PolyVis: Cross-Device Framework for Collaborative Visual Data Analysis

Abeer Alsaiari[1], Andrew Johnson[2], and Arthur Nishimoto[3]

Fig. 1: The visualization declaration scheme can span different devices for rendering: (a) large display, (b) tablet, and (c) HoloLens.

Abstract— **Multi device environments present new opportunities for collaborative visual data analysis and sense making by utilizing each device's strengths and capabilities. However, one of the associated challenges with visual data analysis in multi device environments is the sharing of visual components across devices. We present a framework developed on top of SAGE2 platform for cross-device collaborative visual data exploration. As part of our framework, we contribute the concept of rapid development and assembling of visualizations that can span multiple devices of different modalities. It provides the users with an environment for visualization compositions that delegate the rendering to the target device, allowing them to augment their large display workspace with portable devices for further exploration territories. Facilitated by its intuitive visualization composition pipeline, users with no programming skills such as data analysts can enhance their analytical scope with no coding barriers. We describe the framework, its implementation with a use case, and the rationale behind its design.**

I. INTRODUCTION

Visual analytics “The science of analytical reasoning facilitated by interactive visual interfaces” [1] encompasses a large amount of data that comes form different sources and domains. Therefore, understanding such large datasets is rarely a solitary activity. Collaborative visual data analysis enables multiple users (often called analysts) to work together to collaboratively contribute contextual knowledge that deepens their understanding of the data. The heterogeneity of the datasets and the inclusion of multiple users in such collaborative environments demanded solutions that go beyond the desktop [2][3]. Tiled display walls have been shown to increase the performance of visualization tasks [4] and the productivity of exploratory visual analysis [5]. In recent years, spreading to multi-device settings for co-located collaborative visual data analysis has emerged to leverage other device capabilities.

[1]Abeer Alsaiari, [2]Andrew Johnson, and Arthur Nishimoto[3] are with the Electronic Visualization Laboratory at the University of Illinois at Chicago, Chicago, IL 60607 USA (corresponding author to provide phone: 312-996-3002; fax: 312-413-7585; e-mail: aalsai3, ajohnson, anishi2@uic.edu).

We integrate the SAGE2 large display with portable devices (tablets and augmented reality headset) for co-located multi-device visual data analysis. SAGE2 [6], the successor of SAGE [7], is a middleware developed using web-browser technologies to take multiple displays and unify them as one high-resolution workspace. It enable users to collaboratively share and display their contents on the large display (Fig. 2). Display clients provide information of the corresponding viewport in the workspace via their URLs. Any number of displays on different systems can be joined to form a unified view of the SAGE2 workspace.

SAGE2 native applications are written in JavaScript using SAGE2 API. Applications open simultaneously on the large workspace enabling users to collaboratively interact with them. Users interact with the workspace through UI clients running on their devices using a SAGE2 pointer, which is an html element that collects the native mouse events and propagates them to the corresponding display client for handling. Due to its distributed application and event model, all users input events are passed to the head node server which in turn distributes them to display clients for handling. Each display client has its own instance of running applications and receives events to handle them consistently.

We integrate the SAGE2 large display with portable devices of different modalities like tablets and AR headsets to create additional visual exploration territories. Coupling and coordinating with different devices requires middle modules for data sharing, translation and synchronization due to different platforms interdependency. To tackle this issue, we developed our framework based on declarative visualization design and operation transformation (OT) for seamless migration of visualizations and their interactivity between devices.

Fig. 2: User collaborating during a SAGE2 session where they share digital contents (i.e. PDFs, images, etc.) on the large display. [6]

The next section covers related work about collaborative visual analytics and the use of heterogeneous devices for visual data analysis. We then present the design principles for the proposed framework. The following is the framework overview. The collaborative scenario with expert feedback is presented next. Lastly, we present the future work and conclude the paper.

II. RELATED WORK

Here, we review some of the related work in the areas of collaborative visual analytics and visual data analysis in multi device environments. We derive our design guidelines and principles based on principles from these areas that still apply.

A. *Collaborative Visual Analytics*

Visual analytics is "The science of analytical reasoning facilitated by interactive visual interfaces"[1]. The reasoning process is a collaborative task that is done by multiple analysts due to the heterogeneity of emerging datasets. Therefore, building frameworks to support synchronous and asynchronous collaborative visual analytics was a natural next step. Many Eyes [8] was among the first systems to utilize web technology to provide an asynchronous collaborative mechanism of large-scale data visualization. Vistrates by Badam et al. [9] is a framework based on component model to design data visualization tasks that support synchronous and asynchronous collaborative visual data analysis. In contrast to distributed analysis, Lark [10] was developed to support collocated collaboration. It utilizes the visualization pipelines for direct manipulation on the tabletop. To promote the distributed visual analysis interfaces, Munin [11] and PolyChrome [12] were developed using multiple surfaces and displays.

Both synchronous and asynchronous visual analytics need special considerations due to the unique requirements for each setting. Work partitioning across space and time in asynchronous collaborative settings provides scalability yet introduces new challenges. Heer and Agrawala [13] defined a set of design considerations that identify important aspects for achieving effective collaboration in visual analytics settings. Those aspects with regards to asynchronous collaboration are important to increase the collaboration awareness and work engagement during asynchronous visual analytics. Petra et al. [14] presented an overview of collaborative visualization scenarios and their associated challenges. Other efforts have been made to identify design considerations for specific collaborative settings such as collaboration around tabletops [15] and collaboration in multi-display environments [16].

B. *Heterogeneous Devices for Visual Data Analysis*

Developing novel displays has been a significant effort to support visual data exploration and analysis. Large displays and tabletops support better collaboration in large spaces [17]. Spreading to multi-device settings emerged to support co-located collaboration for visual analytics. McGrath et al. [18] proposed the Branch-Explore-Merge protocol to support the coupled and decoupled visual data exploration around tabletops. Portable devices, i.e. tablets, allowed for private exploration and merging of results onto the shared space, and hence, the branching and merging protocol facilitates flexible levels of exploration territories. Yoshimoto et al. [19] integrated a tabletop and wall display for different view modalities and an interaction metaphor. Gestural interactions are used on a 2D map on the tabletop to provide basic interaction and navigation of the 3D map on the wall. Due to their popularity and portability, tablets, mobile phones and smart watches have also been integrated with large displays and tabletops to steer the interaction and the visual exploration. By leveraging each device's display and input modalities, they provide fluid interplay between them to support the visual data analysis tasks [20].

The current approaches of visual data exploration beyond a single desktop computer enabled new sense-making environment that support analysts needs. Several frameworks proposed different configurations of novel displays to support the analysis tasks. In VisTiles [21], mobile devices were utilized by leveraging their portability and dynamics. VisTiles enables flexible layout and distribution of coordinated multiple views, and therefore aids a user-friendly interface. The coordinated multiple views can adapt to the spatial arrangement of devices enabling new visualization composition and exploration of multivariate data. Other frameworks proposed a display composition environment to utilize the capabilities of heterogeneous devices and extend the visual space for visual data exploration. Munin [11] was a software framework which attempted to unify the composition of the multi device environment through a service-based model. It envisions the anytime and anywhere visual data analysis. Sharing information in a heterogeneous device environment is a challenging task. Like Munin, VisPorter [22] is a multi-device system that enables the lightweight sharing and integration of information among different devices. These systems extend the visual space to enhance the users cognition about their data investigation. Andrews and North [23] proposed the Analysts Workspace by utilizing the spatial affordances of the large high-resolution display to embody resources and create a new sense making space. The recent research efforts handle some of the design and technological challenges in multi device environments. However, more effort is demanded to investigate the cross device interaction and interplay from the perspective of visual data exploration and analysis, in addition to harnessing the challenges of visualization sharing and distribution among different device modalities.

III. Design Principles

(D1) Device agnostic visualization sharing

Generally, there are two ways to develop visualizations. One is a native development for a specific platform, and the other is a web-based development. Unlike native applications, web-based applications can be deployed to any device using web technology. Many frameworks and toolkits were developed based on web technology like D3 [27] and JavaScript InfoVis Toolkit [28] to support information visualization applications. PolyChrome [12], Vistrates [9] and Visfer [26] are all web-based frameworks developed to support the collaborative visual analysis. However, sometimes, going natively cannot be avoided when working with devices like AR/VR headsets. In addition, native applications are necessary to take the full advantage and support of the target device. Going with one way is not enough to support all applications and user requirements. To close this gap, solutions for cross-platform infrastructures are essential [30]. Wagner et al. [29] made an effort to support native applications that can be complied to more than 20 devices based on the Unity3D game engine.

(D2) Support of parallel and joint activities

The style of collaboration between participants is affected by the display setup, the problem under investigation and the analysis metaphors. Studies showed that collaboration around interactive surfaces for information visualization in co-located settings takes the forms of completely independent, partially independent and joint (coupled) work [10][31]. Other studies by Isenberg et al. [25][32] identified the styles of collaboration as a spectrum that varies from loosely coupled to tightly coupled. These findings emphasize the importance of supporting individual and public work, and efficient transitions between styles. Another aspect that is related to the style of collaboration around interactive surfaces, is the use of the space. Territoriality, which is the spatial coordination of collaborative work, also takes three forms as identified by Scott et al. [33]. Users use the space for personal work, group work and for storage.

(D3) Fluid cross-device interaction

Spreading visualizations and the analysis tasks to multi devices requires intuitive cross-device interactions. Information sharing and management should not distract users from the actual analysis. Embodied interactions [17] leverage the proximity of devices to develop interactions that carry out these operations. Badam and Elmqvist [26] presented a cross-device interaction technique for data sharing in ubiquitous environments based on a design elicitation study. The interaction technique leverages the physicality of the devices, to effortlessly share visualizations across devices using a built-in camera and embodied QR codes. In VisPorter [22], gestural interaction was utilized to transfer information across displays in an intuitive and direct way. Their approach was based on the concept of physical references of shared information, rather than using symbolic references such as IDs and URLs.

(D4) Exploiting the physical space

Utilizing physical space is essential in scalable visual data analysis. Andrews et al. [24] showed that analysts exploit the spatial affordances of large displays to serve as an external memory and as a semantic layer for spatial data layout and organization. In collaborative settings around tabletops, users frequently move and organize information to approach their analysis tasks [25]. Multi device ecologies enable users to carry information and form dynamic exploration territories across displays that populate the physical space. The view and the analysis process can be extended to span multiple exploration sites across the physical space. The affordances of the physical space enable the flexible configuration and coordination of devices to approach the task. In addition, physical space is essential to embody information and immerse users in their data.

IV. System Overview

The proposed framework is specifically designed to seamlessly support the collaborative visual data analysis that can span multiple devices of different modalities. Here, we discuss the primary features of the framework. We refer to the design principles (D1-D4) with the description of the framework and how the choice is made to meet these principles.

A. Physical Environment

The proposed framework is built on top of SAGE2 middleware that drives tiled wall displays and unifies them as one high-resolution display. The framework is developed primarily to enable the integration of portable devices with SAGE2 display to compose a heterogeneous visual data analysis environment enhanced with further exploration territories (D4). The spectrum of portable displays can have smart-watches at one end and VR headsets at the other end. Due to the unique requirements of integrating devices from categories at the very ends, we limited our scope to support the integration of portable devices that vary in between like tablets and the HoloLens AR headsets. Any number of mobile devices with a built-in camera and web browsers (i.e. tablets and phones) can be joined to pull and push visualizations from and to other devices (D3). Although the tablet client is written in JavaScript as SAGE2 native applications, the coordination layer is necessary due to the difference in interactivity handling between SAGE2 applications and other JavaScript-based applications. The HoloLens client device extends the exploration into the third space. Each distinct HoloLens client should run on a separate machine.

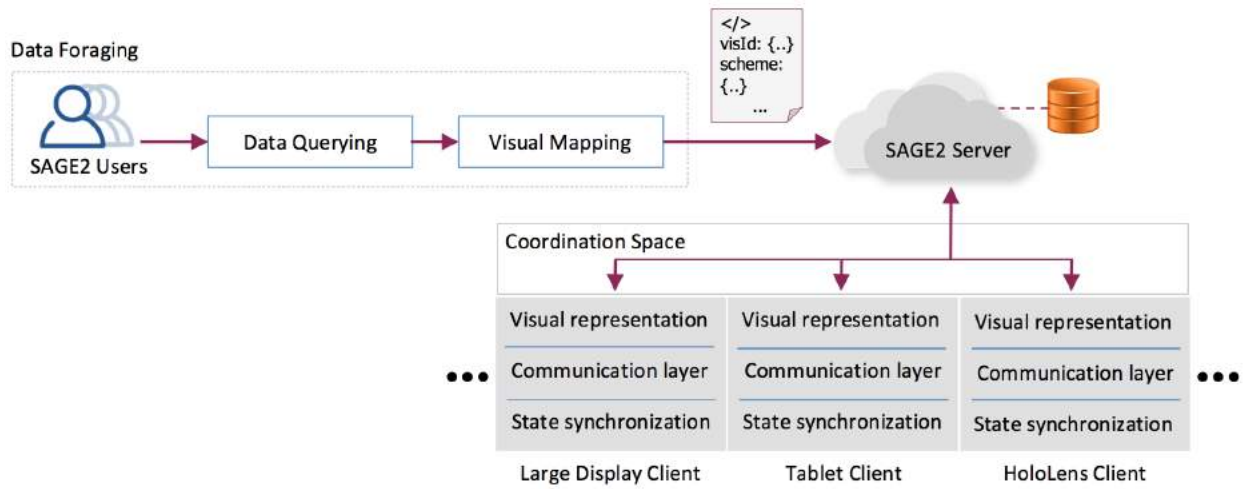

Fig. 3: An overview of the system components. A visualization scheme is defined by the user through a set of filtering and visual encoding specifications. The server coordinate the spanning of the scheme to the target device and coordinate the event wrapping and sharing between devices.

B. Declarative Visualization Design

Developing visualizations can be a tedious process for users with no programming skills, such as data analysts. Therefore, visualization authoring systems and toolkits have been widely adapted in recent years. The presented framework enables the rapid construction of visualizations by following the flow of the information visualization reference model [34]. Here, users play a major role in the visual mapping task that maps each data attribute onto a single visual channel. We treat visualizations as user-configurable semantic units (D1).View transformation is delegated to the target device for rendering. The declarative language is employed to represent the visualization semantic, which is dynamically manipulated by the system throughout the analysis process to maintain a persistent state of the visualization. Grammar-based representation of visualizations has been introduced in many works with various levels of abstraction. While some have a higher level of abstraction for simplicity, others offer a lower level of abstraction for more expressiveness. Examples of these declarative languages include Vega [35], Vega-Lite [36], ggplot2 [37] and ggvis [38]. Unlike other grammar-based applications, we assume a dynamic visualization scheme that gets updated with user interactivity with the visualization.

We employ an all-in-one JSON format to declare three main components of the visualization in our framework. These components are: query specification for data retrieval, visual encoding channels, and interactivity state. We capture those components during user composition of visualization. The interactivity state is captured automatically using our persisting state mechanism and update the scheme accordingly. Fig. 4 shows an example structure of these components. Decoupling the visualization semantic from its view transformation process enabled a seamless migration of visualizations across devices (D1).

C. Events Global Space Encapsulation

We integrate the portable devices with the wall display to enable private, portable and extended exploration of the data. However, concurrent use is a key feature in groupware applications. Therefore, we enable the coupled exploration style between tablets and wall display (D2). That is, interactions on the shared visualization are also maintained and executed in the coupled device for global exploration. Concurrent use requires management of consistency between simultaneous interactions. Operation Transformation (OT) is an early mechanism originally developed to maintain concurrent use and consistency in text editing tools [39]. Its capabilities have been extended over the years to support collaborative groupware applications. Recently, ShareJS [40] used a centralized server to maintain the global state between all clients in online collaborative text editing. PolyChrome [12] adapts the same mechanism to maintain concurrent web-based visualization exploration by pushing DOM events between browsers. DOM Events are wrapped into a global space and inversed on the target display to support different display sizes and configurations. We draw upon this work by encapsulating coarser interaction operations to a global space, so they can be shared and inversed by the target device.

Working with cross-platform requires interactions to be captured and defined in a higher semantic level. Gotz and Zhou [41] organized users' visual analytic activities based on semantic richness. Low-level events, like mouse clicks, have little semantic compared to high-level tasks such as selection and brushing. To support sharing interactions across different platforms, we rely on the action tier and capture the coarser exploration actions defined by [42]. The actions are encapsulated into a global space with higher semantic definition. Then, they could be shared with other devices where they are inversed and interpreted.

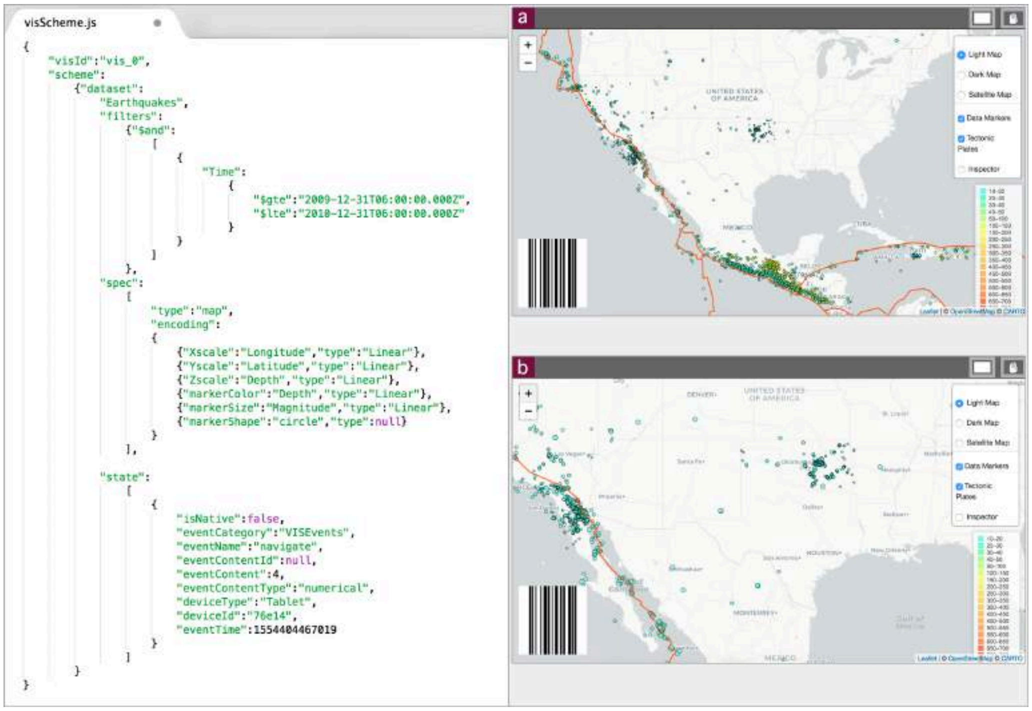

Fig. 4: An example of a visualization scheme structure. (a) visualization at initial state. A new visualization state is pushed to the scheme after an exploration event occurred in (b).

D. Visualization Persist State

In visual analytic systems, users are able to interactively explore the data and change views to generate new hypotheses and results. It is especially important in collaborative settings to share visualizations in their current state.

Most visualization frameworks lack the ability to capture the visual exploration state and the path that led to it. The most challenging aspect is how to capture the visualization state. From the visualization task perspective, interactions in visualization can include a set of low-level events, such as brushing interaction which is composed of the events: mouse-down, mouse move and mouse up. Do we consider the visualization state after each low-level event or after a richer semantic interaction that is composed of a set of low-level events?

The state definition needs to be identified first before any effort to capture it is made. As discussed in the last section, we define operations as data-centric or interaction-centric operations. To enable consistency between different platforms, we chose to define the visualization state based on semantic rich interactions. We enable client side maintenance of a persist state. The state is recorded as the user interacts with the visualization. We defined an intermediate layer to record and push the state to the visualization scheme. When the visualization is shared, the state is recovered according to the device-dependent interactivity and visual channels encoding.

V. EVALUATION

To evaluate the use of the prototype system for the visual data analysis of real world datasets, we conducted a collaborative session with two visualization researchers. Here, we outline the data analysis scenario and discuss feedback from experts.

A. Collaborative Scenario

Two researchers with a background in visualization one has additional experience using immersive technologies conducted a visual data analysis of two geosciences datasets. For reference, we will refer to the users as U1 and U2. The users performed a visual analysis task to ascertain the relationship between injection volume, the pressure of fracking wells and the frequency of earthquakes in Oklahoma State. The earthquake dataset is provided courtesy of http://service.iris.edu/ and the Wells injection dataset is provided courtesy of http://www.occeweb.com/. The users started with the question: Is there any correlation between the injection volume of wells and earthquake events? U1 began by mining the data for all earthquake events during 2010 and then he visualized them on a large display map. He also created a map of the locations of active well during 2010. U2 captured the barcode attached to the map of earthquakes by using the camera of the handheld device to pull the map visualization and performed analysis of the mapped data. He created a line chart to plot the frequency of earthquake events over the year and pushed the chart to the wall. They observed an increase in the number of earthquake incidents during the month of December.

Fig. 5: In a collaborative session, the user on the left is examining data in 3D using a HoloLens device. Data points (Wells) within the blue rectangle on the left map are viewed in 3D via HoloLens. The other user on the right is using a tablet (with linked visualization) to inspect specific areas on the right map

To investigate the temporal relationship with injection volume, he moved to the map of wells and captured the attached barcode. Then, he created another line chart of total volume injection per month. A pattern is observed, so he pushed the chart to the wall and started to discuss with U1. They observed an increase of volume injection during the month of November, which has no temporal relation with the increase in earthquake events, but they made a hypothesis: can a high volume injection cause an increase in earthquake frequency for the next month? U2 used the HoloLens to examine the relative depth of the wells compared to the depth of the earthquakes. They concluded that an additional investigation of the observed pattern is needed for different years and probably for different states to test their hypothesis.

B. Expert Feedback

We collected feedback from the experts regarding the usage of the system for visual data analysis and the benefits of integrating different devices into the process of visual data analysis. U1 mentioned that the use of the tablet gave more freedom of movement, obtain the data they want, process it and push it back. He also believes that this will allow different people to focus on different things of the analysis process. Because of the affordance of portability, both users mentioned that it would be beneficial to use the portable devices as a controlling metaphor to control visualization on other devices (i.e. tablet to control a visualization on large display or on the HoloLens). Controlling here is different than coordinating or linking visualizations. In this context, it means moving visuals around, minimize or maximize them, etc. U2 mentioned that it is useful to view datasets in 2D on the large wall and in 3D on the HoloLens, but the hardest part is to determine what the HoloLens user is seeing. As U1 used the HoloLens to view the data in 3D, he added that it also needs a kind of representation on the large display or any mechanism that would increase the awareness. Experts gave good feedback on how the devices are complementary to each other.

VI. Conclusion and Future Work

In this paper, we have presented the PolyVis framework for the building and promoting of visualizations in multi device environments. It supports visual data exploration by utilizing multiple devices of different modalities. Our primary goal was to maintain consistent sharing and interaction with visualizations across different platforms. To achieve this, we relied on the declarative visualization design and the operation transformation paradigms. We treat visualizations as semantic units (in the form of grammar) to migrate to and render by different devices. SAGE2 users assume a major role in the composition of visualization grammar without any need for programming skills. The interactivity with the visualization is captured and stored in a global space for consistent representation. Therefore, the state of the visualization will be maintained as the data analysis proceeds regardless of the processing device. There are a few areas that we plan to improve in the future. First, the visualization layers at each device only support few visualization types. We plan to extend that to support more advanced types of visualization such as multi lines, stacked bars, parallel coordinate, node-link, etc. We plan also to support the 3D version of these types on the HoloLens client. In addition, as suggested by experts, we would like to implement a mechanism for cross-device multi-coordinated views. With multiple visualizations at a time, it would be beneficial for the visual exploration to connect data points across scattered views.

References

[1] Thomas, J. J., & Cook, K. A. (2006). A visual analytics agenda. IEEE computer graphics and applications, (1), 10-13.

[2] Lee, B., Isenberg, P., Riche, N. H., & Carpendale, S. (2012). Beyond mouse and keyboard: Expanding design considerations for information visualization interactions. IEEE Transactions on Visualization and Computer Graphics, 18(12), 2689-2698.

[3] Roberts, J. C., Ritsos, P. D., Badam, S. K., Brodbeck, D., Kennedy, J., & Elmqvist, N. (2014). Visualization beyond the desktop–the next big thing. IEEE Computer Graphics and Applications, 34(6), 26-34.

[4] Ball, R., & North, C. (2005, April). Effects of tiled high-resolution display on basic visualization and navigation tasks. In CHI'05 extended abstracts on Human factors in computing systems (pp. 1196-1199). ACM.

[5] Reda, K., Offord, C., Johnson, A. E., & Leigh, J. (2014, April). Expanding the porthole: leveraging large, high-resolution displays in exploratory visual analysis. In CHI'14 Extended Abstracts on Human Factors in Computing Systems (pp. 2047-2052). ACM.

[6] Marrinan, T., Aurisano, J., Nishimoto, A., Bharadwaj, K., Mateevitsi, V., Renambot, L., & Leigh, J. (2014, October). SAGE2: A new approach for data intensive collaboration using Scalable Resolution Shared Displays. In 10th IEEE International Conference on Collaborative Computing: Networking, Applications and Worksharing (pp. 177-186). IEEE.

[7] Renambot, L., Rao, A., Singh, R., Jeong, B., Krishnaprasad, N., Vishwanath, V., ... & Goldman, G. (2004, September). Sage: the scalable adaptive graphics environment. In Proceedings of WACE (Vol. 9, No. 23, pp. 2004-09).

[8] Viegas, F. B., Wattenberg, M., Van Ham, F., Kriss, J., & McKeon, M. (2007). Manyeyes: a site for visualization at internet scale. IEEE transactions on visualization and computer graphics, 13(6), 1121-1128.

[9] Badam, S. K., Mathisen, A., Rdle, R., Klokmose, C. N., & Elmqvist, N. (2019). Vistrates: A Component Model for Ubiquitous Analytics. IEEE transactions on visualization and computer graphics, 25(1), 586-596.

[10] Tobiasz, M., Isenberg, P., & Carpendale, S. (2009). Lark: Coordinating co-located collaboration with information visualization. IEEE transactions on visualization and computer graphics, 15(6), 1065-1072.

[11] Badam, S. K., Fisher, E., & Elmqvist, N. (2015). Munin: A peer-to-peer middleware for ubiquitous analytics and visualization spaces. IEEE Transactions on Visualization and Computer Graphics, 21(2), 215-228.

[12] Badam, S. K., & Elmqvist, N. (2014, November). Polychrome: A cross-device framework for collaborative web visualization. In Proceedings of the Ninth ACM International Conference on Interactive Tabletops and Surfaces (pp. 109-118). ACM.

[13] Heer, J., & Agrawala, M. (2008). Design considerations for collaborative visual analytics. Information visualization, 7(1), 49-62.

[14] Isenberg, P., Elmqvist, N., Scholtz, J., Cernea, D., Ma, K. L., & Hagen, H. (2011). Collaborative visualization: Definition, challenges, and research agenda. Information Visualization, 10(4), 310-326.

[15] Wallace, J. R., & Scott, S. D. (2008, October). Contextual design considerations for co-located, collaborative tables. In 2008 3rd IEEE International Workshop on Horizontal Interactive Human Computer Systems (pp. 57-64). IEEE.

[16] Waldner, M., & Lex, E. (2009). Design considerations for collaborative information workspaces in multi-display environments.

[17] Dourish, P. (2004). Where the action is: the foundations of embodied interaction. MIT press.

[18] McGrath, W., Bowman, B., McCallum, D., Hincapi-Ramos, J. D., Elmqvist, N., & Irani, P. (2012, November). Branch-explore-merge: facilitating real-time revision control in collaborative visual exploration. In Proceedings of the 2012 ACM international conference on Interactive tabletops and surfaces (pp. 235-244). ACM.

[19] Yoshimoto, Y., Dang, T. H., Kimura, A., Shibata, F., & Tamura, H. (2011, November). Interaction design of 2D/3D map navigation on wall and tabletop displays. In Proceedings of the ACM International Conference on Interactive Tabletops and Surfaces (pp. 254-255). ACM.

[20] Horak, T., Badam, S. K., Elmqvist, N., & Dachselt, R. (2018, April). When David meets Goliath: Combining smartwatches with a large vertical display for visual data exploration. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (p. 19). ACM.

[21] Langner, R., Horak, T., & Dachselt, R. (2018). VisTiles: Coordinating and Combining Co-located Mobile Devices for Visual Data Exploration. IEEE Transactions on Visualization and Computer Graphics, 24(1), 626-636.

[22] Chung, H., North, C., Self, J. Z., Chu, S., & Quek, F. (2014). VisPorter: facilitating information sharing for collaborative sensemaking on multiple displays. Personal and Ubiquitous Computing, 18(5), 1169-1186.

[23] Andrews, C., & North, C. (2012, October). Analyst's Workspace: An embodied sensemaking environment for large, high-resolution displays. In 2012 IEEE Conference on Visual Analytics Science and Technology (VAST) (pp. 123-131). IEEE.

[24] Andrews, C., Endert, A., & North, C. (2010, April). Space to think: large high-resolution displays for sensemaking. In Proceedings of the SIGCHI conference on human factors in computing systems (pp. 55-64). ACM.

[25] Isenberg, P., Tang, A., & Carpendale, S. (2008, April). An exploratory study of visual information analysis. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (pp. 1217-1226). ACM.

[26] Badam, S. K., & Elmqvist, N. (2019). Visfer: Camera-based visual data transfer for cross-device visualization. Information Visualization, 18(1), 68-93.

[27] Bostock, M., Ogievetsky, V., & Heer, J. (2011). D data-driven documents. IEEE transactions on visualization and computer graphics, 17(12), 2301-2309.

[28] Belmonte, N. G., (2013). JavaScript InfoVis Toolkit.[Online]. Available: https://philogb.github.io/jit/, Accessed on March 7, 2019.

[29] Wagner, M., Blumenstein, K., Rind, A., Seidl, M., Schmiedl, G., Lammarsch, T., & Aigner, W. (2016, July). Native cross-platform visualization: A proof of concept based on the Unity3D game engine. In 2016 20th International Conference Information Visualisation (IV) (pp. 39-44). IEEE.

[30] Blumenstein, K., Wagner, M., & Aigner, W. (2015, December). Cross-platform infovis frameworks for multiple users, screens and devices: Requirements and challenges. In Workshop on Data Exploration for Interactive Surfaces DEXIS 2015 (p. 7).

[31] Vogt, K., Bradel, L., Andrews, C., North, C., Endert, A., & Hutchings, D. (2011, September). Co-located collaborative sensemaking on a large high-resolution display with multiple input devices. In IFIP Conference on Human-Computer Interaction (pp. 589-604). Springer, Berlin, Heidelberg.

[32] Isenberg, P., Fisher, D., Morris, M. R., Inkpen, K., & Czerwinski, M. (2010, October). An exploratory study of co-located collaborative visual analytics around a tabletop display. In 2010 IEEE Symposium on Visual Analytics Science and Technology (pp. 179-186). IEEE.

[33] Scott, S. D., Carpendale, M. S. T., & Inkpen, K. M. (2004, November). Territoriality in collaborative tabletop workspaces. In Proceedings of the 2004 ACM conference on Computer supported cooperative work (pp. 294-303). ACM.

[34] Card, S. K., & Mackinlay, J. (1997, October). The structure of the information visualization design space. In Proceedings of VIZ'97: Visualization Conference, Information Visualization Symposium and Parallel Rendering Symposium (pp. 92-99). IEEE.

[35] Satyanarayan, A., Wongsuphasawat, K., & Heer, J. (2014, October). Declarative interaction design for data visualization. In Proceedings of the 27th annual ACM symposium on User interface software and technology (pp. 669-678). ACM.

[36] Satyanarayan, A., Moritz, D., Wongsuphasawat, K., & Heer, J. (2017). Vega-lite: A grammar of interactive graphics. IEEE transactions on visualization and computer graphics, 23(1), 341-350.

[37] Wickham, H. (2016). ggplot2: elegant graphics for data analysis. Springer.

[38] Chang, W., & Wickham, H. (2015). ggvis: Interactive grammar of graphics. R Package Version 0.4.2. http://CRAN.R-project.org/package=ggvis.

[39] Ellis, C. A., & Gibbs, S. J. (1989, June). Concurrency control in groupware systems. In Acm Sigmod Record (Vol. 18, No. 2, pp. 399-407). ACM.

[40] ShareJS. http://sharejs.org/, accessed March 2019.

[41] Gotz, D., & Zhou, M. X. (2009). Characterizing users' visual analytic activity for insight provenance. Information Visualization, 8(1), 42-55.

[42] Munzner, T. (2014). Visualization analysis and design. AK Peters/CRC Press.