

# Towards Multi-User Multi-Level Interaction

Marc Streit, *Student Member, IEEE*, Hans-Jörg Schulz,  
Dieter Schmalstieg, *Member, IEEE*, and Heidrun Schumann

**Abstract**— The necessity of incorporating experts from various domains in order to understand and draw meaningful conclusions from complex and massive amounts of data is an undisputed fact. In order to create and effectively use such a collaborative information workspace it is vital to understand the interaction processes involved. Established, high-level interaction patterns work well for single user, single data source scenarios. However, they cannot simply be applied to the collaborative analysis of heterogeneous data. In this paper we propose a *Multi-User Multi-Level Interaction* concept which differentiates between operations in view and data domain while considering the relations and transitions between data on different levels of granularity. Hence, the users' interaction can be formalized as a seamless path of navigation. This in turn helps to gain a deeper understanding of the interaction process and allows to efficiently steer it to accelerate data analysis. We demonstrate the applicability and benefits of our concept by means of a clinical use case scenario which aims at finding the best treatment for cancer patients.

**Index Terms**—Interaction, Information Seeking Mantra, visual analysis, collaboration, multi-display environment.

## 1 MOTIVATION AND BACKGROUND

Interdisciplinary applications require the integration of domain experts from various fields in the data analysis process. Each of these experts has a specific perspective on the data, pays attention to different details, and reasons along the lines of his/her own particular domain. Organizing this multifaceted interplay between large amounts of complex data, multiple domain experts from different areas, and the laborious back and forth between exploration and confirmation of the analysis process is a challenging task. This task is what collaborative environments have set out to support and to advance, as the results that can be gained from an interdisciplinary, collaborative data analysis outweigh technical problems. One essential problem is interaction with the complex, heterogeneous data spaces in these environments: due to the multidisciplinary nature, data is available in various forms (full text documents, images, statistical tables, etc.), in various representations (tabular, tag clouds, visualizations, etc.), and on multiple levels of detail. Each of which is meaningful to at least one of the participating domain experts and all of them need to be integrated into one seamless, interactive analysis process to allow fruitful collaboration.

State-of-the-art applications and interaction paradigms mostly focus on single user interaction and are tailored to one specific application domain. Yet, for a scenario as described above the established tried and tested interaction patterns do not suffice. Hence, new multi-user interaction concepts for data from different domains and on multiple levels of detail must be established. We do so in this paper by introducing a novel concept that addresses the challenges posed by multi-user, multi-level interaction. The applicability of this concept is exemplified by the analysis of clinical data from cancer patients in a collaborative information workspace described in the companion paper by Waldner et al. [12] (see Figure 1). In this case, biomedical experts from different fields come together to collaboratively analyze their respective data to make a joint decision on a patient's diagnosis and further treatment plans. In detail, the experts and their data are:

- **the oncologist:** CT/MR-scan of the tumor, treatment history
- **the pathologist:** tissue samples of the tumor autopsy
- **the geneticist:** data on the genome-wide regulation of the genes
- **the biologist:** genes' regulation in the context of the cellular processes, i.e. pathway graphs

Although each expert has his/her core field of expertise (i.e. data),

they often also have profound knowledge in related domains. The data forms a natural hierarchy shown in Figure 2. This illustrates the multi-level aspect of the data, emerging naturally from the interdisciplinary setup. This is not a special case, but occurs frequently, as other examples of such hierarchies show – e.g., of the assembly hierarchy of a whole network of electronic devices down to the individual logic gate in the field of electrical engineering [1] or the refinement process in software engineering from the specification documents down to the actual code.

The collaborative workspace being utilized by our use case is an adaptation of the Caleydo Biomedical Visualization Framework (<http://www.caleydo.org>) [9, 10] for the Deskothèque multi-display environment [5]. Similar setups have been described, e.g., for an office environment called “*The office of the future*” [6] or for an entertainment scenario called “*Smart Living Room*” [3]. Because of this diversity of possible applications, this paper discusses not only the implications of our concept for our special use case, but also its consequences for these setups in general.

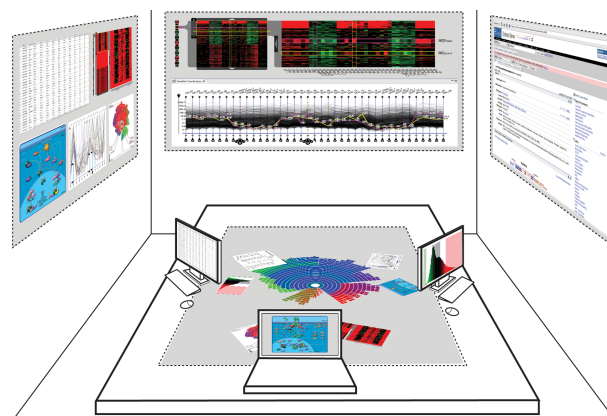


Fig. 1. Illustration of a collaborative information visualization scenario in a multi-display environment [12].

## 2 MULTI-USER MULTI-LEVEL INTERACTION

Most of the common data exploration patterns work well in a single user, single data source scenario. A particularly successful example is Shneiderman's *Information Seeking Mantra* (Overview first - zoom and filter - details on demand) [8]. While this pattern is of course also valid for more than one user and more than one data source, the characteristic properties of these scenarios are not captured by it. The two most crucial ones are:

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- *Marc Streit and Dieter Schmalstieg are with Graz University of Technology, E-mail: {streit,schmalstieg}@icg.tugraz.at.*
  - *Hans-Jörg Schulz and Heidrun Schumann are with University of Rostock, E-mail: {hjschulz,schumann}@informatik.uni-rostock.de.*

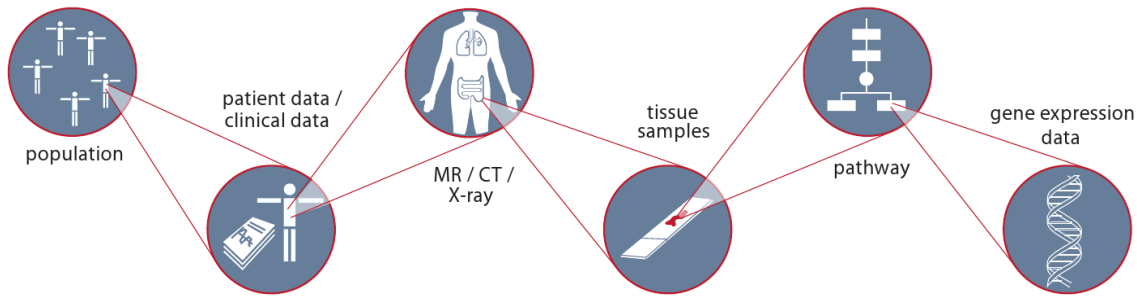


Fig. 2. Patient-centered data hierarchy starting with a population on the top and going down to the genes' regulation data of each patient. The detail of one level is the overview of the next level beneath.

- **Seamless navigation**, which describes the possibility to browse the data smoothly across the boundaries of the individual data sources. This property is important, as interaction patterns have to bridge the different data domains to ensure seamless navigation. For the *Information Seeking Mantra*, this means that for example, the detail of one data domain is the overview of another one and vice versa.
- **Integral data analysis**, meaning the common practice to intertwine visual and algorithmic analysis in the spirit of *Visual Analytics*. For Shneiderman's Mantra, e.g., the non-visual "zoom out" could be an aggregation operation, whereas the "zoom in" could be a query refinement. The users can then choose whether to do a visual analysis or to switch to the available algorithmic tools and use them in combination with the visual ones, according to which are the best fit to the analysis task at hand.

The latter of these two properties has been addressed by Keim in his *Visual Analytics Mantra* (Analyze first - show the important - zoom, filter and analyze further - details on demand) [4] and of course it also remains valid in the context of multiple users and data sources. Yet, one of the most important points for our scenario, namely the integration of the visualization from overview to detail across all data domains remains unspecified by Keim's mantra, making it not straight-forward to be applied here. Hence, this section embraces the *Information Seeking Mantra*, as well as the *Visual Analytics Mantra* and proposes a novel interaction concept that captures the above two points. The applicability of our concept and its practical benefits are discussed in a concrete biomedical application case.

## 2.1 Concept

The main idea, which is outlined in Figure 3, is to make a distinction not only between data and view domain [7], but also between the different application levels. This way, jumps and switches between data and view, and also between different application levels can be expressed by the concept. This is important, as different users in our collaborative scenario are responsible for different parts of the analysis and different levels of the data.

Basically, the concept applies the steps of the *Information Seeking Mantra* to each data level in the application hierarchy. And it does this not only for the view domain, but also for the data domain. This allows to differentiate in which domain operations are performed and yields the following categorization:

- **View operations** only affect the visual representation of the data. Examples are distortion based lens effects, geometric zoom, etc.
- **Data operations** affect the data by algorithmic means, from simple numerical operations to complex data mining methods.
- **Data+View operations** affect both domains. An example is any "Visual Query" mechanism that is triggered by the user in the visual representation, which carries out a query in the data domain, and reflects the result as a change in the view domain.

As a consequence, the overall multi-user interaction process of the different users' operations forms a path up and down the application

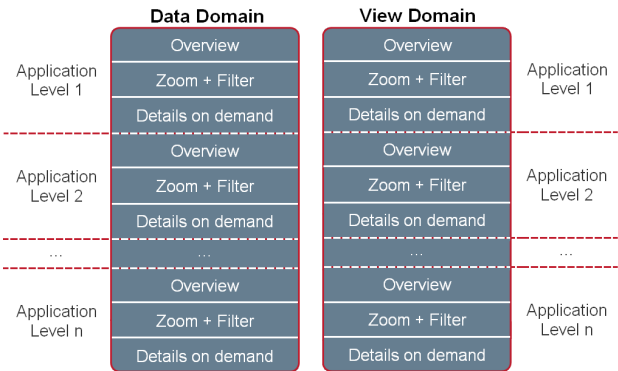


Fig. 3. The *Multi-User Multi-Level Interaction* concept separates the view and data domain while considering the relations and transitions between the application levels.

levels and across the data and view domain. The seamless transition between multiple application levels is ensured by the assumed hierarchical nature of the data sources. The stippled lines in Figure 3 illustrate this natural shift from one level into the next.

Conceptually, all analysis paths across multiple domain levels (in our case from the population of patients down to their individual gene expressions) and across multiple interaction levels therein (from overview to detail) are possible. However, in real world scenarios restrictions for the navigation are introduced. The constraints can either be implied by the nature of the data (e.g., missing data) or by the role of the analyst (e.g., security clearances). The knowledge about the constraints allows a guidance of the users through the domains and levels. In some situations multiple paths of interaction lead to the same result for the users. While one path could be potentially faster, another one might better support the users at keeping their mental map. In such cases the application designer can actively guide the user by promoting certain interaction paths, but without denying any of the other possibilities. While for example an expert user would take the faster way, the novice user should be guided along the path which supports the mental map best. Therefore, the awareness of the application designer of these constraints is vital in order to provide suitable visualization and interaction techniques. This knowledge also enables the application designer to preprocess most of the needed data along the most promising exploration path, in order to prevent time-consuming switches to the data domain and back. E.g., if a clustering is already precomputed, it is readily available to be included in the view domain and the interactive exploration process can continue instantly.

## 2.2 Use case

For demonstrating the proposed interaction concept we chose an exemplary use case from our clinical scenario: experts from four domains meet to discuss the treatment of a cancer patient. The use case bases on feedback from our medical partners on the Caleydo software

as well as by studying their offline workflow in everyday collaborative situations. By accessing patient data from the whole spectrum of application levels (cf. Figure 2), the biomedical experts perform a collaborative analysis. Table 1 shows the interaction path through the data and view domain. In addition, the table states which domain experts actively interact on which level of the data hierarchy for each task.

When examining this and multiple other analysis paths from the biomedical application domain, we encountered certain reoccurring patterns within the extracted flow of visual data analysis. Three notable examples are:

- **The Information Seeking Mantra**, which often remains intact, if not interrupted by switches between different data sources. This can be observed, e.g., in steps 3-5 and 9-11.
- **Visual queries**, which are triggered by performing some action in the view representation. They carry out a query in the data domain and reflect the result as a change in the view domain. Again, this pattern occurs usually with the application level staying the same. This can be observed, e.g., in steps 11-13.
- **View to data switches** that occur by themselves and not as a part of a visual query pattern, are mostly switches between different application levels that are not seamlessly supported visually. If the switch would be seamless, the users could just use the detail view of the higher application level as the overview of the underlying one. If that is not possible, the users have to switch back to the data domain and generate a different representation before they can proceed. Examples for the seamless transition are, e.g., steps 5 and 7, examples for view to data switches can be seen in steps 13-14 and 16-17.

As a transition between application levels usually implies a switch of the analyst in charge, e.g., from the biologist to the geneticist and oncologist from step 16 to 17, once made explicit, these patterns help to effectively coordinate the analysis process throughout all different domain levels and between the different experts in a multi-user multi-level scenario like this.

### 3 IMPLICATIONS

As the concept is introduced and demonstrated by means of a real world analysis example, the next step is to discuss the hence resulting implications. While the first part addresses general considerations from the concept, the second section discusses the specific implications for smart environments.

#### 3.1 General Implications

Although a seamless multi-level application hierarchy may exist, in some cases there can be data missing for one or more levels. The reasons can range from restrictions due to security concerns to the irrelevance of certain data sources for a specific use case scenario. For example, in the biomedical application scenario presented in Figure 2, an analysis task could aim at the discovery of new gene functions for which the magnetic resonance images and tissue samples are not needed. However, for providing a seamless (visual) transition from patients to pathways the missing levels are crucial to keep up the users' mental map. One possible approach to fill these gaps in the hierarchy is the integration of reference or sample data sources. This makeshift could be taken from external sources or alternatively also be extracted from available reference data sets. In our case this could be anatomical atlases or data from patients with similar medical records. These data sets bridging the gaps have to be explicitly marked as such, so that it becomes obvious that they are just means to facilitate a smoother exploration and analysis and are not part of a patient's data set.

The opposite to the absence of data in the hierarchy can also occur: the availability of multiple facets of the same data at the same level. Examples in terms of our use case are data sets on the organ level acquired by different imaging techniques – e.g., magnetic resonance, computer tomography, and X-ray images. These multiple facets of the same data introduce an ambiguous navigation path between the levels, where it is unclear which path to choose through the hierarchy. At this point the users' profiles and roles during the analysis can help

#	Task description	User	App.	Data	View
1	Show overview of cancer patient	onc.pat			Ovv
2	Investigate patient's clinical data	onc.pat			Z+F
3	Show tumor CT scan	onc			Ovv
4	Investigate finer tumor structures	onc			Z+F
5	Show microscopy images of tissue	pat			DoD = Ovv
6	Search patients with similar tumor	onc.pat		Z+F	
7	Show list of resulting patients	onc.pat			DoD = Ovv
8	Cluster gene expression of these patients	gen.pat		Ovv	
9	Show hierarchical heat map	gen.pat			Ovv
10	Select cluster	gen.pat			Z+F
11	Select gene	gen.pat			DoD
12	Query gene in online database	gen.pat		DoD	
13	Show info about gene in browser	gen.pat			DoD
14	Search for pathways in which gene occurs	bio.gen		Z+F	
15	Show thumbnail list of pathways	bio.gen			Z+F
16	Investigate genes in specific pathways	bio			DoD
17	Filter patients where gene is deregulated	gen.onc		Z+F	
18	Show list of filtered patients	onc.pat		Z+F	
19	Investigate their treatment and outcome	onc.pat			DoD

Table 1. Interaction path in a sample use case where biomedical experts aim to select a cancer treatment for a specific patient. The decision is based on reference cancer patients data collected at the clinic. Based on the down-regulation of a gene known to be one of the causing factors of the tumor, similar patients are filtered and taken as a foundation for the treatment decision. For every task the involved expert is stated: oncologist (onc), pathologist (pat), geneticist (gen), and biologist (bio). The levels of interaction are referred as: overview (Ovv), zoom and filter (Z+F), and details on demand (DoD).

to optimize the navigation path. Another optimization can be made by looking for recurring interaction patterns and adapting the application to make them readily available and easy to use. An example for the Caleydo Visualization Framework is the bucket representation with visual links. It was specifically introduced to make switching between different visual representations, a common pattern in our use case, easier and more intuitive.

#### 3.2 Specific Implications for our Use Case

While the multi-level aspect is inherent in the application scenario, it is the multi-user aspect that distinguishes between the complexity of coordinating for a seamless interaction path through the multi-level data. In general, one can differentiate three cases:

- The **single-user** case, which is what the Caleydo framework is aimed at. It allows a seamless navigation through the multiple application levels by providing a linked multi-view visualization on a single output device.
- The **static multi-user** case, which is targeted by the adaptation of the Caleydo framework for the Deskotheque environment. This environment provides a fixed set of displays and projection areas to facilitate multi-user interaction.
- The **dynamic multi-user** case, where the set of the involved users is not static, but changes over time. In this so called smart environments, also the device ensemble of available displays is changing as users connect and disconnect their brought devices (netbooks, laptops, PDAs, etc.) with the environment during run-

time. A detailed discussion on this case' realization and its usage for a medical scenario is given in [11].

It can be observed that with each of these cases, the complexity of coordinating multiple data levels to be shown on multiple displays for multiple users is increasing. The challenges this poses are abundant and range from the distribution of the data to the available display devices (or views in the single-user case) to the assurance that privacy concerns are met. Our *Multi-User Multi-Level Interaction* concept provides a conceptual and concrete way to model all these complex dependencies and to derive solution approaches that finally achieve real seamless collaborative data analysis.

Collaborative information workspaces, such as described in [12], differentiate between private and public displays. In the simplest case, each domain expert displays his/her domain data on a private display – e.g., in Figure 1 three users from different domains are sitting around a table, each with a private view on a single monitor. Besides the plain distribution of views, the users' roles can further be facilitated to provide tailored visualizations, as a user's working domain influences the chosen visualization technique and terminology used for annotation purposes. Different domains can then be bridged either by a simple coordination of visualizations among the (private) displays or by the combination of data from different sources in public visualizations. Public displays, i.e., projection walls which are visible for multiple users, can host these integrative visualizations. This also allows multiple users to work on the same task.

The physical separation between public and private displays can also be used to circumvent privacy issues, by showing sensitive data only on private displays. In a clinical scenario, the biologist may not be allowed to see the clinical history of patients for privacy reasons. The control over the individual displays enables the collaborative environment to grant or deny access to experts depending on their role, either allowing them to roam freely within all available data sources or just within the absolutely necessary parts. Even annotations could differ, providing patient details in private views, but being anonymized in the public views. Thereby, the anonymization does not affect the linking of the individual views. Selections and other interactions are reflected throughout the whole ensemble of displays.

In dynamically changing environments, it is furthermore essential to have access to a wide range of information: the spatial model of the environment, the participating subjects and their roles, the underlying data, and the workflow of the analysis tasks. All these are essentially targeted by the proposed *Multi-Level Multi-User Interaction*, as it allows to specifically define in detail what (data set) is visible to whom (expert user) in which way (visualization technique) with which goal (aim of this analysis step) and in which order (workflow) – capturing the entire analysis session and going well beyond the pure definition of individual analysis tasks. Having this knowledge beforehand, enables the environment not only to provide a suitable data set from the specified application level to the experts who fit the role and have the necessary security clearance, as it is outlined in Table 1. But instead, the explicit knowledge of probable interaction paths and the resources needed for each step allow to adapt to a dynamically changing environment. E.g., if a certain analysis path requires an expert who is currently not present or a data source which is not available, a different path of analysis can be chosen, if one exists. To reach such a high level of coordination in a dynamic multi-user environment is a challenging task. Now, that the infrastructure as detailed in [11] is up and running, the first step for future research is to investigate how this solutions can be integrated with Caleydo to enhance the single-user scenario to a smart one that adapts to changing constraints.

#### 4 CONCLUSIONS AND FUTURE WORK

We presented the *Multi-User Multi-Level Interaction* concept as a way for formalizing the collaborative information seeking process of multiple domain experts working with heterogeneous data. The concept allows to model, analyze and consequently optimize and adapt the interactive workflow in complex environments. Although we introduced and demonstrated it by means of a static multiple user scenario, the

presented concept can also be scaled down to a single-user, single-display setup and scaled up to a dynamic multi-user scenario, both being subject of future research.

In the single-user case, instead of deciding on which display to show which view of what kind of data, it can be used to decide which space of the screen (e.g., which wall of Caleydo's bucket representation) to use for which kind of data and how to link them appropriately. On an even smaller scale, extracted interaction paths and patterns do also help to automatically arrange and tailor the visualizations to data on different levels of granularity with the aim of providing a seamless exploration process. Once defined in terms of our interaction concept, this process can even be potentially accelerated by optimization (e.g., preprocessing) along predefined common interaction paths.

In the dynamically changing multi-user case, the extracted knowledge can potentially contribute to solutions for many of the challenges that dynamic smart environments face. With a holistic model of the entire workflow, it should be possible to overcome minor disturbances of the analysis process by an adaptation of the process according to the currently available resources and users.

So far, the *Multi-User Multi-Level Interaction* concept primarily focuses on the information seeking workflow, as defined by Shneiderman and Keim. However, the concept is most certainly applicable to a broader range of high-level interaction patterns, e.g., for data manipulation. Hereby, the *Information Seeking Mantra*, as it is embedded in our interaction concept, can be replaced with a different pattern, e.g., by Baudel's data manipulation process [2]: view adjustment, selection, and editing. Hence, it seems even possible to generalize our concept to any step-wise definable interaction pattern.

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