Image Browsing on Large High-Resolution Displays

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Abstract

Visual exploration of large image data sets is a common and widely performed task. With the ubiquity of cameras, personal image collections are growing. Even when working with large high-resolution displays, collections are typically too large to display all images. In this work, we present two full-body, hands-free zooming interaction techniques for image exploration on large high-resolution displays that allow users to freely move in front of the display. We compare these techniques with state-of-the-art image browsing, where a large number of images is presented in a static grid. The first technique selects and enlarges whole columns by full-body-tracking of the user. The second technique additionally uses the height of the users head to select a single picture as a focus point. The results show that novel interaction techniques and visualizations for image sets on large high-resolution displays are required and can enhance the advantages of such displays.

Author Keywords

Large displays; high resolution; image browsing; full-body interaction; fisheye; zoom; visual exploration

ACM Classification Keywords

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Background

The steadily increasing number of digital cameras, smartphones, and lifelogging cameras results in a massively growing number of digital photos. This large number of digital images creates the need for novel and efficient exploration tools. In our work, we are especially interested in so-called *large high-resolution displays* (LHRDs) – “displays whose combined size and resolution approach or exceed the visual acuity of the user” [2, 11].

LHRDs allow displaying a high number of images while keeping details recognizable. However, common image galleries contain even more pictures, than it is possible to show on such displays. Hence, navigation and zooming techniques are still required.

Furthermore, such displays enable to spatially arrange visual content. The spatial arrangement helps users to explore and understand information [5]. Additionally, previous work shows that LHRDs encourage users to navigate physically, instead of virtually [3]. Knudsen et al. analyzed how data analysts would interact with LHRDs [7]. The results indicate that spreading content combined with physical navigation is appreciated by users for analyzing data. Liu et al. show that LHRDs support information sorting [10]. These findings indicate that LHRDs are well suited for image exploration. However, previous work shows that we have to rethink user interfaces for LHRDs [8], as the interface should be divided into a central focus area and peripheral areas that present additional context data.

Inspired by *BodyLenses* [6] to utilize the users body position, and *MAGIC-pointing* [9] to utilize the users focus point to perform tasks, we designed and implemented an image viewer for LHRDs. The image viewer can display sets of images in three different modes and can adjust the size of the images according to the user’s position relative to the display in the two novel modes. In this paper, we present the working prototype with three different visualizations (see Figure 1) and a first preliminary user study.

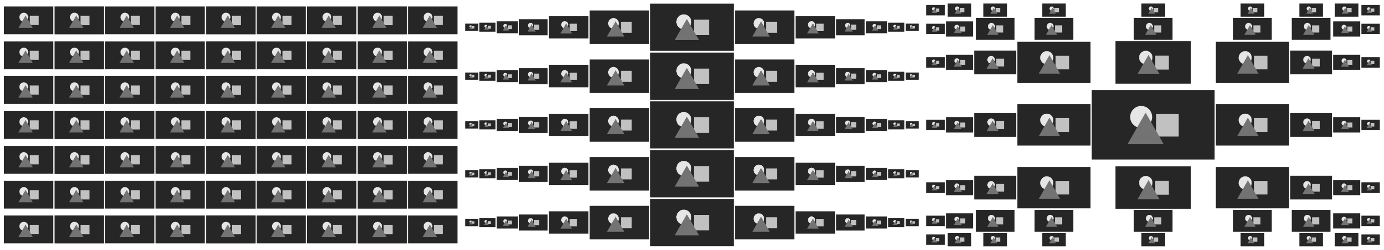
Interaction Techniques

The image sets are displayed in a grid. The number of images displayed can be defined by the user. The kind of visualization and interaction is set by the three following modes:

Static Mode The visualization in this mode is static and the sizes of the images cannot be changed. Furthermore, all images have the same size. This visualization mode is similar to most state-of-the-art image viewers (see Figure 2).

Column Mode The user can focus one column of images by moving to the left or to the right. By approaching the display, the focused column gets zoomed in on. The size of the images in the neighboring columns is increasingly reduced the further away they are from the focused column. By doing this, the additional space that is needed to display the enlarged images can be utilized without the need to push the images at the border out of the screen. Therefore, all images are still visible although they are represented in a smaller fashion.

Fisheye Mode The zooming is not only applied to columns but also to rows (see Figure 3). The selection of the column works in a similar fashion as in the Column Mode, additionally the vertical position of the users head is used to select which row is focused. Therefore, the focused picture is in front of the users head. The zooming applied in this technique works like a fisheye lens. However, by enlarging all images in a row and a column, we avoid distortion of images.



(a) Static Mode **(b)** Column Mode **(c)** Fisheye Mode

Figure 1: Comparison of the visualizations explored in this paper.

Apparatus

We combined four displays in portrait mode, resulting in a total display size of 2.7×1.13 meters and a resolution of 8460×3840 pixels. The LHRD displayed images in 12 columns and 7 rows. A Microsoft Kinect v1 was used to detect the user’s position in relation to the LHRD. The Kinect was positioned behind the participants to get a bigger field of view for tracking the user. We used the Skeletal Tracking feature of the Kinect SDK to retrieve the user’s distance to the display, the horizontal and vertical position of the head.

User Study

In the user study, we compared the three visualization methods, two of them included full-body-interaction, and examined how well these support the exploration of large image sets. We used a repeated-measures design with the interaction techniques as the independent variable, resulting in three conditions. For every condition, we measured the task completion time and error rate for a search task. The search task was identifying details of particular images. We used three different sets of images. After every condition, we asked about the experience using a 7-point Likert scale. In the end, we conducted semi-structured interviews with all participants to obtain qualitative feedback.

We recruited 20 participants (4 female) through university mailing lists. The age of the participants ranged from 19-42 years ($M = 23.25, SD = 5.05$), all participants had normal or corrected-to-normal vision.

The average task completion time for the static mode ($M = 52.35s$, $SD = 28.52$) was shorter compared to the column mode ($M = 69.70s$, $SD = 31.05$) and to the fisheye mode ($M = 101.60s$, $SD = 66.06$). However, the error rate was higher for the static mode ($M = 0.8, SD = 0.83$) than for the column mode ($M = 0.45, SD = 0.69$) and for the fisheye mode ($M = 0.4, SD = 0.75$).
The participants’ agreement to the statement “*Overall this task was – very easy. . . very hard*” revealed that they rated the static mode ($M = 2.1$, $Mdn = 2$,$SD = 1.25$) to be easier compared to the column mode ($M = 2.65$, $Mdn = 2$, $SD = 1.35$) and fisheye mode ($M = 2.65$, $Mdn = 3$, $SD = 1.31$). The agreement to the statement “*I was satisfied with the ease of completing this task*” revealed that they rated the static mode ($M = 2.35$, $Mdn = 2$,$SD = 1.42$) to be more satisfying compared to the column mode ($M = 2.80$, $Mdn = 2.5$, $SD = 1.36$) and fisheye mode ($M = 3.20$, $Mdn = 3$, $SD = 1.64$). The participants’ agreement to the statement “*I was satisfied with the amount*

Figure 2: A user browsing an image collection using the *Static Mode*. All images are of the same size.

of time it took to complete this task” revealed that they rated the static mode ($M = 2.40$, $Mdn = 2$,$SD = 1.54$) to be more satisfying compared with the column mode ($M = 2.70$, $Mdn = 2$, $SD = 1.66$) and fisheye mode ($M = 3.30$, $Mdn = 2$, $SD = 1.59$).

In the interviews, the feedback from most participants was positive regarding the implemented interaction techniques. Eight participants favored the fisheye mode and rated it as the most appealing, followed by the column mode (7), and the static mode (5). The evaluation of the participants’ comments showed that 11 participants mentioned the zooming based on the position is a helpful feature as this allows are more detailed and responsive exploration of the presented images.

Conclusion

In this work, we report our investigation of image browsing on large high-resolution displays. We implemented three visualizations, one state-of-the-art and two novel visualizations with full-body-tracking interaction methods. Furthermore, we subsequently evaluated them in a user study with 20 participants.

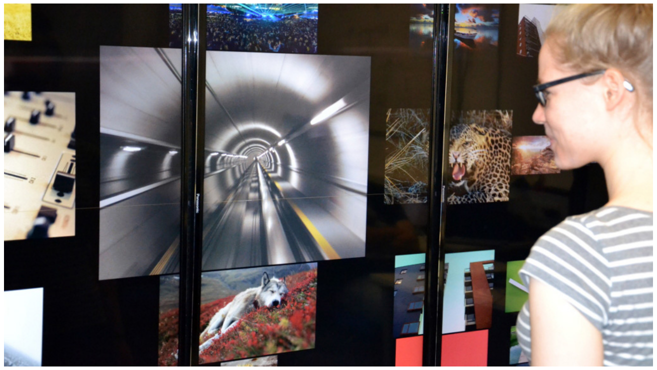


Figure 3: A user browsing images using the *Fisheye Mode*. The user’s position is used to zoom in on the focused image.

Our results indicate that even small changes in the user interface influence on user performance. In particular, it is surprising that the fisheye mode seems to prevent errors, while the exploration time in this mode increases. Hence, our results show the need for further and structured design analysis of image exploration tools on LHRDs.

Even if there is already a scientific discussion, how physical navigation is influencing task performance [3, 4], we see the need to compare in the next step different navigation techniques for image exploration. Furthermore, the design space of displaying large image sets on LHRDs is widely unexplored. In this work, we started with a fundamental grid approach. However, it is not clear if this is the most appealing arrangement. Ahlström et al. [1] present promising approaches for image browsing on tablet computers. Hence, it would be valuable to analyze if the presented approaches are also well-suited for image exploration on LHRDs.

With this work, we provide a starting point for novel interfaces for image browsing on LHRDs. We presented two interaction techniques for image browsing on LHRDs. The results of the presented user study indicate that the fish eye technique supports precise detail detection.

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