M. Herczeg & M. C. Kindsmüller (Hrsg.): Mensch & Computer 2008: Viel Mehr Interaktion.
München: Oldenbourg Verlag, 2008, S. 247-256

Interaction Techniques for Case Selection in Medical Computer Based Training Systems

Ragnar Bade[1], Jeanette Cordes[2], Maik Mewes[2], Bernhard Preim[2]

MeVis BreastCare GmbH & Co.KG[1]
Simulation and Graphics, University of Magdeburg[2]

Abstract

The vast majority of medical computer-based training (CBT) systems aim at problem-oriented case based training. A crucial issue in the design of CBT systems is the selection of appropriate cases for a representative collection of medical cases. Another issue is the presentation of those case collections to the users. With simple numbered list (e.g. Case 1, Case 2, …) goal-oriented case selection driven by learning objectives and clinical problems is not feasible. In this paper, we investigate interactive information visualization techniques, which promise a more sophisticated case selection. We analyze, compare, and empirically evaluate their appropriateness for case selection in medical CBT systems. Whereas analysis results show superiority of interactive information visualization techniques, the empirical evaluation reveals preference of the target group for simple tabular representations.

1 Introduction

The vast majority of medical computer-based training (CBT) systems aim at problem-oriented case-based training. Reflecting clinical practice, case-based training confronts learners with a patient, its clinical history and a specific clinical (diagnostic, treatment planning, or surgical) problem. A major quality aspect of CBT systems is a representative collection of clinical cases (e.g. reflects all relevant types and variants of diseases, therapies, and complications). Nevertheless, the importance of the case collection is not well reflected by the user interface of state of the art CBT systems. Common CBT systems provide a simple numbered list (e.g. Case 1, Case 2, …) for case selection. Such simple lists do not support efficient goal-oriented selection of training cases, which is crucial for self-improvement and further training of professionals (e.g. surgeons). Here individuals themselves motivate and direct their training. This is often driven by individual interest or current demands (e.g. preparation for a specific surgical procedure).

We hypothesize that a lack of efficient facilities for goal-oriented selection of training cases diminishes acceptance of CBT systems in further surgical education. Following this hypothesis, we investigate interactive visualization techniques to improve case selection in CBT systems. In Section 2, we analyze the case selection task in medical CBT systems and derive requirements for appropriate and efficient case selection. We identify general case selection criteria and common case selection scenarios, which we will illustrate with application specific examples borrowed from the LiverSurgeryTrainer and a SpineSurgeryTrainer (Cordes et. al 2007). Both are novel CBT systems still under development with focus on surgery planning. Since the identified case selection scenarios exhibit many similarities to common tasks in information visualization and visual analytics, we analyze and compare several interactive visualization techniques from that domain in Section 3. This analysis highlights the superiority of advanced visualization techniques for case selection in comparison to numbered lists and simple tabular representations. In contrast to these findings, our subsequent empirical evaluation (Section 4) reveals a preference of physicians for "conservative" case selection techniques (e.g. simple tables). This leads us to a Most Advanced, Yet Acceptable case selection interface via Faceted Browsing within tables.

2 Requirements for Case Selection Techniques in Case-based Training in Medicine

An initial number of 5 to 15 representative cases are quite common for medical CBT systems. This number grows with age and popularity of the systems. The authoring of new cases with editing and preparation of multimedia content (especially for medical CBT systems) is very complex (see Mirschel 2004). Thus, in general the number of cases remains below or around a representative collection of 100 cases.

2.1 Case Selection Criteria

We distinguish between three groups of case selection criteria (see also Mirschel 2004):

Domain specific criteria are directly related to the learning objectives and the CBT system's medical domain. The type, location, and degree of diseases are common domain specific criteria. In case selection scenarios, these criteria are crucial to identify and select training cases that deal with a specific medical problem. For example, the number, location, size, and type of tumors are relevant domain specific criteria in applications for tumor treatment (e.g. the LiverSurgeryTrainer). The location and level of herniated disk dislocation are domain specific criteria in the SpineSurgeryTrainer.

Patient related criteria include properties like patient's name, age, sex and portrait. These criteria are important to remember, identify and communicate patients/cases in a natural and familiar way.

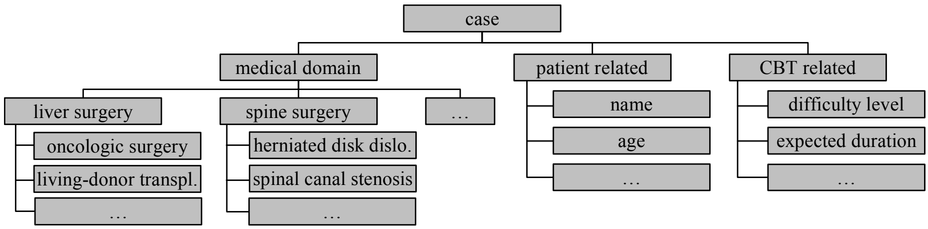

Figure 1: Hierarchical categorization of case properties in medical CBT systems

Training system related metadata for each case like degree of difficulty and the expected amount of time required to run through and complete a case.

Figure 1 illustrates the hierarchical categorization of case properties in CBT systems with respect to the discussed criteria groups. Hence, an appropriate visualization technique for case selection should support this diversity of parameters per case and ideally allows hierarchical grouping.

2.2 Case Selection Scenarios

In self-motivated and further education, learners direct their learning according to individual interest or current demands. In common, those learners search for cases that fit their current needs or interests. For example, they may search for the most recent case they started to process, a case that best fits a real patient, or a case that can be passed within a give time slot.

We identified four general types of Case Selection Scenarios (see also Mewes 2008):

Linear Case Processing is the simplest case selection scenario, where learners process all cases in the default order provided by the CBT system. Since this actually does not require interactive case selection, it is commonly used in novice training. It plays a minor role in self-motivated and further education and thus it is not discussed any further.

Simple Selection Scenarios involve the search for one or more cases with respect to a small manageable number of selection criteria (e.g. searching for a case of herniated disk dislocation with a level of transligamentous extrusion in the SpineSurgeryTrainer). This commonly may require only a few sorting operations in a table.

Complex Selection Scenarios involve several case selection criteria and may require comparison between cases (e.g. a learner searches for already passed cases of hepatic resection of hepato cellular carcinoma with his/her poorest results). This may require a wide variety of interactions like sorting, filtering, and comparing of cases. Appropriate techniques for case selection may provide facilities for zooming and filtering.

Explorative/Overview Scenarios involve any available selection criteria to explore, compare, and gain insight into the case collection. For example, a learner who uses a specific CBT system for the first time may explore the case collection of that CBT system to get an impression of the medical problems covered by this CBT system. Furthermore, this scenario applies for case authors that search for empty ore weakly filled areas of the parameter domain to add cases that fill the gap. These scenarios may heavily benefit from advanced zooming, filtering, and focus+context techniques.

While we actually list linear case processing for the sake of completeness here, an ideal interactive case selection technique should support the three remaining scenario types. Generalizing the case selection task with respect to the described criteria and scenarios, we recognize much similarity to common tasks in information visualization and visual analytics. These domains deal, among other things, with the navigation and exploration of multivariate datasets. A case collection is actually a database with multivariate data. Furthermore, the number of variables per dataset (here: case selection criteria) as well as the number of datasets in a database (here: cases in a case collection) are comparable. Thus, interactive visualization techniques from the information visualization and visual analytics domain may be feasible for case selection in medical CBT systems.

2.3 Value of Case Selection

In this paper, we state that an appropriate facility for case selection plays an essential role for user acceptance. If learners cannot select a case that fits their current learning interests, they will not use the system. Furthermore, motivation and probability of repeated use may decrease, if learners realize only in a late state that a processed case dose not fit the expected learning objectives.

Nevertheless, the interactive case selection is only a small part of a CBT system and it is performed beside the direct objective (education and training) of these systems. Thus, appropriate case selection techniques should immediately allow learners to select cases efficiently and target-oriented. In this context, immediately means that learners should not need separate training to manage the case selection.

3 Analytic Comparison of Advanced Visualization Techniques for Case Selection

The analysis of the case selection task and the identification of requirements for appropriate case selection techniques imply that simple numbered lists (e.g. Case 1, Case 2, …) are not appropriate for efficient and comfortable case selection. In the following, we start with the analysis of common "conservative" techniques used for case selection and step towards more advanced techniques borrowed from information visualization and visual analytics.

Lists of simple numbered cases as well as lists with full text descriptions without interactive filtering facilities are quite common for case selection in medical CBT systems (see Figure 2 (top)). Those lists are manageable only if they do not exceed a number of ca. 15 cases. With up to 100 entries, even *Simple Selection Scenarios* will frustrate learners, thus those lists are completely inappropriate for efficient target-oriented case selection.

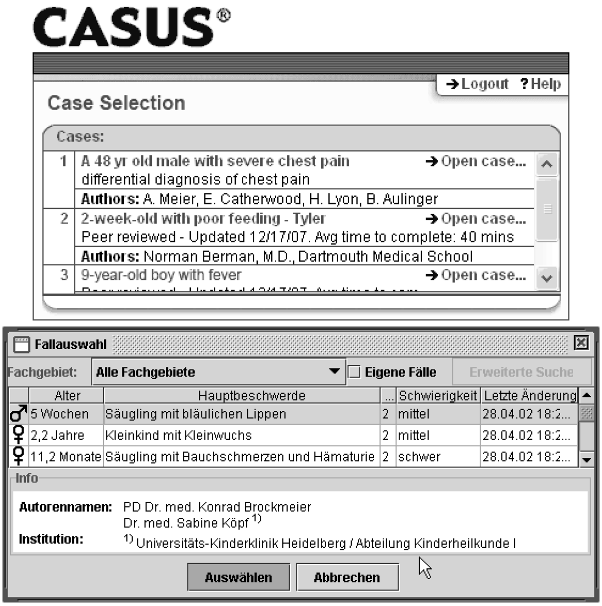

Figure 2: Case selection in common CBT systems: (top) case selection list in CASUS (Instruct AG 2008, modified), (bottom) case selection table in CAMPUS (Heilbronn University 2008, modified)

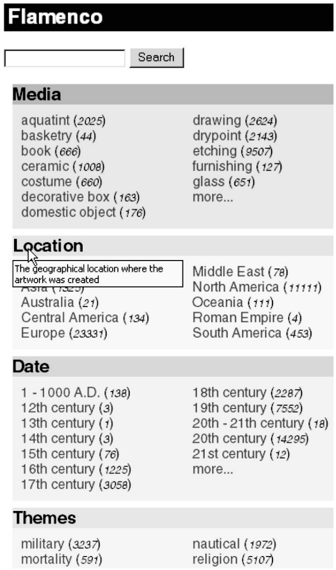

Figure 3: Faceted Browser "Flamenco" to search for fine art images with parameters (media, location, ...) and available values (Yee et al. 2003, modified)

Tables are quite common in a broad range of applications and CBT systems (see Figure 2 (bottom)). Thus, a vast majority of users is familiar with sorting and selection of a table's rows and columns. The main drawbacks of tables are the pure textual representation of data and the huge amount of space required for each dataset. Pure text representations do not allow efficient comparison of cases as well as detection of outliers etc. Furthermore, tabular representations of case collections most likely require horizontal and vertical scrolling that hamper the recognition of and the comparison between cases. Hence, tables may be appropriate for efficient case selection in *Simple Selection Scenarios* but not for *Complex Selection* and *Explorative/Overview Scenarios*.

Faceted Browsers (FBs) represent an interactive search interface for databases (Yee et al. 2003). A FB initially presents a selected number of dataset parameters (here: case selection criteria) and available values. For example, in Figure 3 parameters: themes (military, religious, ...), time periods (12th … 21st century) and media (etching, ceramic, …) are used in a database of fine arts images. By selection of one of the available values of all parameters, the database is filtered for datasets of that parameter value. Then the user interface adapts to the filtered subset and presents only those parameters and values in this subset.

FBs support *Simple Selection Scenarios* and a subset of *Complex Selection Scenarios* due to the easy to use filter mechanism and the numbered amount of datasets with a specific parameter value (see Figure 2, Yee et al. 2003). Since context is lost during the interactive filtering, FBs may not allow efficient case selection for *Explorative/Overview Scenarios* and some *Complex Selection Scenarios* that require a serious amount of case comparison.

The **Table Lens (TL)** integrates graphical data representation and focus+context visualization into tables (Rao & Card 1994). TLs visualize each data value in the table by a small colored bar. The bar's width graphically represents the value of an underlying quantitative data value or its color and horizontal location encodes qualitative and nominal data, respectively. Since these bars require less screen space, TLs can visualize much more datasets and data values compared to traditional tables. Furthermore, sorting of data values yield a bar chart representation of the data value distribution (see Figure 4). Besides sorting of rows and columns, additional interaction facilities allow zooming of interesting parts. Data values in the current zoom/focus region(s) (covered by (a) virtual lens(es)) are presented textually and visually in the context of the other data. Hence, TLs allow comfortable case comparison and overviews, which support *Complex Selection Scenarios* and *Explorative/Overview Scenarios*.

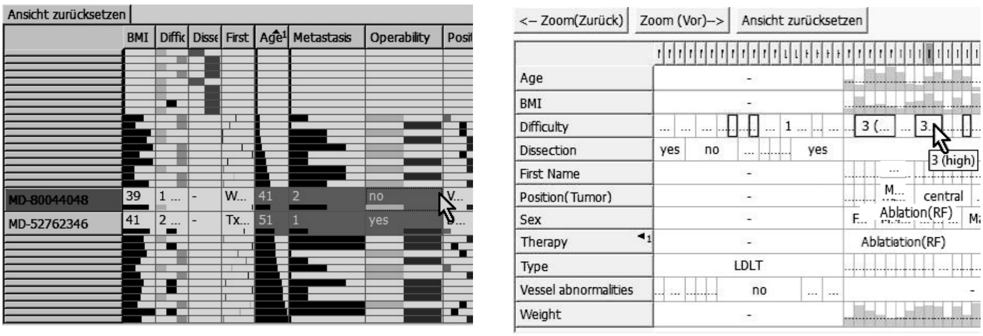

Figure 4: Case selection via: (left) Table Lens (33 cases) and (right) InfoZoom (87 cases) (Mewes 2008, modified)

With **InfoZoom (IZ)** there is no strict partitioning of columns and rows in a table (Spenke 2001). IZ switches rows and columns, so that a column represents each dataset/case. Then in each row, neighboring columns with the same data value are connected. Thus, each row has a different number of columns (see Figure 4 right). The size and number of the columns in a row then visualizes the value distribution of a specific parameter over all datasets/cases in the database. Furthermore, IZ visualizes the data values in each row by line charts, similar to the bar charts of the TL.

Beside standard sorting and reordering of rows, IZ provides interactive zooming and filtering facilities. Users can mark different parameter values and zoom into a subset of the database with cases of that parameter values. Different publications illustrate that the IZ is highly capable for visual exploration and analysis of databases in the financial, formula one racing and medical domain (Spenke & Beilken 1999, 2000; Spenke 2001). Due to the compressed visualization and interactive filtering facilities, IZ may efficiently support *Complex Selection Scenarios* and *Explorative/Overview Scenarios* in CBT systems as well.

Parallel Coordinates (PC) (Inselberg 1990, 1997), draw for each parameter a separate coordinate axis in parallel next to each other. A dataset (case) and its parameter values are then represented by a line that crosses each axis at that point that represents the value of that parameter (see Figure 5). Interaction techniques allow to highlight and filter all lines (cases) within a given value range of a parameter, for example, by selecting the desired region at the parameter's axis (see Martin & Ward 1995). Filtering and the visual representation of each case as a line allow interactive exploration, fast overview, and intuitive comparison (e.g. just the similarity of the track of two lines illustrates intuitively the similarity of two datasets). Thus, PCs may support *Complex Selection Scenarios* and *Explorative/Overview Scenarios* in CBT systems.

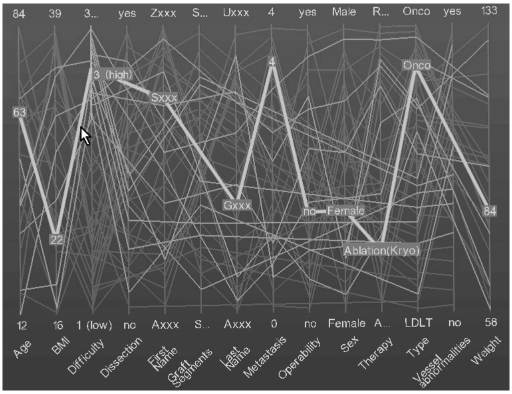

Figure 5: Case selection via Parallel Coordinates (46 cases). The user filtered for cases of difficulty level 3-(high) highlighted (pale red). The case under the mouse pointer gets highlighted (green). (Mewes 2008, modified)

The results of the analytic investigation of tables, FB, TL, IZ, and PC indicate a superiority of TL, IZ, and PC. Furthermore, the results of former evaluations demonstrate the effectiveness of these techniques in information visualization and visual analytics (e.g. Rao & Card 1994, Spenke 2001, González & Kobsa 2003, Brunsdon et. al 1998).

Nevertheless, from these studies we can draw no definitive conclusions for case selection tasks. Main differences are the moderate number of cases, the high number of case parameters (selection criteria) as well as the target group and the circumstances that data analytics is not the main application here. Furthermore, separate training of these techniques is not feasible here, thus immediate usability is crucial. The high complexity and lack of familiarity of the advanced visualization techniques may decrease their usability for case selection in medical CBT systems. Hence, this should be empirically evaluated in that context.

4 Empirical Evaluation of Interactive Visualization Techniques for Case Selection

In Section 3, we found that the TL, IZ, and PC support all three relevant case selection scenarios. Nevertheless, their appropriateness for immediate use (without separate training) and efficient target-oriented case selection by physicians (target group) needs a thorough investigation.

4.1 Design and Procedure

Aiming at physicians, surgeons, consulting surgeons, and senior surgeons we developed a downloadable application that could be downloaded and performed individually by each participant. This is crucial to recruit domain professionals in consideration of their sparse spare time. Data was automatically recorded and emailed to us. In a few cases, informal discussions after the evaluation were held.

The study used a within-subject design. Each participant had to use tables (T), TL, IZ, and PC in a randomize order. Initially, all participants had to assess their level of experience with each visualization technique and they had to provide information about their background and qualification (e.g. medical science, computer science, …). Then, for each visualization technique, a block of five case selection tasks had to be processed. Before each block, a short video walks through all features of the current visualization technique (e.g. sorting, reordering of columns, filtering, …). After passing all blocks participants had to assess the appropriateness as well as the subjective efficiency of all visualization techniques. After each case selection task and at the end, participants could add free-text comments. The whole procedure took about 45 minutes.

For each visualization technique, we presented five tasks, representing different case selection scenarios. As database we used the LiverSurgeryTrainer case collection, added artificial cases, and took subsets of different size of this collection for the different tasks. Thus, the case collection varied between tasks but we kept it constant for each task between the different visualization techniques. Furthermore, we used a fixed order of the tasks: (1) easy to solve *Simple Selection* task with a collection of 46 cases, (2) difficult *Complex Selection* task and 86 cases, (3) easy *Complex Selection* task and 31 cases, (4) tuff *Explorative/Overview* task with 91 cases, and finally (5) again a *Simple Selection* task with 41 cases.

4.2 Results

Data from 31 participants (9 physicians and 22 computer scientists) was used in the analysis. Comparing the time used, the computer scientists were slightly faster than the physicians with all visualization techniques (Figure 6). While there are only slight differences in time used for the different visualization techniques in the group of computer scientists, the study reveals much bigger differences in time used in the group of physicians. Physicians performed best with PC, followed by IZ and tables. Their performance was worst with TL. Actually the physicians were significantly faster with PC than with TL ($n=7$, $df=6$, $t= 3.01$, $p<0.05$). The difference between tables and PC was not significant but showed the same trend ($n=7$, $df=6$, $t=1.95$, $p<0.1$). Thus, the study revealed that PC decreases time used for case selection tasks in the target group, but none of the techniques considerably quickens case selection in the group of computer scientists.

In a final step, participants were asked for that visualization technique which they would recommend for case selection in medical CBT systems. As illustrated in Figure 7, computer scientists most likely recommended IZ, whereas physicians preferred tables. Only one physician recommends PC. This subjective rating contradicts the quantitative results.

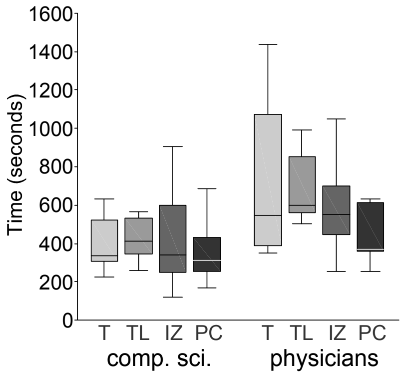

Figure 6: Box-plots of time used to complete all case selection tasks with separate results for computer scientists and physicians

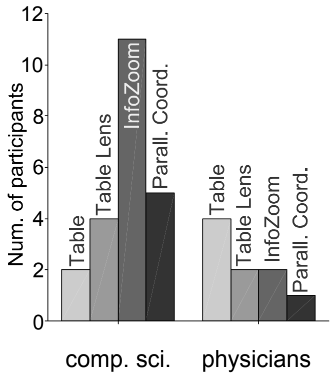

Figure 7: Number of participants that prefer and would recommend the different visualization techniques for case selection

4.3 Discussion

Even physicians were faster with PC than with the other techniques, they preferred tables for case selection and strongly argue for that in comments on the study. In free-text comments and informal interviews, physicians criticized the unfamiliarity and the higher degree of mouse interaction (e.g. clicks) required by the advanced visualization techniques compared to the more familiar tables. Furthermore, participants of this study requested for filtering techniques as provided by FB (see Section 3.3).

5 Conclusion

In this paper, we draw attention to efficient case selection in medical CBT systems. Since we hypothesize that a lack of efficient facilities for goal-oriented selection of training cases diminish acceptance of CBT systems in further surgical education, we investigated and empirical evaluate different visualization techniques for case selection. Analytic results clearly favor Table Lens, InfoZoom, and Parallel Coordinates, whereas concerning task completion time the target group performed best with Parallel Coordinates. Nevertheless, subjective rating and user satisfaction of the target group clearly favor tables over all other visualization techniques. Reasons may be the familiarity of the target group with tables and a “conservative” attitude towards novel visualization techniques. Following the MAYA-principle from industrial design (e.g. see Hekkert et. al 2003), we favor a Most Advanced, Yet Acceptable case selection interface based on a tabular presentation of available cases in combination with Faceted Browsing facilities for case selection in CBT systems.

References

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1998). *An Investigation of Methods for Visualising Highly Multivariate Datasets*. Technical report, AGOCG.

Cordes, J., Mühler, K., Oldhafer, K. J., Stavrou, G., Hillert, C., & Preim, B., (2007) Szenariobasierte Entwicklung eines chirurgischen Trainingssystems. *11. Workshop der GMDS AG)*, 17-30.

Heilbronn University (2008). *CAMPUS Teaching and Learning System*. http://www.medicase.de/common/media/classicplayer/player_nosound.html. last updated 04/20/2006, last visited 03/06/2008.

Hekkert, P., Snelders, D., & van Wieringen, P. C. W. (2003) 'Most advanced, yet acceptable': Typicality and novelty as joint predictors of aesthetic preference in industrial design. *British Journal of Psychology, 94*, 111–124.

Inselberg, A. (1990). Parallel Coordinates: a tool for visualizing multi-dimensional geometry. In *IEEE Vis'90*, 361–378.

Inselberg, A. (1997). Multidimensional detective. *In IEEE InfoVis'97*, 100–107.

Instruct AG (2008). CASUS Online, http://clipp.instruct.de/player/app/cases2.html, Version 6.0.0b1, last visited 03/06/2008.

Martin, A. R. & Ward, M. O. (1995). High Dimensional Brushing for Interactive Exploration of Multivariate Data. *In IEEE VIS'95*, 271-278.

Mewes, M. (2008). *Implementierung und Evaluierung von Visualisierungs- und Interaktionstechniken in Patientendatenbanken*. Master's thesis, Dept. of Computer Science, University of Magdeburg.

Mirschel, S. (2004). *Erstellung eines Prototypen für ein fallbasiertes Lernsystem in der Leberchirurgie*. Master's thesis, Dept. of Computer Science, University of Magdeburg.

Rao, R. & Card, S.K. (1994). The Table Lens: merging graphical and symbolic representations in an interactive focus + context visualization for tabular information. In *ACM CHI '94*, 318–322.

Spenke, M. & Beilken, C. (1999). *Visual, Interactive Data Mining with InfoZoom – the Financial Data Set. 'Discovery Challenge', Principles and Practice of Knowledge Discovery in Databases*.

Spenke, M. & Beilken, C. (2000). InfoZoom – analyzing formula one racing results with an interactive data mining and visualization tool. In *Management information systems, vol.2*, 455-464.

Spenke, M. (2001). Visualization and interactive analysis of blood parameters with InfoZoom. In *Artificial Intelligence in Medicine, 22*(2), 159-172.

Yee, P., Swearingen, K., Li, K., & Hearst, M. (2003) Faceted Metadata for Image Search and Browsing. In *ACM CHI'03*, 401-408.