Space-Time Cubes,” in *Proceedings of the 3rd HistoInformatics Workshop*. <http://ceur-ws.org>, Krakow, 2016, vol. 1632, pp. 20–24.
 - [54] M. Whitelaw, “Generous Interfaces for Digital Cultural Collections,” *Digit. Humanit. Q.*, vol. 9, no. 1, 2015.
 - [55] B. Bach, P. Dragicevic, D. Archambault, C. Hurter, and S. Carpendale, “A review of temporal data visualizations based on space-time cube operations,” in *Eurographics conference on visualization*, 2014.
 - [56] M. Posner, “Getting started with Palladio,” *Miriam Posner’s Blog*, 23-Nov-2014. .
 - [57] R. E. Roth *et al.*, “User studies in cartography: opportunities for empirical research on interactive maps and visualizations,” *Int. J. Cartogr.*, vol. 3, no. sup1, pp. 61–89, 2017.
 - [58] N. Andrienko, G. Andrienko, and P. Gatalaky, “Exploratory spatio-temporal visualization: an analytical review,” *J. Vis. Lang. Comput.*, vol. 14, no. 6, pp. 503–541, Dec. 2003.
 - [59] E. Mayr, M. Smuc, and H. Risku, “Many roads lead to Rome: Mapping users’ problem-solving strategies,” *Inf. Vis.*, vol. 10, no. 3, pp. 232–247, 2011.
 - [60] R. Chang, C. Ziemkiewicz, T. M. Green, and W. Ribarsky, “Defining insight for visual analytics,” *IEEE Comput. Graph. Appl.*, vol. 29, no. 2, pp. 14–17, 2009.
 - [61] T. Gonçalves, A. P. Afonso, and B. Martins, “Improving spatial awareness for human trajectory visualization in space-time cubes,” in *Human-Computer Interaction*, 2015, pp. 327–334.
 - [62] M. Smuc, E. Mayr, T. Lammarsch, W. Aigner, S. Miksch, and J. Gärtner, “To score or not to score? Tripling insights for participatory design,” *IEEE Comput. Graph. Appl.*, vol. 29, no. 3, 2009.
 - [63] N. Kerracher, J. Kennedy, and K. Chalmers, “The design space of temporal graph visualisation,” in *Proceedings of the 18th Eurographics Conference on Visualization (EuroVis ’14)*, vol. Short, N. Elmquist, M. Hlawitschka, and J. Kennedy, Eds. Swansea: Eurographics Association, 2014.