This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2016.2598796, IEEE Transactions on Visualization and Computer Graphics

GazeDx: Interactive Visual Analytics Framework for Comparative Gaze Analysis with Volumetric Medical Images

Hyunjoo Song, Jeongjin Lee, Tae Jung Kim, Kyoung Ho Lee, Bohyoung Kim, and Jinwook Seo

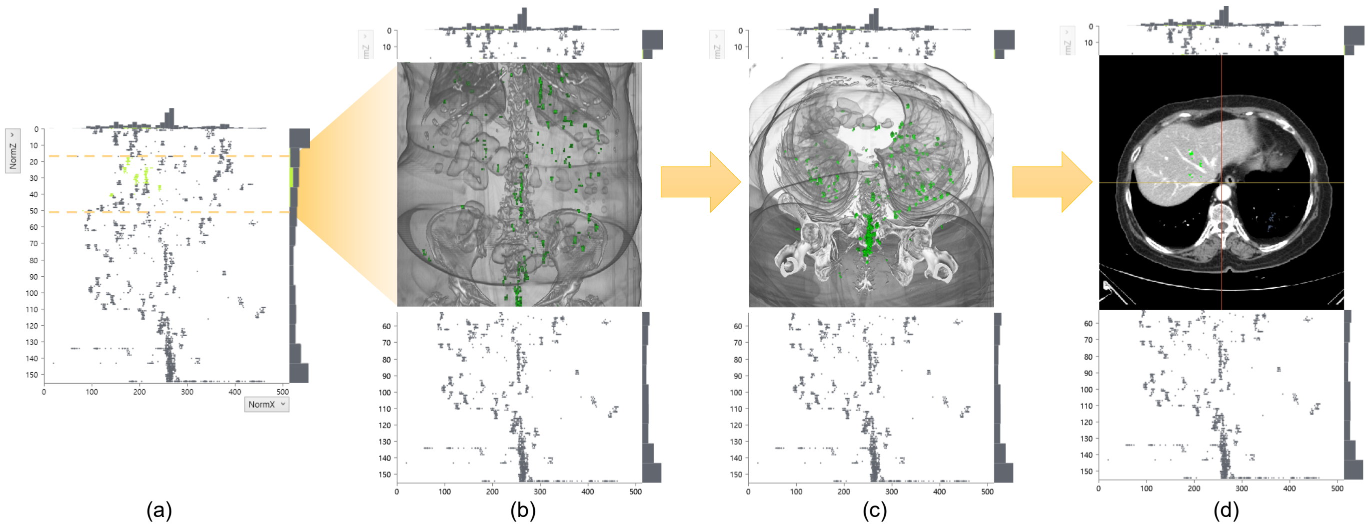


Fig. 1. Animated context-embedded interactive scatterplot (CIS). (a) Gaze points are selected by users or filtered by a criterion in the x-z scatterplot. (b) The scatterplot gets divided into three parts, and the middle area is vertically expanded into a 3D VR image. (c) 3D VR representation rotates around the horizontal axis. (d) The *x-y* plane (i.e., axial image), which is invisible in the original *x-z* scatterplot, appears with gaze points overlaid to help users look into the data from different but related aspects in a single view.

Abstract—We present an interactive visual analytics framework, GazeDx (abbr. of GazeDiagnosis), for the comparative analysis of gaze data from multiple readers examining volumetric images while integrating important contextual information with the gaze data. Gaze pattern comparison is essential to understanding how radiologists examine medical images, and to identifying factors influencing the examination. Most prior work depended upon comparisons with manually juxtaposed static images of gaze tracking results. Comparative gaze analysis with volumetric images is more challenging due to the additional cognitive load on 3D perception. A recent study proposed a visualization design based on direct volume rendering (DVR) for visualizing gaze patterns in volumetric images; however, effective and comprehensive gaze pattern comparison is still challenging due to a lack of interactive visualization tools for comparative gaze analysis. We take the challenge with GazeDx while integrating crucial contextual information such as pupil size and windowing into the analysis process for more in-depth and ecologically valid findings. Among the interactive visualization components in GazeDx, a context-embedded interactive scatterplot is especially designed to help users examine abstract gaze data in diverse contexts by embedding medical imaging representations well known to radiologists in it. We present the results from two case studies with two experienced radiologists, where they compared the gaze patterns of 14 radiologists reading two patients' volumetric CT images.

Index Terms— Eye tracking, gaze visualization, gaze pattern comparison, volumetric medical images, context-embedded interactive scatterplot, interactive temporal chart

1 Introduction

In the radiologic medical field, gaze researchers (mainly radiologists) have conducted gaze analyses to investigate possible causes that can affect diagnostic performance, and these results have been used as a basis for improving diagnosis practice or for developing a new training methodology for apprentice radiologists. In prior gaze analysis studies, researchers collected eye tracking data from their peer radiologists, and examined whether and how factors such as expertise level [17] and prior knowledge about patients [21] affect diagnosis. There are other factors that could affect diagnosis, such as window settings. The window setting (i.e., brightness and contrast of images in radiology image review) is one of the important types of contextual information that determines the visibility of organs and lesions during diagnosis, and thus should be considered in gaze analysis in the radiology field. However, most prior studies controlled the window settings (i.e., collected the gaze data under a fixed window setting) rather than treated it as an independent factor. Reflecting

- *Hyunjoo Song and Jinwook Seo are with Seoul National University. E-mail: hjsong@ hcil.snu.ac.kr and jseo@snu.ac.kr.*
- *Jeongjin Lee is with Soongsil University. E-mail: leejeongjin@ssu.ac.kr.*
- *Tae Jung Kim is with Samsung Medical Center. E-mail: taejung.kim1@gmail.com.*
- *Kyoung Ho Lee is with Seoul National University Bundang Hospital. E-mail: kholee@snubh.org*
- *Bohyoung Kim is with Hankuk University of Foreign Studies. E-mail: bkim@hufs.ac.kr*

Manuscript received xx xxx. 201x; accepted xx xxx. 201x. Date of Publication xx xxx. 201x; date of current version xx xxx. 201x.
For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org.
Digital Object Identifier: xx.xxxx/TVCG.201x.xxxxxxx/.

dynamic real-world practices, such contextual information should be included in the analysis to improve the external validity of eye tracking studies in the radiology field.

To analyze gaze data along with various contextual information, an interactive visual analytics framework that can embed and visualize the contextual data is required. However, since there has been no such a framework available for radiologic gaze research, most prior gaze research relied on comparison using manual juxtaposition of static gaze results in different conditions [3]. Although comparison using manual juxtaposition has revealed meaningful findings, it is not scalable to the large amount of gaze data and various contextual information in actual practice.

An interactive visual analytics framework for scalable radiologic gaze research should support exploratory analysis, especially by providing filtering and brushing interactions to incorporate important contextual information for diagnosis. For example, radiology gaze researchers often want to analyze only gaze points within an area of interest (e.g., a certain organ or lesion). Such interactive region-based filtering could provide insight to the factors affecting the difference in gaze patterns between different groups (e.g., experts and novices).

As the dimension of stimuli (i.e., an image being presented to participants in a gaze experiment) expands from 2D (e.g., X-ray and mammography) to 3D (e.g., CT and MRI), a visual gaze analytics framework should be accompanied by new, relevant visual representations and interaction techniques. The widespread adoption of 3D medical imaging systems has recently led to an increasing number of eye tracking studies for diagnosis of 3D volumetric images (e.g., a sequence of CT or MR images) [3]. However, the gaze analysis methods in recent studies of 3D volumetric images have changed little from those of 2D images. In the case of 2D images, radiologists focus on a single static image, whereas with 3D images, radiologists freely scroll up and down through a stack of cross-sectional images. As a result, comparative gaze studies with 3D volumetric images pose new challenges in designing an interactive visual analytics framework for radiologic gaze research, taking into account not only the sheer amount of stimuli and gaze data but also the complexity due to the added dimension.

In this paper, we propose an interactive visual gaze analytics framework, GazeDx (abbr. of GazeDiagnosis), for use by radiologists to analyze diagnostic gaze data and contextual data captured while their peers while their peers were reading volumetric medical images. We first summarize related works in two categories: visualization for gaze analysis and diagnostic gaze analysis in radiology. With a taxonomy of contextual information in Section 3, we then describe the design rationale and details of the visual analytics framework in terms of visualization, interaction, and comparison in Section 4. In Section 5, we present case studies performed in collaboration with 14 radiologists (7 chest and 7 abdomen radiologists), followed by a discussion section with summarized insights from the studies and a conclusion section.

2 Related Work

2.1 (Comparative) Visualization for Gaze Analysis

There are many prior studies that present visualization techniques for analyzing eye tracking data. Blascheck et al. [2] proposed a taxonomy to classify the visualization techniques for eye tracking data. It includes stimulus-related (e.g., static vs. dynamic, passive vs. active, and 2D vs. 3D) and visualization-related categories (e.g., temporal, spatial, and spatio-temporal; static vs. animated; single user vs. multiple users; 2D vs. 3D; in-context vs. not in-context; and interactive vs. non-interactive). According to their classification, there are only a couple of prior studies on dynamic and active stimuli comparing multiple users with interactive visualizations. Kurzhals et al. [12] provided an extensive summary of prior work on visual analytics approaches for evaluating visualizations using gaze tracking in the visualization community.

Scanpath visualization and analysis are one of the major tools for comparative gaze analysis. West et al. [31] labeled each AOI with a character and utilized string comparison algorithms for fixation sequence analysis. Kurzhals et al. [13] proposed ISeeCube that uses Space-Time Cube along with a timeline visualization to show AOI-based scanpaths of different viewers. It was designed for video stimuli with dynamically changing AOIs. Tsang et al. [28] introduced eSeeTrack to compare fixation patterns on dynamic 3D scenes such as surgical simulation. The orderings of fixations from multiple users were explored and compared with eSeeTrack, but they were not visualized in context. Pfeiffer [19] also used 3D scenes as stimuli and visualized gaze data using a 3D scanpath and a 3D attention volume. A scene from diagnosis with volumetric medical images is similar to video stimuli rather than the 3D scene. However, its innate volumetric structure and familiarity of its anatomical structure among intended users (i.e., radiologists) distinguish the scene from ordinary video stimuli in existing eye tracking studies. Moreover, categorization of fixations and saccades, which is defined in the *x*-*y* plane (i.e., within a cross-sectional image), is not well defined for the cases with navigation in depth (i.e., *z* directional cross-slice navigation) [3]. Thus, using raw gaze data, we built attention maps for each cross-sectional image as an alternative to applying a fixation filter [7] and provided coordinated spatial and temporal views that could enable visual comparison of gaze sequences (described in section 5.3).

2.2 Diagnostic Gaze Analysis in Radiology

In the medical field, a variety of quantitative and qualitative gaze analysis studies have enriched the understanding of how radiologists read various types of medical images. Kundel and Follette [10] compared the visual search patterns of experts and novices during a study of radiographic chest images. In addition to conducting the quantitative analyses based on fixations to compare first hit time and decision errors, they juxtaposed readers' scan paths and compared them considering years of experience. Quantitative comparison using fixation and qualitative comparison with juxtaposed gaze patterns were two main research methods. For example, Kundel et al. [11] found that experts had a holistic perception during diagnosis by analyzing quantitative measures such as first fixation time and the ROC index and juxtaposing multiple scan paths. Such work focused on analysis of a single static 2D image. This is not applicable to volumetric images, which GazeDX is designed for.

Recently, researchers started to conduct gaze tracking studies with volumetric images. Lala and Nakazawa [15] proposed a system to correlate collected gaze points with a stack of medical image slices shown in a diagnostic system without modifying the source codes. They recorded the screen during diagnoses and used an algorithm to match each video frame to a specific image slice. While this approach is more ecologically valid than developing a separate gaze collection application, it is incapable of collecting diverse diagnostic contexts (e.g., windowing information). Consulting expert radiologists, we developed an integrated gaze collection application that is equipped with core features of existing diagnostic systems.

Atkins et al. [1] proposed using a static scatterplot, called a navigation chart, to visualize temporal viewing sequences of a single observer using time on the *x*-axis and slice number on the *y*-axis. In this paper, we enhance the plot to provide improved interactivity and flexibility while supporting semantic zooming with multiple visual representations. Phillips et al. [20] used a series of cross-sectional brain MRI images in their study and showed the gaze data in two different views. The first view accumulated fixations throughout the volume into a single 2D view with fixations on the current image highlighted in a unique color during scrolling in stack viewing mode. This view cannot show depth information that is important for 3D gaze data. The second view superimposed the gaze plot on a vertical stack of 2D images. Mimicking 3D, this view suffered from occlusion and visual clutter. As a remedy to this problem, Song et al. [26] adopted a volume-rendering technique to show 3D gaze data along with a 3D rendering of the volume. However, manual juxtaposition outside the framework was still required for inter-reader comparison. As well, the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2016.2598796, IEEE Transactions on Visualization and Computer Graphics

Table 1. Types of Contextual Information

Type	Clinical (Static)		Procedural (Dynamic)	
	Practitioner-related	Image-related	Execution-related	Evaluation-related
Description	Background information of a practitioner that affects diagnosis, studied by a number of prior works in medical field.	Clinical information from the images, controlled in previous studies on diagnostic gaze data.	Interactions performed by a practitioner during diagnosis.	Personal biometric response from diagnosis.
Example	Prior knowledge about a patient Personal strategy Purpose of diagnosis Specialty (e.g., chest, abdomen) Expertise level	Organ related information - Location and size Lesion related information - Location and size	Scrolling Adjusting the window setting - Preset (predefined setting) Partial magnification	Pupil size Distance to monitor Biometric signals - EEG/ ECG/ EDA response

ability to analyze related contextual information in concert with gaze data during diagnosis was not possible.

Most similar to our work, Drew et al. [3] proposed a gaze visualization method with volumetric images based on a volume-rendering technique while characterizing the visual search of experts. They divided the image area into four quadrants and displayed a color-coded navigation chart to identify two different visual search strategies: (1) drillers with consecutive gaze patterns in a certain quadrant, and (2) scanner with gaze patterns distributed across different quadrants. While this approach visualizes the gaze patterns from volumetric images, it still relied on the conventional static juxtaposition strategy for comparison. In GazeDx, we not only overcome the limitations of existing approaches by designing visualization and interaction for more effective comparative gaze analyses with volumetric images, but also encourage exploratory multidimensional exploration of the data while incorporating largely ignored important contextual information in the gaze analysis.

3 Contextual Information in Gaze Analysis

Contextual information has often been controlled during diagnostic gaze collection and analyzed individually outside the analysis tool. In this work, we integrate contextual information with diagnostic gaze data to enable interactive and holistic exploration. Contextual data for medical diagnosis ranges from clinical (e.g., expertise level and specialty of the radiologist, prior knowledge about the patient) to procedural information (e.g., interactions during the diagnosis, response from the radiologist). The majority of prior work compared gaze patterns with different clinical conditions while controlling other procedural conditions. For instance, Manning et al. [17] recruited radiologists with different levels of expertise and instructed them to solely concentrate on lung nodules. It is a typical hypothesis-driven gaze tracking study with high internal validity. However, in real-world practice, chest radiologists also have to examine the mediastinum during a chest CT reading, which requires radiologists to change brightness and contrast of an image (Fig. 7). Thus, for a more ecologically valid study, it is necessary to support exploratory analysis while integrating dynamically changing procedural as well as static clinical information into the analysis process. In this section, we categorize the contextual information by its characteristics (Table 1), and then explore the design space of our framework in terms of visualization in the following section.

Clinical context refers to static factors that are closely related to diagnosis; as such, many radiology researchers have attempted to evaluate its effect on diagnosis. Clinical context is fixed during a single study session, in contrast to dynamic procedural context, which will be explained later. Clinical context can be categorized into two types: practitioner-related context and image-related context (i.e., stimuli for an eye tracking study). The practitioner-related context includes prior knowledge about the patient, personal diagnosis strategy (i.e., order of exploration), purpose of the diagnosis (e.g., follow-up examination for a certain disease, ordinary examination), level of expertise, specialties (e.g., chest or abdomen), and level of fatigue. The image-related context includes information about organs and lesions, such as location and size.

Procedural context includes dynamic factors collected during diagnosis and can reveal the procedural information at the time of diagnosis. Since most of the information is not directly related to clinical implication, prior studies tended to control the values rather than analyzing them in situ. However, procedural context can be crucial, as it could significantly affect the perception of stimuli or the acuity of practitioners during the diagnosis. We categorize the procedural context into two types: execution- and evaluation-related context. Radiologists generally execute actions (i.e., change visualization parameters) to reflect their intentions during diagnosis. For instance, they adjust the brightness and contrast of the image (i.e., adjust the window setting value) to concentrate on different organs or lesions. While the window setting is strictly controlled in most prior gaze studies in radiology, such context dynamically changes in real practice: radiologists consistently change the window setting values and such a contextual change determines the visibility of a specific area in the image at a specific time point. Another example of executing commands for a diagnosis of volumetric images is scrolling, where important contextual information is the slice number of a currently shown image to determine the 3D depth values. Evaluation-related context includes biometric signals from a practitioner for evaluating the outcome of the actions, which are multimodal data [2] that could reveal the practitioner's acuity during diagnosis. For example, one can use pupil size, EEG, ECG, or EDA signals to deduce stress or fatigue levels during diagnosis.

4 GazeDx: Interactive Gaze Analytics Framework

The main design goal of GazeDx is to facilitate radiologists' comparative analysis of gaze patterns from multiple readers while taking into account important contextual information. Adopting the visual information-seeking mantra [24], GazeDx first shows the overviews of the gaze data of multiple readers to spur interactive exploratory analysis and allows users to select a small set of readers for detailed comparison. It then enables users to investigate the multidimensional aspects of individual readers' gaze data.

Following the mantra, we designed GazeDx to have two main tabs: overview and comparison view. Users begin their gaze analysis in the overview tab, where they can check the overall similarity relationships among all readers in a similarity matrix view (Fig. 2A) based on a rank-by-feature framework [23, 25]. They can also examine the overall spatial (Fig. 2D) and temporal (Fig. 2C) diagnostic exploration patterns of readers using small multiples. Once they set their target readers for a detailed comparative analysis in the overview tab, they move on to the comparison view tab (Fig. 5), where they can compare the gaze patterns of the selected readers in greater detail, taking into account important contextual information.

4.1 Design Rationale

To achieve the main design goal, we first identified design requirements for GazeDx by conducting interviews with radiologists and extensively reviewing clinical research using gaze analysis in the

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2016.2598796, IEEE Transactions on Visualization and Computer Graphics

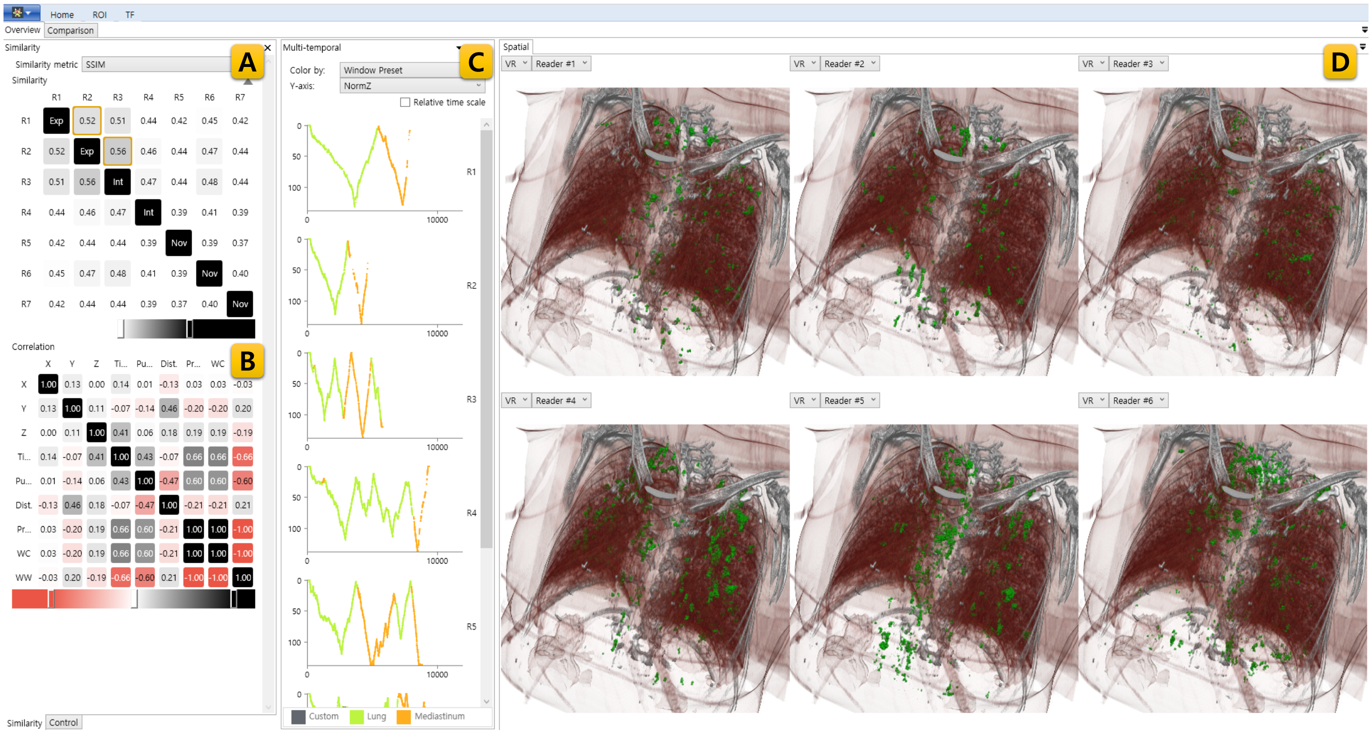


Fig. 2. GazeDx interface for chest normal case (**Overview** tab). (A) Similarity matrix showing pairwise similarity between readers computed with SSIM (Structural Similarity). (B) Correlation matrix showing correlation between each pair of dimensions. Background of each cell in both matrices is color coded by its magnitude. (C) Multi-temporal view with interactive temporal charts. (D) Spatial view showing gaze data superimposed on 2D MPR (axial, coronal, and sagittal) or 3D VR images.

radiology field. We designed GazeDx to meet the design requirements. In this section, we describe our rationale behind the visualization and interaction design for GazeDx.

Reduce cognitive load on radiologists. As GazeDx aims to help radiologists analyze gaze data collected during clinical diagnosis, we adopted visual representations familiar to radiologists: 2D multi-planar reformation (MPR) images (axial, coronal, and sagittal images) and 3D volume rendering (VR) image. We used them to provide important clinical contexts during gaze analysis mainly by superimposing abstract gaze data over the familiar representations.

Support comparative visualization of multiple gaze data. One of the ultimate objectives of the gaze tracking study is to identify the differences in gaze patterns, and then explore the sources of the differences. To achieve the objective, it is essential to support visual exploration of multidimensional gaze data from multiple readers. Thus, we utilized two proven comparative visualization techniques: (1) small multiples designed to encourage and facilitate comparisons of multiple readers with a view for each reader, and (2) a rank-by-feature framework to support effective exploration of multiple dimensions.

Include contextual information in multidimensional analysis of gaze data. There is a great deal of important contextual information in radiological gaze analysis studies as discussed in section 3 and Table 1. Despite the importance of these factors in the real-world diagnosis, most prior work neglected such information or analyzed the information separately from the gaze data. We included such important contextual information in our interactive comparative gaze analysis framework to support rich, exploratory multidimensional analysis with ecological validity considered.

Provide flexible exploration of large gaze data. Most eye tracking studies used a fixation filter to cluster a large number of raw gaze points into fixations and saccades. However, most of the fixation filters are designed for 2D stimuli so that they were inapplicable to three-dimensional gaze points from a diagnosis of volumetric images. Thus, we had to use raw gaze points and had to accumulate the points into scalar volume (i.e., gaze field [26]) using a Gaussian filter for a 3D visualization. Since we used a 60Hz gaze tracker, a five-minute diagnosis generated up to 18,000 gaze points, and to support the flexible exploration of such a large amount of gaze data, we provided not only multi-level visual summaries and aggregations, but also interactive selection and filtering capabilities. Specifically, we introduce a novel filtering technique based on segmentation of clinically meaningful structures.

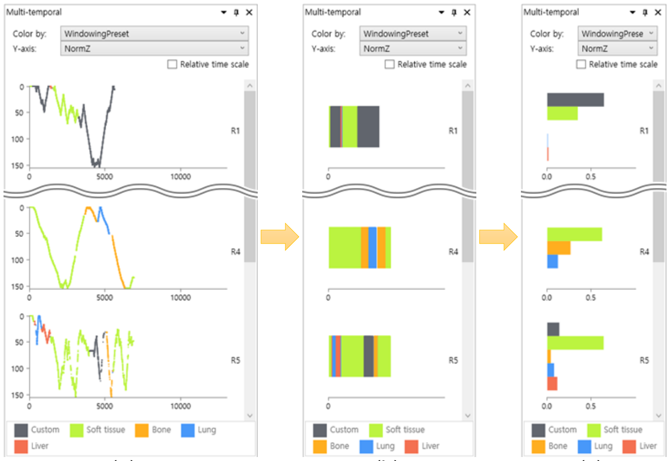
Support interactive temporal analysis. Temporal information of gaze data has played a pivotal role in clinical gaze tracking studies: a metric to measure diagnosis efficiency [17], inferring strategies of scanning [3], and defining the phase within a single diagnosis [20]. Moreover, volumetric images can be thought of as dynamic stimuli in gaze tracking studies since the scene (as stimulus) changes over time as radiologists actively scroll through a long stack of images (i.e., “the stimulus becomes dynamic” [2]). Thus, we incorporated visual representations, such as interactive temporal charts, to show temporal information related to gaze data in our tool.

4.2 Visual Representations in GazeDx

4.2.1 Context-embedded Interactive Scatterplot (CIS)

In our framework, we associate a great deal of contextual information with each gaze point to form a collection of multidimensional data points. In order to support visual exploration from diverse perspectives of such data, we designed a scatterplot with configurable axes and contextual background (Fig. 1 and Fig. 5B). Depending on the property of a selected axis, the range and origin of the axis change to make the scatterplot more intuitive and understandable to users. For spatial variables *x* and *y*, and variables for contextual information, the origin is placed at the bottom left of the scatterplot, as is usual in the typical Cartesian coordinate system. However, a spatial variable *z*, which is derived from slice index, is placed in an inverted direction when mapped to the vertical axis of the scatterplot (in ascending order from the top). We made this design decision because radiologists are familiar with the inverted mapping for the *z*-axis in practice. Unlike abstract contextual information, gaze points from volumetric medical images can be mapped to the human body, and thus it is more natural to put gaze points on the first slice to the top with the smallest *z* value.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2016.2598796, IEEE Transactions on Visualization and Computer Graphics



(a) (b) (c)

Fig. 3. Semantic exploration of temporal aspect of gaze data by transition of the temporal representation according to space availability. (a) Navigation chart. (b) Stacked bar chart. (c) Bar chart.

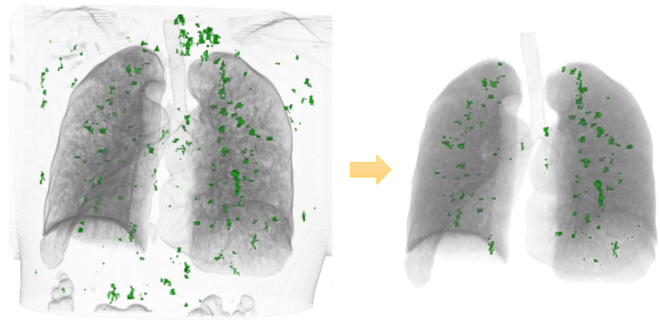
The scatterplot is further extended by embedding medical imaging representations familiar to radiologists in the background. This embedding can provide rich anatomical context for gaze analysis. Even though a scatterplot is an effective visualization to reveal bivariate relationships, it is not intuitive for radiologists to connect the points in the scatterplot to the anatomical structure of the human body, which is of greater clinical significance. Therefore, we embedded contexts that are more meaningful and intuitive into the scatterplot by integrating familiar medical imaging representations. When a group of gaze points is selected in the scatterplot (as described in section 4.3.2), a user can right-click on it to investigate it in situ in a 2D MPR representation naturally embedded in the scatterplot without switching views.

To make this transition easy to follow and depict innate 3D structures of stimuli, we designed a multi-stage animation. Assume gaze points are selected by users or filtered by a criterion (detailed in section 4.3.2) in the scatterplot with spatial variables *x* and *z* mapped to its horizontal and vertical axes, respectively. If users right-click on any area in the *x*-*z* scatterplot (Fig. 1a), the scatterplot is divided into three parts: upper area, middle area with selected gaze points, and remaining lower area. Then the middle area is expanded vertically, transforming itself into a 3D VR image where the selected gaze points are placed on a 3D representation of a patient's body that carries greater clinical meaning (Fig. 1b). Afterward, the 3D VR representation with the gaze points rotates around the horizontal axis to show the *x*-*y* plane of the volumetric images (Fig. 1c). Finally, the *x*-*y* plane (axial image) appears with gaze points overlaid (Fig. 1d). The user can scroll up and down *x*-*y* plane images by using wheel scrolling. In this way, gaze points projected on the same position in the original *x*-*z* scatterplot appear and can be examined in the *x*-*y* plane image, enabling users to compare the selected gaze data in a single space (i.e., CIS) in terms of all three spatial dimensions.

We further improve CIS by attaching two histograms on the top and right sides of the scatterplot to show the marginal distribution of gaze points across horizontal and vertical dimensions, respectively. We determined the size of bins based on the Freedman-Diaconis rule [5] to increase the robustness of the histograms. These histograms can help ease the over-plotting problem of gaze points when numerous regions of interest are located closely and can show marginal distributions of gaze points with distinct colors upon selection and filtering (described in section 4.3.2) by users (Fig. 5B).

4.2.2 Temporal Chart

The temporal dimension is yet another important perspective that could reveal meaningful differences between readers [1]. In GazeDx, users can check the overall temporal gaze patterns of multiple readers using small multiples of a temporal chart (i.e., navigation chart [1]) (Fig. 2C). The original navigation chart is a type of scatterplot that plots the index of gazed slice (mapped to *y*-axis) over time (mapped to *x*-axis). We generalized the original navigation chart, enriched the visual encoding options, and designed user interactions to make an interactive version of the navigation chart, which we call the "interactive temporal chart." It is enhanced to support both absolute and relative time scales, as the time taken to make a diagnosis differs between readers. In the absolute time scale, users can easily compare the difference in diagnostic duration (who finished the image review quickly or slowly), and one can use the relative time scale to examine the similarity in and difference between the overall temporal patterns of gaze for multiple readers, regardless of duration. Compared to the original navigation chart, it is improved in two ways: (1) configurable *y*-axis, and (2) color-coding capability with categorical values (e.g., expertise level and windowing information). As an example, one can map pupil size to *y*-axis, and color-code each point by a window setting to inspect whether the image brightness and contrast influence the temporal trend of pupil size in a single view.



(a) (b)

Fig. 4. Gaze points filtered by human anatomy of the lung. (a) All gaze points before filtering, and (b) after anatomical filtering with the lung segmentation result.

We further extended the interactive temporal chart to support semantic level-of-detail exploration [18] of the temporal aspect of gaze data with three visual representations: (1) navigation chart, (2) stacked bar chart, and (3) bar chart (Fig. 3). The interactive temporal chart transforms its view from a navigation chart to a stacked bar chart as the space becomes smaller: information mapped on the *y*-axis is neglected, and the change of categorical contextual information over time is plotted in the chart. With this representation, one compares the readers based on the changes of categorical contextual information over time. When the available space becomes even smaller, gaze data is aggregated into groups depending on selected contextual information, and the proportion of each group is visualized using a bar chart. Consequently, one can check the distribution of the selected categorical contextual information.

4.3 Interacting with Contextual Information

The number of gaze points for each reader is more than ten thousand even for a short three-minute diagnosis; examining them all at once easily exceeds one's perception capability. Moreover, the inclusion of contextual information in gaze analysis increases the number of dimensions. To support the flexible exploration of such large amounts of multidimensional gaze data from diverse perspectives, GazeDx provides interactive selection and filtering capabilities to help users efficiently select and compare groups of gaze points in which they are interested. Our review of existing gaze analysis systems and gaze-based clinical research led us to (1) a filtering interaction based on human anatomy, which enables users to filter gaze points within an anatomical structure of interest; and (2) a selection interaction using freehand drawing, which is, we believe, the most flexible selection interaction based on direct manipulation.

4.3.1 Selection and Filtering by Human Anatomy

It is common in gaze-based radiology studies to investigate whether readers' gaze points are in a region of interest that is usually an organ

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2016.2598796, IEEE Transactions on Visualization and Computer Graphics

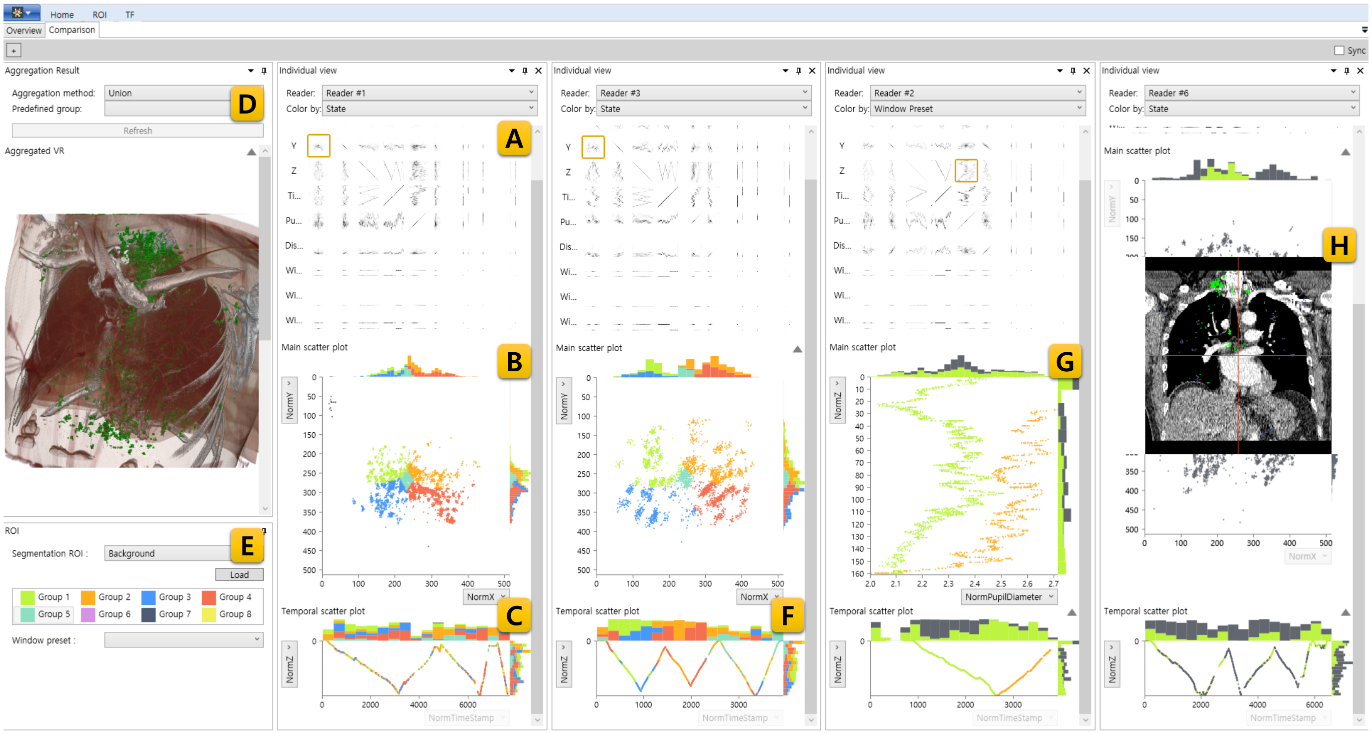


Fig. 5. GazeDx interface for chest normal case (**Comparison** tab). (A) Scatter plot matrix. (B) CIS: context-embedded interactive scatter plot with gaze points grouped to five clusters. (C) Interactive temporal chart. (D) Aggregation pane showing aggregated gaze data for the readers in individual view panes. (E) ROI selection pane with "Segmentation ROI" filter and "Window preset" filter. Interactive temporal charts in (C) and (F) clearly show the difference in gaze pattern between scanner and driller strategy (frequently changing color in (C), scanner; relatively consistent color in (F), driller). (G) CIS with horizontal axis of pupil diameter and vertical axis of slice index, where the gaze data is color-coded by window preset (left-shifted green cluster for lung, and right-shifted orange cluster for mediastinum setting). (H) CIS with embedded coronal plane image.

or a lesion. However, it is extremely labor intensive, if not impossible, to define such a region of interests in an existing gaze analysis system. We introduce an ROI-based filtering technique that utilizes segmentation results as ROIs. We extract an organ or a lesion of interest (e.g., lung, liver, metastasis, and nodule) a priori by using an external segmentation tool. Using these segmentation results, GazeDx supports clinically meaningful spatial filtering. If one selects a segmentation result using the combo box of "Segmentation ROI" (Fig. 5E), GazeDx shows only the gaze points within the segmented result to help users examine the gaze patterns confined to the corresponding organ or lesion (Fig. 4).

Such an anatomical spatial filtering can support multidimensional exploration of gaze data when examined using configurable axes of CIS for the contextual information. Combined with the windowing information that is important contextual information affecting the visibility of stimuli (organs or lesions), anatomical spatial filtering could enable gaze comparison in terms of diagnostic performance or behavior. For instance, in the lung (window) setting for chest scans, the structures inside lungs are clearly visible, whereas the mediastinum (region between two lungs) and soft tissue are greatly saturated to a point where they become almost indistinguishable (Fig. 7a). In the mediastinum (window) setting, the mediastinum and soft tissues are visible; the lung is mostly black (Fig. 7b). By combining the anatomical query with the windowing information, one can easily identify spatially mismatching gaze points. For example, by selecting "Segmentation ROI" of the lung, one can easily find gaze points on lungs with the mediastinum setting, which indicates that a reader gazed at the mostly invisible lungs. Such gazing can be understood as worthless or as the result of other human factors, regarding the diagnostic performance or behavior.

4.3.2 Selection and Filtering by Freehand Drawing

We also introduced interactive selection of gaze data with freehand boundary drawing in CIS, which reflects radiologists' natural diagnosis practice of drawing on the visual stimuli to get more information. Since CIS could plot the gaze data using customized axes, freehand drawing provided more flexibility than implementing a dedicated filter to each dimension in gaze data. Users can select multiple groups of gaze points using this interaction. Upon drawing a boundary, selected gaze points within the boundary are highlighted in a specific color selected on the leftmost pane (Fig. 5E). To support multiple view coordination, the selected gaze cluster is highlighted in that specific color in the interactive temporal chart below CIS. The assigned color applies to the two histograms on the top and right sides of CIS and to the interactive temporal chart below. Thus, one can investigate gaze points of interest from diverse perspectives by taking advantage of the configurable axes feature in CIS.

This interaction technique using freehand drawing can also help users compare gaze patterns between the two phases of radiologists' diagnostic process: skimming and verification [1]. When a radiologist diagnoses a volumetric CT or MR image, he/she usually makes a decision after scrolling up and down the whole image several times, wherein the last scroll is regarded as the verification phase, and the prior scrolls are regarded as the skimming phase. If one draws a boundary surrounding the gaze points for the last scroll and draws another boundary surrounding the remaining gaze points in the interactive temporal chart, he/she can compare the gaze points in those two gaze clusters in the upper CIS from multidimensional perspectives while changing its horizontal and/or vertical axes.

4.4 Comparison of Multiple Eye-Tracking Data

4.4.1 Arrangements of Visualizations for Comparison

Among the three visual designs for comparison [6], we used superposition and juxtaposition of visual representations to support inter-reader comparisons. As superimposition of gaze data over visual stimuli is effective for interpretation [27], we adopted a number of spatial representations for stimuli, such as 2D MPR (i.e., axial, coronal and sagittal) and 3D VR representations. Using these representations relieved cognitive burden of the target users (i.e., radiologists), as they

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TVCG.2016.2598796, IEEE Transactions on Visualization and Computer Graphics

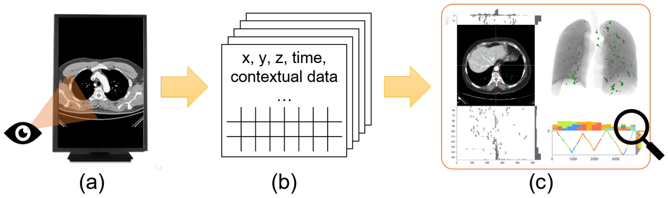


Fig. 6. System architecture and work flow. (a) Gaze collection application collects gaze points along with contextual information. It produces (b) gaze data correlated with image slices, which are then analyzed in (c) the GazeDx framework.

have been using the visualizations in their clinical practices. Then, we prepared juxtaposed views of gaze data superimposed on stimuli visualization in a small multiples design to encourage comparison of multiple gaze data. There was a prior work proposing a similar approach [26], but we enable more flexible arrangements of small multiple views. For each view, one can determine whose gaze data is displayed in which spatial representation. One can organize views of multiple gaze data in a 2×3 grid layout (Fig. 2). In each row or column for a gaze data, different types of spatial representations can be shown for the gaze data. All views are synchronized upon user interactions (e.g., rotation of the volume in 3D view) to facilitate the exploratory analysis.

4.4.2 Comparison along with Contextual Information

Gaze tracking studies in the radiology field have controlled and analyzed a great deal of contextual information along with gaze data to find clinical implications. We reserved a separate space (i.e., a comparison tab) for comprehensive gaze comparison by including contextual information (Fig. 5). It consists of two types of vertical panes: the aggregation pane for showing aggregation results and selecting segmentation ROI, and individual view panes for showing each selected gaze data in a separate pane. Three visualization components can be used in each individual view pane: a **scatterplot matrix** to see projected gaze data on scatterplots for all variable pairs (Fig. 5A), **CIS** to investigate an attributes pair that is selected in the scatterplot matrix (Fig. 5B), and an **interactive temporal chart** (Fig. 5C) to examine the temporal aspect of gaze data.

As the amount of contextual information grows, one must perform an exponentially increasing number of pairwise comparisons to review the gaze data for all possible pairs of information. However, one can easily perceive overall gaze patterns with a **scatterplot matrix**, and then click on a specific cell (Fig. 5A) to see the corresponding scatterplot in the aforementioned **CIS** for analysis on gaze points of interests, as described in section 4.3. The selection in the matrix can be synchronized across all view panes to encourage comparison across readers. We also included an **interactive temporal chart** in each individual pane to reveal holistic insights by linking temporal dimension, which is one of the key analytical dimensions in gaze-based clinical studies [1], with other dimensions.

Researchers compared the gaze patterns of multiple readers after stratifying the readers by a contextual categorical variable (e.g., expertise level) in many prior studies [10, 17, 21]. To facilitate such analytical needs, GazeDx provides users with an aggregated overview for comparison between groups (for example, experts vs. novices) (Fig. 5D). Users can interactively define a new group of readers (e.g., experts, intermediates, and novices) by selecting the readers in the individual view panes. GazeDx builds a new aggregated collection of gaze data for the corresponding readers using one of the aggregation options (e.g., *union* to obtain full gaze coverage of the selected group and *intersection* to retrieve the commonly gazed region by the selected group). The aggregated data is visualized as a 3D VR representation in the aggregation pane.

4.4.3 Quantitative Similarity Comparison

To facilitate the overall exploration of inter-reader similarity in terms of the covered area in a diagnosis, we took an approach based on the rank-by-feature framework [22, 23]. Regarding the visual representation of the similarities, we adopted a permutation matrix, which has been used to present pairwise relationships for multiple elements and has proven to be effective for a multidimensional visual structure [9]. Upon selecting a similarity ranking criteria, a color-coded permutation matrix (i.e., similarity matrix) shows a succinct overview of similarity relations among numerous different readers (Fig. 2A). Each color-coded cell represents a similarity value between a corresponding pair of readers. A diagonal cell shows important contextual information, i.e., the expertise level for the corresponding reader (Exp for expert, [R1, R2]; Int for intermediate [R3, R4]; and Nov for novice [R5, R6, R7]). In this work, we adopted SSIM (Structural SIMilarity) as a similarity measure, which is known to be comparable or superior to other complex metrics due to its simulation of the human visual system [30].

Table 2. DICOM files used in case studies

Body part	Usage	Dimension	# of images	Remarks
Chest	Training	512 x 512	154	Normal
	Main study	512 x 512	161	Normal
	Main study	512 x 512	137	Lesions (multiple nodules)
Abdomen	Training	512 x 512	150	Normal
	Main study	512 x 512	155	Normal
	Main study	512 x 512	110	Lesions (huge hepatic mass)

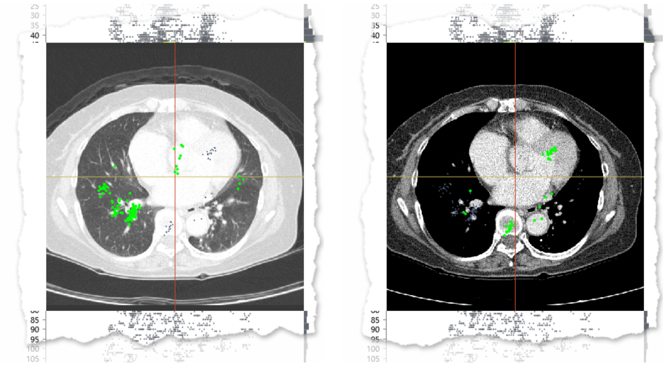
5 Case Studies with Radiologists

We followed the Multi-dimensional In-depth Long-term Case studies (MILCs) [23, 25] to evaluate the efficacy and effectiveness of GazeDx as an interactive visual analytics framework. Specifically, GazeDx is designed for analysis of multiple gaze data from diagnoses with volumetric images. A comparative evaluation study was not feasible because there were no comparable gaze analytics systems able to handle large multidimensional gaze data from multiple readers. We conducted two case studies, each with a different body part, at a university hospital. We acquired gaze data from 14 radiologists (seven chest radiologists and seven abdominal radiologists). We collected their gaze data while each radiologist read two patients' CT images. After collecting gaze data, the two most experienced radiologists among the 14 performed comparative gaze analysis on the collected gaze data of their colleagues (including their own) with GazeDx. We used a modified pair analytics method [14] for our case studies, where the main designer of GazeDx interacted with the system, and the two radiologists directed the analysis using their expertise in the field.

5.1 Case Study Protocol

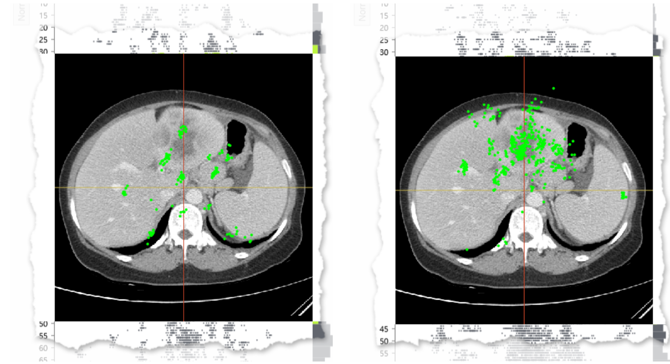
We conducted two case studies following a protocol with three phases: preparation, gaze collection and evaluation. In this section, we describe the protocol in detail.

In the preparation phase, we communicated with two expert radiologists (one chest and one abdominal radiologist) daily to discuss tasks and datasets for gaze acquisition. The experts shared their opinions to create a realistic experimental setting that resembles their actual daily reading. Based on their comments, we built an independent gaze collection application that resembles the PACS (Picture Archiving and Communication System) in terms of appearance and functionality. We had to additionally develop a function of collecting contextual information (e.g., gazed slice number) for all gaze points, which is not supported by PACS. With this function, we were able to collect the gazed slice number for every gaze point precisely and analyze the collected data in GazeDx (Fig. 6). We revised our original task to request a short report after the diagnosis. One expert advised that radiologists tend to examine images more carefully when asked to write a report, which they do in clinical practice. Another important comment from the discussion was



(a) (b)

Fig. 7. Axial images embedded in CIS, showing gaze points of a reader for the chest lesion case. (a) In the lung window setting, the gaze points are scattered largely on both lungs and the mediastinum even though the mediastinum becomes too saturated to see detail. (b) In the mediastinum window setting, the gaze points are distributed mostly on the mediastinum.



(a) (b)

Fig. 8. Axial images embedded in CIS, showing gaze points of (a) an expert and (b) a novice for the abdomen lesion case. (a) The expert's gaze points are relatively scattered on the image even with the clearly notable lesion (large hepatic mass). (b) The novice's gaze points are distributed mostly on the lesion.

enabling readers to use a set of predefined window settings, as in their clinical practices. In practice, radiologists quickly adjust the window value using hotkeys. The gaze collection application and GazeDx provide readers the same hotkeys for window value selection.

Each expert helped us select three datasets for each body part: one for a training session, one without any lesion (a normal case), and one with notable lesions (a lesion case) (Table 2), which enables the gaze comparison between the two cases. Then, we consulted the experts again to establish which region is reviewed closely in each window setting to facilitate the segmentation of ROIs. Consequently, we prepared the segmented ROIs of the lung and the rest of the body for chest CT data; and lung, liver, and the rest of the body for abdomen CT data using proper segmentation algorithms [8, 16].

In the gaze collection phase, we collected actual gaze data. Prior to the gaze data collection, participants had a training session to use the application for as long as needed to become accustomed to the interface. Training sessions took less than five minutes for all participants, as the application was designed carefully to emulate PACS they use in practice. The eye tracker was calibrated using nine-point calibration prior to the main session. In the main session, each participant was asked to review images as if for real diagnosis and compose a brief report of final diagnosis. The gaze collection application recorded the gaze data along with contextual information. Each session took approximately 15 minutes, including training.

In the evaluation phase, we introduced GazeDx to the two expert radiologists. A modified pair analytics method [14] was used where the main developer played the role of visual analytics expert, and the radiologists played the role of subject-matter experts. During the evaluation phase, our radiologists quickly became accustomed to GazeDx and were able to use the application with less assistance from the main developer. We met the expert radiologists four times during three weeks of evaluation. We improved visual representations and interactions during this phase by accepting experts' feedback. We asked each expert to compare the collected gaze data of seven readers using GazeDx, and to find any notable similarities and differences between the readers and datasets. We further collected diagnostic comments regarding notable gaze patterns discovered with GazeDx.

5.2 Apparatus

For gaze data collection, we used a computer connected to a 20-inch Barco medical monitor, and a Tobii X60 eye tracker with 0.4° optimum accuracy. The average distance from participants to the eye tracker was approximately 65 cm. For gaze analysis, an NVIDIA GTX 760 GPU was used.

5.3 Chest Radiologists

Following the case study protocol described above, we conducted a case study with seven chest radiologists: two with more than 16 years' experience (expert; R1 and R2), two with about four to six years' experience (intermediate; R3 and R4), and three in the first to second year of residency (novice; R5, R6, and R7). All practitioners were asked to review chest images for diagnosis (Table 2). Following data collection, one of the senior chest radiologists was asked to compare the gaze data using GazeDx.

Using the normal case, the radiologist first examined the overview using 3D VR images in the spatial view (Fig. 2D) and the similarity matrix in the similarity view (Fig. 2A). Readers were labeled as R1 to R7 to reflect level of expertise in descending order of expertise. He found that the expert radiologists had a more similar gaze pattern (dark gray) than the novices (light gray).

Next, he used the multi-temporal view for more detail (Fig. 2C). He found that the novices tended to use the image scroll more frequently than the experts did and that the experts' gaze forming a straight line, while novices exhibited a large number of gaze fluctuations. He also found a tendency among all readers to exhibit a stiff angle with the mediastinal setting (orange for mediastinum vs. green for lung) (Fig. 2C).

Following analysis of the overall gaze data, our expert radiologist moved to the comparison tab to investigate individual gaze patterns. He first used CIS with spatial variables x and y mapped to its horizontal and vertical axes (Fig. 5H). Next, he divided the plotting area into five regions, each with distinct colors: upper-left, upper-right, lower-right, lower-left, and central regions so as to determine whether readers are scanners or drillers [3] (Fig. 5C and 5F). Gaze points in the interactive temporal chart below were painted in the same colors. Here, he could easily discern a difference in viewing styles between those who scroll images while spreading their gaze in a wider area in a single image (R1, scanner) (Fig. 5C), and those who scroll images while focusing their gaze on a localized area (R3, driller) (Fig. 5F).

Gaze data was further examined to look for a correlation between pupil diameter and human anatomy. The expert selected the cell corresponding to the pair of slice index and pupil diameter (see orange rectangle above Fig. 5G). He noted two distinct clusters with a notable valley on both lung and mediastinal settings (left green cluster, lung setting; and right orange cluster, mediastinum setting) (Fig. 5G).

The expert then examined his own gaze pattern in the lesion case. In particular, he focused on the windowing information affecting the stimuli visibility in the images. In the individual view pane, he expanded an axial plane image in CIS by drawing freehand and selecting most of his gaze data. He looked at his gaze across both lung and mediastinal images by changing the window preset filter. Interestingly, he found a notable difference in gaze pattern: in the mediastinal setting, his gaze was directed solely at the mediastinum; however, in the lung setting his gaze was concentrated on both lung and mediastinum (Fig. 7). This is of interest since the mediastinum becomes saturated in the lung setting, making it difficult see the details in this area. On completion of this task, our expert concluded that the context-embedded nature of CIS is useful for examining anatomies without shifting his attention to other views.

5.4 Abdominal Radiologists

Seven abdominal radiologists participated in the case study, including two with more than 10 years' experience (expert; R1 and R2), two with approximately four years' experience (intermediate; R3 and R4), and three in their first to third year of residency (novice; R5, R6, and R7). After collecting their gaze data during diagnoses of two sets of CT images, we asked one expert abdominal radiologist to compare the gaze data using GazeDx.

Starting with the normal case, the expert radiologist first examined the spatial views and the similarity view in the overview tab, looking at an overall uniformity between readers. Next, he moved onto the multi-temporal view, where he noticed a similarity across all readers in terms of gaze pattern except R4. Upon examination of R4's gaze, he observed that R4 had not applied the liver window setting during diagnosis. By shortening the width of the multi-temporal view and checking the bar chart (Fig. 3C) using the mouse, he confirmed that R4 did not apply the liver setting as there was no bar for the liver setting in R4's bar chart.

During review of the overview tab, the expert came to have an interest in a group comparison based on expertise level: in particular, the indices of gazed slices over time. Using the comparison tab, he selected the expert group from the aggregation pane and the corresponding cell in the scatterplot matrix. From the histogram on the right of the interactive temporal chart below CIS, he noticed that the experts' gaze was directed to the upper abdomen compared to other groups. This was explained by the upper abdomen housing a number of major organs as compared with the lower abdomen. It indicated that experts tended to maintain their gaze on the area of concentrated organs during diagnosis.

Gaze comparison was next performed with the lesion case. He was interested in the gaze difference between experts and novices when diagnosing an apparent lesion—in this case, a large hepatic mass. After adding four individual view panes for two experts and two novices (R1, R2, R5, and R6), he expanded the axial images in all CISs. By scrolling systematically through the images, he found that experts' gazes were evenly distributed throughout the abdomen despite the overt presence of the hepatic mass (Fig. 8a). Conversely, novices' gazes were concentrated on the mass itself, with much less attention paid to other abdominal organs (Fig. 8b).

6 Discussion

After the case study, the experts suggested using GazeDx as a tool for training novices. This idea came to them while using the gaze data aggregation. We could build a type of gaze pattern model by aggregating gaze data from multiple expert radiologists. Such a gaze model can be used as an important reference in educating novices. By visualizing and comparing the gaze model from the experts as suggested by Vitak et al. [29], trainers (e.g., faculty radiologists) could teach trainees (e.g., residents) to read radiologic images systematically and effectively as experts. Further, GazeDx could be useful for general quality assurance, which assesses the diagnostic quality of any readers, including general radiologists. The similarity between the gaze model and gaze data from a reader, quantified by a proper similarity measure, could be used as an indicator of how well the reader covers diagnostically important regions.

GazeDx introduced a novel ROI-based filtering technique that utilizes anatomical segmentation results of organs (e.g., lung, liver) or lesions. Using this filtering, one of the experts effectively identified whether a reader actually paid attention to a certain organ (in our case study using abdomen images, the liver) during diagnosis. This technique is more advantageous when the gaze data are from cross-sectional volumetric images: without keeping a visual attention on an interesting region (i.e., organ, lesion), users can easily examine whether the gaze data is in or out of the region by applying this ROI-based filtering. In addition, this filtering, exploiting the segmentation results of important organs or lesions, helps users maintain the same medical context as in diagnosis during the gaze analysis.

In the evaluation phase of the case study, the expert radiologists actively used most of the components in GazeDx; however, they used the similarity matrix (Fig. 2A) and correlation matrix (Fig. 2B) less frequently. They examined those two components that provided overall comparison results at the beginning of the evaluation. But, after gaining overall insights on the dataset, they seldom used those components. Rather, they commented that instead of providing the similarity or correlation for the entire gaze data, it would be more helpful to show a partial similarity or correlation. Thus, it would be meaningful to extend those components to update the values upon users' selection of ROIs, showing partial comparison results within a specific organ or within a certain time span, as in ISeeCube [13].

As noted previously, one of the premises of eye tracking studies on medical diagnosis is that readers identify lesions using their foveal vision. However, previous studies have noted the significance of peripheral vision during diagnosis [4], and instances of this were noted during our case study. There were a number of gaze points existing in less diagnostically meaningful areas in a given window setting. According to the expert radiologist, these gaze points occurred when readers were using their peripheral vision. However, a prior work on chest X-rays [29] discussed that the difference in scan path of individuals is due to the difference in scanning strategy. Considering this discussion, it should be further investigated whether a reader actually used peripheral vision or not. If we could distinguish when readers use their peripheral vision during diagnosis, we could adopt existing computation models of peripheral vision [32] into GazeDx. However, knowing when peripheral vision is in action during visual exploration is also a challenging problem.

7 Conclusion and Future Work

In this paper, we presented an interactive visual analytics framework called GazeDx to support gaze pattern comparisons for volumetric medical images. We designed visual representations and interactions to compare multiple gaze data effectively, focusing on multidimensional aspects of the data while incorporating clinically relevant contextual information (especially windowing information) into the analysis process. The resulting framework showed efficacy in both explorative and comparative data analysis and in incorporation of a real world diagnosis environment. An enhanced scatterplot (namely CIS) and interactive temporal chart played meaningful roles in achieving the design goal. The two case studies conducted with two expert radiologists showed that GazeDx has the potential to be an effective research tool for eye tracking studies in medicine. Moreover, we gained meaningful ideas that could guide our design improvements for GazeDx. Our framework can be applied to other fields such as manufacturing field where similar stimuli (e.g., industrial CT images) are used for inspection of faults in mechanical parts.

The embedded familiar medical image representation provided users with useful additional contexts regarding the scatterplot in a CIS view, but the user interaction on the embedded representation could be further enriched. For example, when users rotate the representation with mouse interaction, we could even change the axes of the surrounding scatterplot to match the rotated representation. However, such an interaction should be restricted to the cases where the gulf of evaluation is not wide.

Acknowledgments

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No. NRF-2014R1A2A2A03006998), by Seoul National University Bundang Hospital Research Fund (No. 13-2014-001), and by the Hankuk University of Foreign Studies Research Fund of 2016. Bohyoung Kim and Jinwook Seo are the corresponding authors.

References

[1] M.S. Atkins, J. Fernquist, A.E. Kirkpatrick, and B.B. Forster, "Evaluating Interaction Techniques for Stack Mode Viewing," *Journal of Digital Imaging*, vol. 22, no. 4, pp. 369-382, 2009.

[2] T. Blascheck, K. Kurzhals, M. Raschke, M. Burch, D. Weiskopf, and T. Ertl, "State-of-the-Art of Visualization for Eye Tracking Data," *Proc. of EuroVis 2014 State-of-the-Art Reports*, 2014.

[3] T. Drew, M.L. Vo, A. Owal, F. Jacobson, S.E. Seltzer, and J.M. Wolfe, "Scanners and Drillers: Characterizing Expert Visual Search Through Volumetric Images," *Journal of Vision*, vol. 13, no. 10, article 3, 2013.

[4] S.M. Ellis, X. Hu, L. Dempere-Marco, G.Z. Yang, A.U. Wells, and D.M. Hansell, "Thin-Section CT of the Lungs: Eye-tracking Analysis of the Visual Approach to Reading Tiled and Stacked Display Formats," *European Journal of Radiology*, vol. 59, no. 2, pp. 257-264, 2006.

[5] D. Freedman and P. Diaconis, "On the Histogram as a Density Estimator: L2 Theory," *Zeitschrift für Wahrscheinlichkeitstheorie und Verwandte Gebiete*, vol. 57, no. 4, pp. 453-476, 1981.

[6] M. Gleicher, D. Albers, R. Walker, I. Jusufi, C.D. Hansen, and J.C. Roberts, "Visual Comparison for Information Visualization," *Information Visualization*, vol. 10, no. 4, pp. 289-309, 2011.

[7] Holmqvist, M. Nyström, R. Andersson, R. Dewhurst, J. Halszka, and J. van de Weijer, *Eye Tracking: A Comprehensive Guide to Methods and Measures*. Oxford University Press, pp. 231-248, 2011.

[8] H. Hong, J. Lee, and Y. Yim, "Automatic Lung Nodule Matching on Sequential CT Images," *Computers in Biology and Medicine*, vol. 38, no. 5, pp. 623-634, 2008.

[9] B. Kim, B. Lee, and J. Seo, "Visualizing Set Concordance with Permutation Matrix and Fan Diagram," *Interacting with Computers*, vol. 19, no. 5-6, pp. 630-643, 2007.

[10] H.L. Kundel, and P.S. La Follette, Jr., "Visual Search Patterns and Experience with Radiological Images," *Radiology*, vol. 103, no. 3, pp. 523-528, 1972.

[11] H.L. Kundel, C.F. Nodine, E.F. Conant, and S.P. Weinstein, "Holistic Component of Image Perception in Mammogram Interpretation: Gaze-tracking Study," *Radiology*, vol. 242, no. 2, pp. 396-402, 2007.

[12] K. Kurzhals, B. Fisher, M. Burch, and D. Weiskopf, "Evaluating Visual Analytics with Eye Tracking," *Proc. Workshop on Beyond Time and Errors: Novel Evaluation Methods for Visualization (BELIV '14)*, pp. 61-69, 2014.

[13] K. Kurzhals, F. Heimerl, and D. Weiskopf, "ISeeCube: Visual Analysis of Gaze Data for Video," *Proc. ACM Symp. Eye Tracking Research and Applications (ETRA '14)*, pp. 43-50, 2014.

[14] B.C. Kwon, B. Fisher, and J.S. Yi, "Visual Analytic Roadblocks for Novice Investigators," *IEEE Symp. Visual analytics Science and Technology (VAST '11)*, pp. 3-11, 2011.

[15] D. Lala and A. Nakazawa, "Heat map Visualization of Multi-slice Medical Images through Correspondence Matching of Video Frames," *Proc. ACM Symp. Eye Tracking Research and Applications (ETRA '16)*, pp. 119-122, 2016.

[16] J. Lee, N. Kim, H. Lee, J.B. Seo, H.J. Won, Y.M. Shin, Y.G. Shin, and S.-H. Kim, "Efficient Liver Segmentation Using a Level-Set Method with Optimal Detection of the Initial Liver Boundary from Level-Set Speed Images," *Computer Methods and Programs in Biomedicine*, Vol. 88, no. 1, pp. 26-38, 2007.

[17] D. Manning, S. Ethell, T. Donovan, and T. Crawford, "How Do Radiologists Do It? The Influence of Experience and Training on Searching for Chest Nodules," *Radiography*, vol. 12, no. 2, pp. 134-142, 2006.

[18] K. Perlin, and D. Fox, "Pad: An Alternative Approach to the Computer Interface," *Proc. ACM SIGGRAPH Conf. Computer Graphics and Interactive Techniques (SIGGRAPH '93)*, pp. 57-64, 1993.

[19] T. Pfeiffer, "Measuring and Visualizing Attention in Space with 3D Attention Volumes," *Proc. ACM Symp. Eye Tracking Research and Applications (ETRA '12)*, pp. 29-36, 2012.

[20] P. Phillips, D. Manning, T. Donovan, T. Crawford, and S. Higham, "A Software Framework for Diagnostic Medical Image Perception with Feedback, and a Novel Perception Visualization Technique," *Proc. SPIE-Medical Imaging 2005,* vol. 5749, pp. 572-580, 2005.

[21] W.M. Reed, J.T. Ryan, M.F. McEntee, M.G. Evanoff, and P.C. Brennan, "The Effect of Abnormality-Prevalence Expectation on Expert Observer Performance and Visual Search," *Radiology*, vol. 258, no. 3, pp. 938-943, 2011.

[22] J. Seo, and B. Shneiderman, "A Rank-by-Feature Framework for Interactive Exploration of Multidimensional Data," *Information Visualization*, vol. 4, no. 2, pp. 99-113, 2005.

[23] J. Seo, and B. Shneiderman, "Knowledge Discovery in High-Dimensional Data: Case Studies and a User Survey for the Rank-by-Feature Framework," *IEEE Trans. on Visualization and Computer Graphics*, vol. 12, no. 3, pp. 311-322, 2006.

[24] B. Shneiderman, "The Eyes Have It: A Task by Data Type Taxonomy for Information Visualizations," *IEEE Symp. Visual Languages*, pp. 336-343, 1996.

[25] B. Shneiderman, and C. Plaisant, "Strategies for Evaluating Information Visualization Tools: Multi-dimensional In-depth, Long-term Case Studies," *Proc. AVI Workshop Beyond Time and Errors, Novel EvaLuation Methods for Information Visualization (BELIV '06)*, pp. 38-43, 2006.

[26] H. Song, J. Yun, B. Kim, and J. Seo, "GazeVis: Interactive 3D Gaze Visualization for Contiguous Cross-Sectional Medical Images," *IEEE Trans. on Visualization and Computer Graphics*, vol. 20, no. 5, pp. 726-739, 2014.

[27] S. Stellmach, L. Nacke, and R. Dachselt, "Advanced Gaze Visualizations for Three-dimensional Virtual Environments," *Proc. ACM Symp. Eye Tracking Research and Applications (ETRA '10)*, pp. 109-112, 2010.

[28] H.Y. Tsang, M. Tory, and C. Swindells, "eSeeTrack—Visualizing Sequential Fixation Patterns," *IEEE Trans. on Visualization and Computer Graphics*, vol. 16, no. 6, pp.953-962, 2010.

[29] S.A. Vitak, J.E. Ingram, A.T. Duchowski, S. Ellis, and A.K. Gramopadhye, "Gaze-Augmented Think-Aloud as an Aid to Learning," *Proc. ACM SIGCHI Conf. Human factors in Computing Systems (SIGCHI '12)*, pp. 2991-3000, 2012.

[30] Z. Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli, "Image Quality Assessment: From Error Visibility to Structural Similarity," *IEEE Trans. on Image Processing*, vol. 13, no. 4, pp. 600-612, 2004.

[31] J.M. West, A.R. Haake, E.P. Rozanski, and K.S. Karn, "eyePatterns: Software for identifying patterns and similarities across fixation sequences," *Proc. ACM Symp. Eye Tracking Research and Applications (ETRA '06)*, pp. 149-154, 2006.

[32] J. Wu, C. Zheng, X. Hu, and F. Xu, "Realistic Simulation of Peripheral Vision Using an Aspherical Eye Model," *Proc. Eurographics* 2011, pp. 37-40, 2011.