When David Meets Goliath: Combining Smartwatches with a Large Vertical Display for Visual Data Exploration

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Figure 1. Visual data analysis using large displays and smartwatches together. Cross-device interaction workflows discussed in our conceptual framework allow for a unique interplay between these two types of devices. For instance, multiple analysts can extract data from views on a large display (left) to their smartwatches (middle) and compare the data on other visualizations distributed over the large display by physical navigation followed by direct touch (right) or remote interaction. This pull/preview/push interaction metaphor can be extended to many visualization tasks. The watch enhances the large display by acting as a user-specific storage, a mediator, and a remote control, and further aids multiple users working in concert or by themselves.

ABSTRACT
We explore the combination of smartwatches and a large interactive display to support visual data analysis. These two extremes of interactive surfaces are increasingly popular, but feature different characteristics—display and input modalities, personal/public use, performance, and portability. In this paper, we first identify possible roles for both devices and the interplay between them through an example scenario. We then propose a conceptual framework to enable analysts to explore data items, track interaction histories, and alter visualization configurations through mechanisms using both devices in combination. We validate an implementation of our framework through a formative evaluation and a user study. The results show that this device combination, compared to just a large display, allows users to develop complex insights more fluidly by leveraging the roles of the two devices. Finally, we report on the interaction patterns and interplay between the devices for visual exploration as observed during our study.

Author Keywords
Cross-device interaction; visual analysis; data exploration; multi-display environment; large display; smartwatch.

ACM Classification Keywords
H.5.2. Information Interfaces and Presentation (e.g., HCI): UI.

INTRODUCTION
Large interactive displays are increasingly being used for data exploration due to increased availability and exciting new possibilities for both user interaction and information visualization. Such displays can show more information than traditional displays by enlarging, combining, or coordinating multiple visualization views [1, 25], incorporating physical navigation [3, 7, 33], and supporting multiple users working at the same time [3, 33]. However, for all their advantages, large displays also yield new challenges. Tools and menus can clutter the interface and obscure important information as well as be out of reach for a user and, thus, forcing physical movement that can lead to fatigue. Furthermore, parallel exploration by multiple users requires personalized visualizations and interactions, while avoiding conflicts and supporting coordination among users [50]. Finally, this is all exacerbated by the complex nature of visual sensemaking tasks [13, 56].

Given these challenges, we propose to utilize personal devices in combination with a large display to support the users' tasks during sensemaking. While this general approach has been studied in the past [19, 32, 49, 51], we focus here on smartwatches because they feature multiple advantages over traditional hand-held devices. Beyond being lightweight and non-intrusive, their key advantage is that they are wearable. This not only frees the user's hands to interact with the large display, it also provides anytime access without the need for persistent hand-held usage while leveraging proprioception for eyes-free, on-body interaction [2, 45]. This characteristic also applies the other way around: established and familiarized workflows on the large display are in no way affected; instead the smartwatch offers the possibility to enhance these workflows in an unobtrusive way. Given these advantages, their combination with large displays is compelling, yet this idea has so far not been explored in the literature.

In this paper, we combine smartwatches with large displays to allow the watch to serve as a personalized analysis toolbox. In this function, the watch supports the multivariate data exploration on a large display interface containing multiple views (cf. coordinated and multiple views [46]). The devices represent two extremes—like David and Goliath—of interactive surfaces in many ways (e.g., small vs. large, private vs. public, mobile vs. stationary), which yields several fundamental design challenges for their combination. To tackle these, we first derive the basic roles of the two devices by drawing on the literature as well as an example data analysis scenario. Based on these considerations, we propose a conceptual framework defining the specific interplay between the smartwatch and the large display. Within this framework, users can interact with the large display alone, and also benefit from the watch as a container to store and preview content of interest from the visualizations, and manipulate view configurations. Figure 1 shows an example of these interactions with our framework.

We evaluated the prototype implementation of our conceptual framework through, (1) a formative evaluation to guide the design process, and (2) a follow-up user study to understand the interaction patterns and developed insights compared to a standalone large display interface. Overall, our contributions in this paper include the following:

1. *Generalized design considerations* for combining two distinct device types—smartwatches and large displays—based on the literature and an example visual analysis scenario;
2. A *conceptual framework* and a *web-based implementation* incorporating smartwatches in visual analysis tasks with a large interactive display during visual sensemaking;
3. Feedback from a *formative evaluation* illustrating the utility of our concepts and guiding our interaction design; and
4. Results from a *user study* that reveal more fluid interaction patterns—flexibility and ease in developing complex insights—when using our specific device combination.

RELATED WORK

Our literature review spans (1) the use of large displays for visual analysis and (2) research on smartwatches in general as well as their use for visual data analysis.

Visualization on Large Interactive Displays

Large displays have long been of special interest to the visualization and visual analytics community, presumably due to their large screen real estate and the potential for collaborative analysis [1]. The size of such displays allows for using *physical navigation* to support the classic visual information seeking mantra [48]: get an overview of the data from a distance, and move closer to the display to access more details [1, 10, 21, 25]. This general characteristic has motivated work explicitly focusing on physical navigation and spatial memory: Ball and North [6] as well as Ball et al. [7] showed that physical navigation is an efficient alternative to virtual navigation; however, the effects depend on the actual setup, interface, and tasks [27, 29, 38]. Especially in multi-user scenarios, proxemics [8, 22, 39] is used to provide personalized views or lenses. With BodyLenses by Kister et al. [33], the general design space of such lenses was explored, whereas Badam et al. [3] focused on the combined use of proxemics and mid-air gestures to support multi-user lenses for visual exploration. In general, large displays can be beneficial for co-located collaborative scenarios [26], especially as they can promote different collaboration styles [28, 43] and benefit from physical navigation [28]. However, challenges regarding territoriality [12, 28], coordination costs [43], and privacy [15] must be considered.

Some of these challenges can be tackled by adding additional devices, thus creating multi-device environments (MDEs). Personal devices such as smartphones and tablets are well-suited for these combinations. While these devices can also create MDEs on their own [23, 34], the combination with a large display allows to separate shared and private information more easily and enables users to switch between working in concert and working alone [40]. A key operation in a MDE is the ability to transfer content from one device to another; Langner et al. [35] investigated this for a spatially-aware smartphone and a large display, Chung et al. [19] presented concepts for using a tablet as a document container for sensemaking tasks, and Badam and Elmqvist [4] elicited interactions for information transfer of visualizations between a large display and a hand-held device. Focused on interacting with wall-sized displays in general, Chapuis et al. [16] propose to use a tablet as storage for multiple cursors and content items, while Liu et al. [37] investigated collaborative touch gestures for content manipulation, which could also be performed by remote touch on a tablet. Specifically for data exploration, Spindler et al. [49] incorporated hand-held displays above a tabletop as graspable views to provide altered perspectives onto visualizations. Recently, Kister et al. [32] investigated how analysts can use spatially-aware mobiles in front of a display wall as personal views onto a graph visualization. While these approaches all successfully address challenges with large displays, they require the user to hold an additional device in their hand, which diminishes some of the benefits of a large touch display.

Smartwatch meets Large Interactive Displays

Instead of using a hand-held device to establish contact to a large display, von Zadow et al. [51] used a larger arm-mounted device to allow users to have their hands free and reduce attention switches. In general, arm-mounted devices have already been investigated for some time; e.g., Rekimoto [45] and Ashbrook et al. [2] explored their advantages as on-body input devices and their resulting unobtrusive nature. For smartwatches specifically, most research focused on how to overcome the limitations of these devices, i.e., the limited input and output possibilities. For the latter, haptic feedback [42], mid-air visuals [54], and on-body projections [36] have been proposed. The input space of the smartwatch can be extended by physical controls such as a rotatable bezel [57], mid-air gestures [31], and spatial movements [30]. Furthermore, by incorporating the watches native inertial sensors, touch input on other devices, such as smartphones [17] or tablets [55], can be enriched with pressure or posture information.

The combination of smartwatches with large displays, especially for visual analysis, is underexplored. The CurationSpace of Brudy et al. [14] already utilizes a smartwatch for selecting, adjusting, and applying instruments as well as for providing personalized feedback and content. However, because of the different application case (content curation) and setup (tabletop instead of a vertical display), the presented interaction techniques do not cover important aspects supported by our framework (e.g., distant interaction) and also cannot be applied generally to our domain (visual data analysis). In information visualization, smartwatches are now beginning to be used alone for personal analytics (e.g., tracking daily activity) [18]. However, in general, the lack of research on utilizing smartwatches in MDEs for data exploration is noticeable. Our work in this paper is, to our knowledge, the first of its kind that explores how to best integrate smartwatches with large displays for data analysis, both for individuals and groups.

SCENARIO: ANALYZING CRIME DATA

To better understand the requirements of visual data exploration, as well as to illustrate and validate our interaction concepts, we consider an application scenario of a law enforcement department planning patrol routes within a city. Thanks to an open data initiative, we are able to build on a real dataset of crimes in Baltimore.[1] Here, we will describe the scenario and its involved users, goals, the setup, and challenges.

Consider two police analysts trying to build a tentative plan for patrol routes based on historical crime data within the city. Their goal is to design routes that cover as much as possible of the high-crime areas while still maintaining a police presence throughout the entire city. The analysts meet in an office space that has a large digital whiteboard featuring a high-resolution display and multi-touch support, as seen in Figure 1a. Such rooms are increasingly popular for visual sensemaking scenarios since they enable analysts to work in concert or on their own, view the data from a distance or up close, as well as leave the room and continue their exploration later [4, 12, 33]. In this scenario, the analysts use standard visual analysis techniques [46] to construct an interactive dashboard on the large display capturing the attributes in crime data using different visualizations (e.g., line charts, histograms, scatterplots).

To actually create the patrol plan, the analysts need to observe the crime distributions in these different visualizations. Now, to identify in-depth characteristics of the city's crimes, analysts need to investigate multiple hypotheses over different crime patterns of interest. For instance, to evaluate effects of crime prevention measures in certain districts they must visually verify if downward tendencies are present. These tendencies could exist in an overall trend, but also only for a few districts, crime types, or certain time periods. This sensemaking task by itself involves multiple visual exploration tasks [13, 48, 56]: selecting data items (i.e., crimes) of interest, filtering them, accessing more details about these crimes (elaborate), encoding them on visualizations for other attributes, connecting them across visualizations, and comparing multiple collections of crimes. This exemplifies how, similar to other visual analysis scenarios, crime analysis is also centered around working with data items—collections of crimes—of analyst's interest. During sensemaking, multiple such collections have to be considered in parallel threads of visual analysis and by groups of analysts in collaborative scenarios.

The large display can provide multiple views on the shared large screen real estate to support multiple visual perspectives and help users utilize the space. However, this is not enough; analysts need to deal with two types of challenges. (1) **Display space management:** when interactively exploring the crime records on the large display, analysts need to develop spatial memories of visualized information when seeing or comparing multiple parts of the large display. Also, adding additional views for comparison is not possible when the amount of space is fixed and already taken by other views. (2) **Interaction management:** at the same time, they also need to keep track of the visualizations for multiple crime collections over time to fully develop their insights. Beyond this, each user should be able to manage their personal focus (i.e., views of interest) and points of interest within the focus, and access desired interactions to explore these points, while not affecting other users at the same time. Further, these interactions should not be bound to the large display, instead they should be accessible from both close and distant proximity (e.g., to examine visualizations from an overview distance).

COMBINING DAVID AND GOLIATH: FUNDAMENTALS

To support the outlined scenario, we need a platform to view crime records, store them as separate groups, and compare groups to each other. Further, the platform should support modifying visualization properties to make comparisons more effective. To answer these challenges, we use secondary devices to augment visualization components, enhance user interactions, and ease the visual exploration. For example, as demonstrated by VisTiles [34], this can extend, reconfigure, abstract/elaborate, and connect visualizations between devices—smartphones and tablets in their case. By taking the advantages of wearables into account [2, 45, 51], we address the challenges in using a large interactive display by adding personal smartwatches to the environment. Here we explore the design space of combining smartwatches and large displays to allow for *cross-device interaction* in visual analysis.

Roles of the Devices

Each device in our cross-device setup—smartwatch and large display—has a specific role during visual analysis:

Large Display: By virtue of its size and shared affordance, the large display serves as the primary display that provides multiple visualizations of a multivariate dataset. Consistent with existing work on touch interaction for visualization [9, 20, 47], analysts are able to interact with these visualizations: data elements can be selected by tapping them, the axes can be used to offer additional functionality (e.g., to sort the data), and layouts can be changed by dragging. Bimanual interaction is also possible [47], e.g., to scale visual elements, to span a selection area, and to trigger mode switches. Thanks to its size, the large display can also be used by multiple analysts in parallel, thus serving as a *public and shared display* that is visible and accessible to everyone.

[1] https://data.baltimorecity.gov/

Smartwatch: In contrast, the smartwatch is a personal—and significantly smaller—device only used by its owner. Consequently, the watch is suitable as a secondary display, but can take on different roles. Given the challenges of using the large display in the crime analysis scenario, the secondary device should keep track of the user's interaction activities and corresponding data items. The device can therefore act as a *user-specific storage*—a container for points of interests or parameter settings—that can be easily accessed any time. This role can further be extended by allowing the user to manage the stored content on the watch itself (e.g., combining, manipulating, or deleting content items). In the interest of managing the available display space while supporting multiple users, the secondary device enhances the interaction capabilities to support a wide range of exploration tasks. The smartwatch can serve as a *mediator* (cf. Brudy et al. [14]), i.e., defining or altering system reactions when interacting with the large display. This mediation can happen in both an active and passive way: either the watch is used to switch modes, or it offers additional functionality based on the interaction context and the user. Finally, to flexibly use the space in front of the large display, the smartwatch can also take on the role of a *remote control* by allowing the user to interact with visualizations on the large display from a distance.

Elementary Interaction Principles on the Smartwatch

Generally, the smartwatch supports four types of input: simple touch, touch gestures, physical controls, and spatial movements. As the analysts mainly focus on the large display during exploration, the input on the watch should be limited to simple, clearly distinguishable interactions that can also be performed eyes-free to reduce attention switches (cf. Pasquero et al. [42], von Zadow et al. [51]). Therefore, we propose to primarily use three interactions on the watch: *swiping horizontally* (i.e., left or right), *swiping vertically* (i.e., upwards or downwards), and, if available, *rotating a physical control* of the smartwatch [57] as, e.g., the rotatable bezel of the Samsung Gear or the crown of the Apple Watch. For more advanced functionality, long taps as well as simple menus and widgets can be used. Finally, using the internal sensors of the smartwatch, the users' *arm movements* or poses (Figure 2d) can be used to support pointing or detect different states [30, 45, 55].

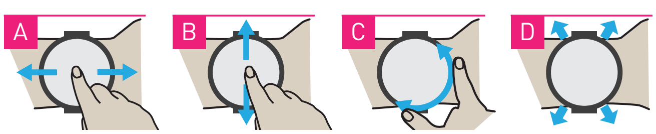

Figure 2. Primary smartwatch interactions: (a) swiping horizontally, i.e., along the arm axis for transferring content; (b) swiping vertically or (c) rotating a physical control for scrolling through stored content; and (d) moving the arm for pointing interaction.

When the smartwatch takes the role of user-specific storage, we assume that users have a mental model of two directions for transferring content; towards the smartwatch or towards the large display. Based on this, a specific axis of the smartwatch can be derived: The *proximodistal axis* (i.e., along the arm) is suitable for transferring content; swiping towards the shoulder (i.e., left or right depending on the arm on which the user wears the watch; Figure 2a) can pull content from the large display onto the smartwatch. Vice versa, swiping from the wrist towards the hand, i.e., towards the large display, can allow to push content back to the visualizations. Additionally, the *axial axis* (i.e. orthogonal to the arm) can be defined as a second axis (cf. von Zadow et al. [51]). We suggest scrolling through the stored content by means of this axis. This can be done by either swiping upwards or downwards (Figure 2b) or rotating the bezel or crown of the watch (Figure 2c).

Zones of Cross-Device Interaction

In general, the cross-device interaction can happen in three zones: either at the large display using *direct touch*, in *close proximity* to the display but without touching it, or from intermediate and even *far distance* (Figure 3a). We expect analysts to work directly at the large display most of the time, thus the touch-based connection is primarily used. As the users' intended interaction goal is expressed in the touch position, i.e., defining on which visualization (part) the analyst is focusing, the smartwatch—acting as a mediator—should incorporate this knowledge to offer or apply functionalities. In contrast, the remote interaction, or distant interaction, enables the analysts to work without touching the display, possibly even from an overview distance or while sitting. As the contextual information of the touch interaction on the large display is missing, the user has to perform an additional step to select the visualization of interest (e.g., by pointing).

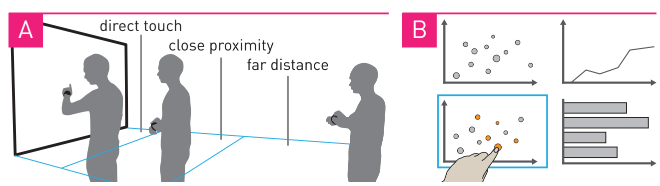

Figure 3. (a) Cross-device interaction can happen with direct touch, in close proximity, or from intermediate or far distance; (b) the scope of user interactions is limited to the views in focus.

As related work on physical navigation illustrates [3, 7, 28, 33], working from an overview distance, close proximity, or directly at the large display is not an either-or decision. There is always an interplay between the three: analysts interact in front of the large display to focus on details, step back to orient themselves, and again move closer to the large display to continue exploration. Consequently, the cross-device interaction should bridge these zones. For instance, an analyst may first work near the large display and perform interactions incorporating the smartwatch (e.g., store data selection). Then she steps back to continue exploration from a more convenient position to see changes in the context of other views on the large display, i.e., to compare different versions of visualizations. This could be even extended by proxemic interaction [39], i.e., automatically offering functionalities based on the distance.

Scope of Interactions in Multi-User Setups

In common coordinated multiple view (CMV) applications [46], changes in one visualization (e.g., selection, filter, encoding) have global impact, i.e., they are applied to all visualization views on the display. As discussed above in our motivating scenario, this behavior may lead to interference between analysts working in parallel [40] on the interface. To

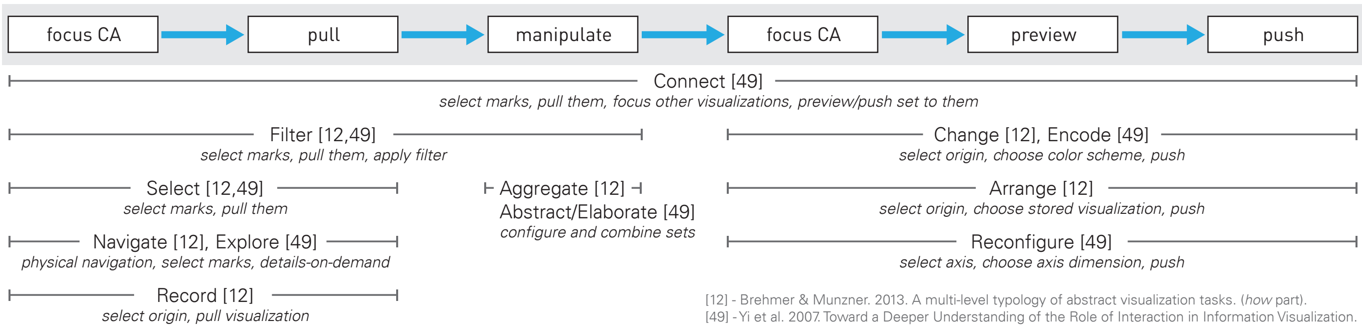

Figure 4. Our framework addresses a wide range of tasks, here illustrated by mapping two established task classifications [13, 56] onto interaction sequences that are enabled by our framework (examples in italics). For some tasks, certain aspects are also still supported by the large display itself, e.g., zooming and panning from *abstract/elaborate* and *explore* [56]. Regarding the typology by Brehmer and Munzner [13], we focus on their *how* part. From this part, a few tasks (*encode*, *annotate*, *import*, *derive*) are not considered as they are going beyond the scope of this paper. *CA: Connective Area*.

avoid this issue, the effects of an interaction should by default only be applied to the visualization(s) currently in focus of the analyst (Figure 3b). Further, we also propose to constrain the scope of an interaction mediated by the smartwatch to a short time period. More specifically, on touching a visualization to apply a selected adaptation from the smartwatch, the resulting change is only visible for a few seconds or as long as the touch interaction lasts. At the same time, there also exist situations where changes should be applied permanently, i.e., merged back into the shared visualization [40]. Therefore, it must be possible to push these adaptations to the large display and keep the altered data visualization.

CONCEPTUAL FRAMEWORK

Our conceptual framework for cross-device interaction between smartwatches and large displays is based on the above fundamentals. By incorporating the different roles of the two devices, the framework supports a multitude of tasks during visual exploration [13, 56]. In the role of user-specific storage, the smartwatch provides access to the data, i.e., points of interest. Both the shared large display and the smartwatch (as remote control) are able to determine or define the context of an interaction. Regarding the task topology from Brehmer and Munzner [13], the combination of these two aspects—data and context—represents the *what* of an interaction, and enables the smartwatch to act as mediator defining the *how*. This mediation enables the analyst to solve a given task coming from questions raised in the scenario (*why*). Our framework provides components that blend together into specific interaction sequences and address the various task classes (Figure 4). In the following, we will introduce these components and describe their interplay. We will also reference the matching tasks from Figure 4 in small caps (EXAMPLE).

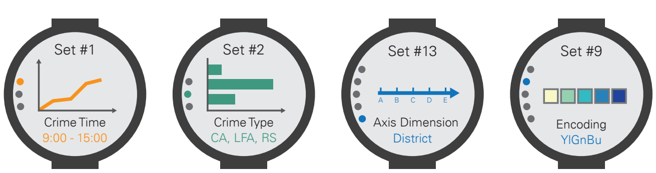

Figure 5. *Sets* are represented by labels and a miniature: for sets with data items, the miniature is based on the view where it was created (left); for sets containing configuration items an iconic figure is shown (right).

Item Sets & Connective Areas

The primary role of the smartwatch is to act as a personalized storage, or data hub, of *sets*. We define *sets* as a generalized term for a collection of multiple entities of a certain type from a dataset. In our framework, we currently consider two different set types: data items and configuration properties (e.g., axis dimension, chart type). These sets can also be predefined; for instance, for each existing axis dimension, a corresponding set is generated. On the smartwatch, the stored sets are provided as a list. As shown in Figure 5, each set is represented by a (generated) description, a miniature view or icon, and further details (e.g., value range). Consistent with the set notion, sets of the same type can be combined using set operations (i.e., union, intersection, complement). Finally, to more efficiently manage sets over time, they are grouped per session. Former sessions can be accessed and restored using the watch.

During the data exploration, the specific region that a user interacts with can provide valuable insights about the user's intent. We define four zones for each visualization—called *connective areas* (CA)—that will provide the context of an interaction: the marks, canvas, axes, as well as a special element close to the origin (Figure 6). In the simplest case, the interaction comprises tapping or circling marks for selection. For the other areas, the user can set the focus on the corresponding view and access suitable functionalities for the specific connective area on the smartwatch. More specifically, this can be done in two ways at the large display: by performing a touch-and-hold (long touch), the focus is set onto the respective area but stays only active for the duration of the hold; by performing a double tap, the focus is kept as long as not actively changed. On focus, stored set content can be previewed on the large display. Therefore, each connective area is primarily associated with a specific set type (Figure 6), thus jointly providing the *what* of an interaction.

While we consider working in close proximity to the large display as the primary mode of interaction, certain situations exist where this is not appropriate or preferred. For instance, a common behavior when working with large displays is to physically step back to gain a better overview of the provided content. To remotely switch the focus onto a different view or connective area, the user can perform a double tap on the smartwatch to enable *distant interaction* and enter a coarse

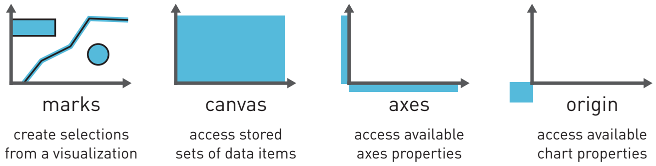

Figure 6. ***Connective Areas*** **(CA) represent semantic components of a visualization that have a specific interaction context with respect to a secondary device (a smartwatch in our case).**

pointing mode. Similar to Katsuragawa et al. [30], the pointing can be realized by detecting the movements of the watch using its built-in accelerometer. Alternatively, it is also possible to scroll through the visualizations instead of moving the arm. In both cases, the current focus is represented as a colored border around the corresponding view on the large display. After confirming the focus, the analyst can select the desired connective area in a second step and then access and preview stored sets. This remote interaction provides the same functionality as the direct touch interaction. Furthermore, users can switch between interaction based on direct touch or on remote access from both close proximity and far distance.

Creating & Managing Sets for Visual Exploration

To gain insights during visual exploration, most of the interaction steps are focused on selecting, manipulating, and previewing data points of interest, as well as applying the previews permanently to a visualization. The interactions for these tasks are mediated by the watch based on context of the user. The concepts enabling these steps also define the *how* of the analyst's task. To create a set, the analyst first selects marks in the visualization on the large display by tapping or lasso selection, and then swipes towards herself on the watch (called *pull*; SELECT). The resulting set is stored on the smartwatch. Now, by again switching the focus on the canvas to another view on the large display (i.e., by holding, double tapping, or pointing), the set currently in focus on the watch gets instantly *previewed* on the target visualization. The preview is only shown for a few seconds, or, in the case of holding, for the duration of the hold. Depending on the visualization type and the encoding strategy (aggregated vs. individual points), the items are inserted as separate elements or highlighted (Figure 7a,b). As the focus is set on a connective area, the smartwatch can still be used for further exploration. For instance, by swiping vertically on the watch or rotating its bezel, the user can switch through the list of stored sets and preview others for comparison. Again, the preview is shown only for a few seconds. To permanently change the view on the large display, a horizontal swipe towards the large display, i.e., the visualization, can be performed on the watch (called *push*; CONNECT). As the push is considered a concluding interaction, the system switches then back to a neutral state by defocusing the view.

Besides data items, visualization properties can also be accessed and adapted. Based on the connective areas, we distinguish between axis properties (e.g., dimension, scale) and chart properties (e.g., chart type, encoding). These configuration sets are mostly predefined, as only a limited number of possible values/configurations exist. For instance, when tapping on an axis, all dimensions as well as scales are offered as

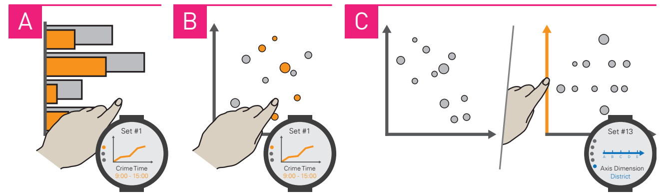

Figure 7. Previewing stored sets results in (a+b) inserting or highlighting the containing data points in the visualization, or (c) adapting the visualization to the respective configuration item (here: axis dimension).

individual configuration sets on the watch. As with data items, scrolling through this list of sets results in instantly previewing the sets, e.g., the marks would automatically rearrange accordingly to the changed dimension or scale (Figure 7c). By performing a push gesture, this adaptation is permanently applied to the visualization on the large display (CHANGE, ENCODE, RECONFIGURE). Naturally, more possibilities for visualization configuration may exist; however, covering all of them is beyond the scope of this work. In addition to single configuration properties, the origin can also provide access to the visualization in its entirety, i.e., a set containing all active properties at once. This allows storing a visualization for later use, or moving it to another spot in the interface (ARRANGE, RECORD).

As an extension to storing sets, the smartwatch also offers the possibility to manipulate and combine sets on the watch. By performing a long tap on a set, these operations are shown in a menu. For all set types, this involves the possibility to combine sets (AGGREGATE). The combination of sets is applied based on a chosen set operation (e.g., union or intersection) and results in a new set. For sets containing data items, sets can also be bundled; pushing or previewing such a bundle shows all the contained sets as separated overlays at once. Furthermore, it is possible to create new filters and change the representation on the watch (i.e., the visualization used as miniature). The filter option allows the analyst to select a property first and then to define the filter condition for this property (e.g., crime date in July 2015). For filter options based on numeric values, sliders are provided (Figure 8a). To delete a set on the watch, a wipe gesture can be performed (Figure 8b).

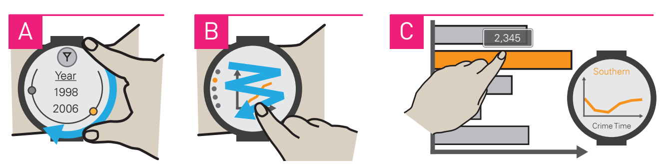

Figure 8. The smartwatch allows (a) applying filters to data item sets; (b) deleting sets by wiping; and (c) displaying additional details-on-demand.

All in all, the *set* metaphor is ideal for visually comparing multiple regions of interest on the large display because data items can be extracted from the views, manipulated or combined on the watch, and then previewed on multiple target visualizations (CONNECT). The ephemeral nature of our proposed preview techniques enables analysts to explore aspects without worrying about reverting to the original state of a visualization. In addition, the set storage further acts as a history of user interactions, to undo, replay, or progressively refine the interactions [48] (RECORD). During the exploration, the watch can also be used for tasks not involving sets. For instance, existing details-on-demand mechanisms on the large display (e.g., displaying a specific value for a mark) can be extended by displaying further details on the watch, e.g., an alternative representation or related data items (Figure 8c; NAVIGATE).

Feedback Mechanisms

For cross-device setups, it is important to consider feedback mechanisms in the context of the interplay between devices, especially to avoid forced attention switches. In our setup, we are able to use three different feedback channels: visual feedback on the large display and on the smartwatch, as well as haptic feedback via the smartwatch. On the large display, the feedback is provided by the system reaction following user interaction, e.g., by previewing content. To further support exploration of different sets, a small overlay on the large display indicates the set currently in focus when scrolling through the list, thus reducing gaze switches between the large display and the smartwatch. The colored border around a visualization indicates if a connective area is focused and thus expecting a smartwatch interaction (the watch acting as a mediator).

We use haptic feedback, i.e., vibrations of the smartwatch, for confirmation. When successfully performing an interaction, e.g., pulling a set onto the watch or pushing it to a visualization, the watch confirms this by vibrating. Alongside with the small overlays described above, this behavior also supports eyes-free interaction with the smartwatch. Further, the watch also vibrates to indicate that additional information or tools are available on the watch: While moving the finger over a visualization, the watch briefly vibrates when a new element is hit to indicate that details-on-demand or more functionality are available. To some degree, this also enables to "feel" the visualization, e.g., through multiple vibrations when moving across a cluster of data points in a scatterplot.

APPLYING CONCEPTS: ENHANCED CRIME ANALYSIS

In the following, we present an interaction walkthrough for the motivating crime data scenario that illustrates the utility of combining smartwatches and a large display.

The first question that one of the police analysts has is whether there are specific high-crime regions within the city over time. She starts by selecting multiple bars representing different types of assaults in a bar chart and saves them into her user-specific storage on the watch by performing a swipe on the watch towards herself (Figure 9a). The watch immediately creates a set and represents it with a miniature of the original bar chart and the selected bar. Further, she also selects the corresponding bar of burglaries, and creates another set. As she can carry the sets, she investigates how the assaults occur in various districts. Triggered by double tapping on other visualizations, the smartwatch mediates the interaction and induces the large display to show a preview of the analyst's set in these views. By rotating the bezel of the watch back and forth, she switches between the previews of the two stored sets and compares their distribution on the large display (Figure 9b). She notices that assaults have happened in neighborhoods surrounding Downtown, while burglaries happened more often in specific suburbs. In order to investigate patterns of assaults during daytime, she taps on a line chart to focus on this view and swipes towards the large display. As a result, the current set on the watch is pushed to the focused chart (Figure 9c). She continues this process for other crime types (e.g., robberies) by identifying data items and previewing them on other views, while tracking the multiple sets on her smartwatch.

Figure 9. (a) Pulling, (b) previewing, and (c) pushing of sets.

A second analyst wants to evaluate the effects of measures taken in a neighborhood. First, he restores a set of crimes for this neighborhood from a former session via the watch menu. By selecting the crimes for the neighborhood on the large display and pulling them, he creates a set similar to the restored one with current data. To compare them, he pushes both sets onto a weapons histogram and recognizes a drop of crimes with firearms but not for crimes with knifes. By double tapping the axis of the histogram, the smartwatch displays the list of available dimensions, and the analyst switches from weapons to crime types (cf. Figure 10a). This allows him to quickly validate his assumption that the drop in firearms is caused by a reduced number of assaults, while the number of robberies is almost unchanged. He can now conclude that the introduced measures only affected assaults.

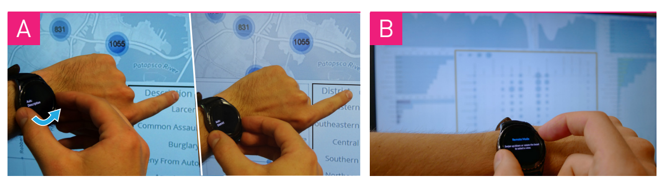

Figure 10. (a) Changing the axis dimensions, and (b) remote control from a distance to set the focus onto a specific visualization view.

Afterwards, both analysts start discussing their insights and step back to get a better overview of all visualizations considered before. The first analyst pushes her stored set remotely to the histogram used by the second analyst. She performs a double tap on the smartwatch, moves the pointer onto the visualization by moving her arm, confirms the focus by tap, selects the canvas (connective area) on the watch, and applies her set (push). They recognize that the patterns are opposed, i.e., assaults dropped in the one neighborhood but raised in the other. With this insight, one analyst leaves to report their observations while the other continues the exploration.

PROTOTYPE IMPLEMENTATION

We developed a web-based prototype to instantiate our conceptual framework for demonstrating and evaluating our ideas. For deployment, we used two different large display setups in our respective universities (U1, U2)—a 84-inch Promethean ActivePanel (U1) and a 55-inch Microsoft Perceptive Pixel (U2). Both setups used the Samsung Gear S2 smartwatch. The watch features a rotatable bezel that can act as an input modality. All devices connect to a Python server that serves the front-end files, handles communication, and performs data operations based on interaction. The server also stores the created sets and manages the sessions. Visualizations are developed with D3.js [11]. The dataset contains roughly 250,000 crimes in Baltimore, MD, USA between 2011 and 2016. Each crime within this dataset is characterized by location, date, time, type, weapon, and geographical district.

In the current version, we focused on the interaction with data points and sets to test the core principles of our framework. The large display shows bar charts, line charts, scatterplots, and a map to visualize different dataset attributes. In each view, users can select marks by touch. On the smartwatch, it is possible to pull a set from the large display onto the watch as well as preview and push it onto other views on the large display (Figure 9). Currently, it is only possible to push one set to a view; pushing a second set replaces the first one. Both pull and push are confirmed by vibration feedback on the watch. Furthermore, the watch allows to combine sets and to remotely selecting views by scrolling through the displayed views on the large display. The current implementation is not able to distinguish multiple users and does not support pointing as well as changing visualization configurations, yet.

FORMATIVE EVALUATION: DESIGN FEEDBACK

We conducted a formative evaluation to receive feedback to validate the fundamental principles of our conceptual framework and inform the design iteration of the final techniques.

Participants. Five unpaid researchers (4 Ph.D. students, 1 post-doc; age 30-48; 1 female; 4 male) from a local HCI lab (thus, experts in interaction design) participated. Three participants focus on visual data analysis in their research, all are familiar with large interactive displays, and one uses a smartwatch on daily basis.

Apparatus and Dataset. We used the setup and dataset as described above. The prototype was an earlier version, thus some of the interaction concepts differed from the framework presented here. In this earlier version, the cross-device interactions required the users to persistently touching the large display (cf. Badam et al. [4]). For instance, to preview a set and to perform a pull/push interaction it was required to touch-and-hold the visualization at the same time.

Procedure. In each session, we first introduced the participants to our application scenario—setup, users, and their tasks and goals. Then, we presented our framework and sequentially explained the different techniques in the prototype. We asked participants to try the techniques on their own while stating their thoughts. Afterwards, we illustrated further concepts of our framework with figures and discussed their implications.

Feedback and Iteration of Concepts

Overall, all participants (P1-5) liked the idea of augmenting visual analysis on a large display with a smartwatch: for instance, they commented that the watch is a multi-purpose device personalized for a single user and—in many cases—available ubiquitously (P1), allowing access to content in different setups, e.g., first at a desktop for preparation, and then later at the large display (P4). It could even be integrated further into the workflow, for instance to authenticate a person when accessing confidential data (P3). Two participants (P1, P4) also noted the advantage of having their hands free for, e.g., performing pen and touch interaction or taking notes.

The feedback also helped us to iterate our concepts. The main concern of the participants was the interface complexity, especially regarding the handling of sets. For instance, they suggested to provide functionalities for grouping and sorting of sets on the watch (P4), which we address now through grouping sets by sessions. We also followed the recommendation to provide an additional description instead of only showing the miniature view for sets on the watch (P3). Regarding the reconfiguration of visualizations, one participant stressed that the offered possibilities should be limited to a list of presets (P2). Two participants (P3, P4) suggested to keep menus for complex adaptations on the large display itself. In general, participants cited our proposed mechanisms for adapting views as a good way to manage user-preferred settings (P1, P3) and to support a dynamic view layout (P4).

Regarding the cross-device interactions, four participants (P1, P2, P4, P5) positively commented that our proposed techniques already keep forced attention switches between the devices at a minimum. Two of them also stressed the importance of interacting from close proximity and their preference to avoid long touches for the pull/preview/push interactions, as they felt that it enables a more casual interaction (P1) and prevents fatigue (P2). We considered these comments in our iteration by easing and streamlining the transition between remote interaction and touch-based interaction. For the remote interaction, opinions diverged whether pointing is adequate (P5) or scrolling through the views with virtual controls is sufficient (P4), therefore we kept both options. One participant added (P3) that this decision presumably depends on the pointing precision and the display size.

USER STUDY: INTERACTION PATTERNS

As illustrated in the interaction walkthrough, our conceptual framework has the potential to ease visual exploration, however, the way the techniques are utilized during sensemaking—and affect the developed observations from data—is not clear. Therefore, we conducted a user study with our large display and smartwatch combination (**LD+SW**), against an equivalent large display interface (**LD**) for visual analysis tasks. This allows us to investigate the interaction patterns during visual exploration, and especially how the context-aware smartwatch and the different roles it takes alter these patterns.

Experiment Conditions. The study comprised two conditions: LD+SW and LD. The LD+SW interface allows participants to: (1) pull data from the large display to create sets (each set gets a unique color), (2) show a preview of sets on target visualizations, (3) push sets to the large display, (4) use the smartwatch as remote control to focus views on the large display, and (5) combine sets on the smartwatch. Except for the last two, equivalent capabilities were created on the LD condition using an overlay menu that appears on long touch. The menu is freely movable. All participants worked with both conditions; the condition order was counterbalanced.

Participants. We recruited 10 participants (age 22-40; 5 female; 5 male) from our universities (U1: P1-P4, U2: P5-P10). Participants were visualization literate with experience in using visualizations with tools such as Excel and Tableau; 4 of them used visualizations for data analysis (for their course or research work). Two of the participants had already taken part in the formative evaluation.

Apparatus and Dataset. The study was conducted in two setups as described in the Implementation section. They only differed in the size of the large display (U1: 84-inch, U2: 55-inch); the smartwatch (Samsung Gear S2), the prototype version, as well as dataset (Baltimore crime) were the same.

Tasks. We used this dataset to develop user tasks that can be controlled for the study purposes. Tasks contained three question types: (**QT1**) finding specific values, (**QT2**) identifying extrema, and (**QT3**) comparison of visualization states [3]. In general, the complexity of a task results from the number of sets and the target visualizations to be considered to answer it. After pilot testing with two participants, we settled on a list of questions with different complexities: for QT1 and QT2 the number of targets was increased to create complex tasks, while for QT3 both the number of sets and the target visualizations were increased. Here are few sample questions used:

1. How many auto thefts happened in Southern district? (**QT1**)
2. What are two most frequent crime types in Central? (**QT2**)
3. What are the differences between crimes in the Northern and the Southern districts in terms of weapons used? (**QT3**)
4. For the two crime types that use firearms the most, what are the differences in crime time, district, and months? (**QT3**)

The task list contained 9 questions overall. Two comparable lists were developed for the two conditions to enable a within-subject study design. These tasks can promote engagement in a cross-device workflow in LD+SW or effectively use the LD.

Procedure. The experimenter first trained participants in the assigned interface by demonstrating the visualizations and interactions. The participants were then allowed to train on their own on a set of training tasks. Following this, they worked on the nine tasks, answering each question verbally. They then moved on to the other condition and repeated the procedure. Afterwards, they completed a survey on the perceived usability of the two interface conditions, as well as on general interaction design aspects. Sessions lasted one hour.

Data Collected. Participants were asked to think out aloud to collect qualitative feedback. Their accuracy for the tasks was noted along with the participant's interactions and movement patterns as well as hand postures by the experimenter in both conditions. All sessions were video recorded and used to review the verbal feedback as well as noted observations.

Results

After analyzing the data collected, we found three main results:

- LD+SW interface allows flexible visual analysis patterns.
- Set management tend to be easier in LD+SW due to less attention switches, and thus simplifying comparison tasks.
- Participants rated the interactions within our LD+SW prototype as seamless, intuitive, and more suited for the tasks.

Here, we explain these results in detail within their context.

Interaction patterns and observed workflows

As we expected, the interaction abilities of both devices in LD+SW and the ability to work from any distance lead to flexible workflows for visual analysis. Therefore, we focused on observing when and how these workflows manifest in our tasks. In simple QT1 and QT2 tasks, participants used the basic touch interaction (long touch, double tap) to preview a set on the target visualization (workflow **F1**). Eight participants used physical navigation to move from one part of the display to the other to perform such tasks, while others did this remotely with their watch. For most of them (7/10), the long touch action was seen to be sufficient to quickly answer these tasks when only a value or extrema must be determined. For comparisons between two sets (QT3) on a target, eight participants preferred to disconnect from the large display by double tapping it and taking two or three steps back to gain a full view of the target visualization (**F2**), while only two remained close and used long touch. On the LD condition, it was not possible to step back since participants had to stay close to the display to switch between sets to compare them.

In more complex tasks where two or more targets were considered, participants in LD+SW further showed this need to step back to get a better view of the large display. While eight participants mostly performed these tasks by moving back-and-forth in front of the display to collect sets and pick target visualizations to make comparisons (**F2**), three participants (P7 did both) used remote controls to access target views to avoid this movement to an extent (**F3**). To track the sets on their smartwatch, four participants held their hand up to view both displays at the same time, while the majority (seven) differentiated sets based on their assigned color. This set awareness was weaker in LD condition; the participants often shifted their focus between the sets menu and the visualizations repetitively to achieve the same. Finally, five participants used the combine option when related sets were already created for previous tasks, avoiding large display interaction (**F4**).

Overall, we observed that participants followed the pattern of *interact, step back, and examine*, as well as *interact remotely* from a distance. Further, they often interacted eyes-free with the watch, although the prototype could be further improved in that regard (e.g., by displaying set labels on the large display as more sets are being previewed). The rotatable bezel of the watch was almost exclusively used for switching sets, thus played an important role acting as a tangible control.

Differences in Developed Insights

Workflows F1-F4 were observed for different tasks on the LD+SW condition. Given these observations, we were interested in the differences in task answers from these workflows compared to their LD counterpart. In QT1 and QT2 tasks, participants answered accurately on both conditions. However, the LD condition was less preferred, e.g., participant P1 stated, "*the interaction in LD was a little complicated and felt slower than with the watch.*" More nuanced patterns existed in participant answers to visual comparison of two or more sets in target visualizations: they made observations about specific values, trend differences in the target, and relative differences in specific data items. To begin with, all participants mentioned specific value-based differences between the sets in the target visualization. To observe trend and relative differences more effectively in LD+SW, participants (following workflows F2 and F3) made use of the possibility to step back from the large display and to switch back-and-forth between sets with the help of the rotatable bezel on the watch. In the LD condition, participants tried to switch back-and-forth by alternately tapping on the sets in the menu, however, this was more error-prone due to the missing physical guidance. As a result, this forced attention switches between set navigation and visual comparison and required some participants to repeat the interaction multiple times to develop their answers. For instance, one participant (P10; worked with LD+SW first) answered a comparison task (QT3, three sets on two targets) by rotating the bezel between the sets twice for each target, while he switched between the sets five times for each target to make a similar comparison on the LD condition.

Finally, in the two large display setups (84-inch vs. 55-inch), the workflows differed slightly regarding the extent of physical navigation (stepping back) and distant interaction (F2, F3), while the answers given by the participants were similar.

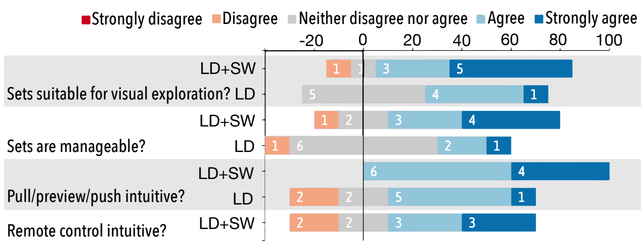

Figure 11. In LD+SW, sets were more suitable for exploration, and more manageable. The interactions were also more intuitive in LD+SW.

Qualitative Feedback

After each session, participants rated the two conditions on a Likert scale from 1 to 5 for two groups of metrics: (1) the overall efficiency, ease of use, and utility, as well as (2) suitability of the devices for set-based tasks and the intuitiveness of the specific interaction designs. Participants rated both conditions to be similar in efficiency, ease of use, and utility for visual exploration. This was expected, as the LD condition supported equivalent operations to the LD+SW. The one negative rating of LD+SW was due to the perceived increased interaction costs with an additional device. For remaining questions, participants found the LD+SW condition to be more suited for set creation and management, and the interactions on LD+SW to be more intuitive. In Figure 11, this pattern is visible with more participants strongly agreeing to these questions in case of LD+SW. As P6 says, "*The interactions correspond to the [cognitive] actions: pull reads data in, and preview/push by activating a focus visualization gives data back.*"

DISCUSSION

Hand-held devices are commonly used as secondary devices [5, 19, 32]. Kister et al. [32] studied the large display and mobile tablet combination, and found workflows where users either stayed at a certain distance or crisscrossed in front of the display wall. Their participants exhibited two distinct exploration styles: distributed between the combined devices, or focused on the mobile. This is in contrast with our user study, where most participants focused on the large display while interacting eyes-free on the watch. This captures the main distinction in coupling with handheld vs. wearables. The role of a wearable is to remain invisible [53] and seamlessly improve the user's primary task. In contrast, hand-held devices generally have more screen space and can show alternate visual perspectives to augment the large display. It therefore goes without saying that neither of them is better than the other, but rather that they have their specific roles and affordances during visual exploration. Our work contributes to this space by considering the novel combination of smartwatches and large displays.

Besides the aspects mentioned in both evaluations, with regard to our framework and its implementation further challenges remain. Regarding multi-user scenarios, current interactive displays are generally not able to distinguish which user is interacting. Thus, the system cannot automatically determine which smartwatch corresponds to a certain touch point. As this issue is relevant to many interactive spaces, experimental solutions exist. For instance, Holz et al. [24] embed a high-resolution camera into a rear-projected multi-touch table to recognize fingerprints, and other approaches [41, 52] use additional Kinect cameras to track users. Utilizing such approaches, our prototype can naturally extend to multi-user scenarios due to the proposed local scope of user interactions on the large display and the independent and ephemeral nature of pull/preview mechanisms with personal smartwatches.

Limitations and Future Work. While our study provides evidence of the utility of our device combination for specific tasks, an in-depth study of open-ended visual exploration (cf. Reda et al. [44]) would broaden this to a larger group of tasks covered in our framework. As a preliminary hypothesis, we expect an increased number and complexity of insights when adding the smartwatch. These aspects can also be investigated for parallel multi-user interaction. Furthermore, our framework should be extended by mechanisms to explicitly promote collaboration during visual explorations by supporting, e.g., concurrent tasks, task coordination, and group awareness. More questions remain to be answered: (1) which tasks in visual analysis can be enhanced by handhelds vs. wearables, and (2) which application scenarios and visualization designs benefit the most from such device combinations. While currently outside the scope, these questions are part of our future work.

CONCLUSION

We presented a conceptual framework to support visual analysis tasks in a multi-device environment, combining two extremes of interactive surfaces: smartwatches and a large interactive display. In our framework, the devices fulfill different roles based on their strengths: the large display provides a multi-view interface, whereas the smartwatch augments and mediates the functionalities by serving as a personalized toolbox. More specifically, in interplay with connective areas on the large display, the smartwatch supports exploration based on sets of both data items and visualization properties: these can be stored, manipulated, previewed in visualizations, as well as applied permanently with the help of the watch. We evaluated our prototype implementation to find interaction patterns with increased movements as well as evidence of the effectiveness of this specific device combination. With this work, we provide a starting point for this promising new class of multi-device environments, which we believe are strongly beneficial for visual analysis tasks and also beyond.

ACKNOWLEDGMENTS

We want to acknowledge the Dagstuhl seminar... This work was supported in part by DFG grant GEMS 2.0 (DA 1319/3-3).

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