

# A Two-Level Adaptive Visualization for Information Access to Open-Corpus Educational Resources

Jae-wook Ahn<sup>1</sup>, Rosta Farzan<sup>2</sup>, Peter Brusilovsky<sup>1</sup>

<sup>1</sup> University of Pittsburgh, School of Information Sciences,  
Pittsburgh, PA 15260  
{jaa38, peterb}@pitt.edu

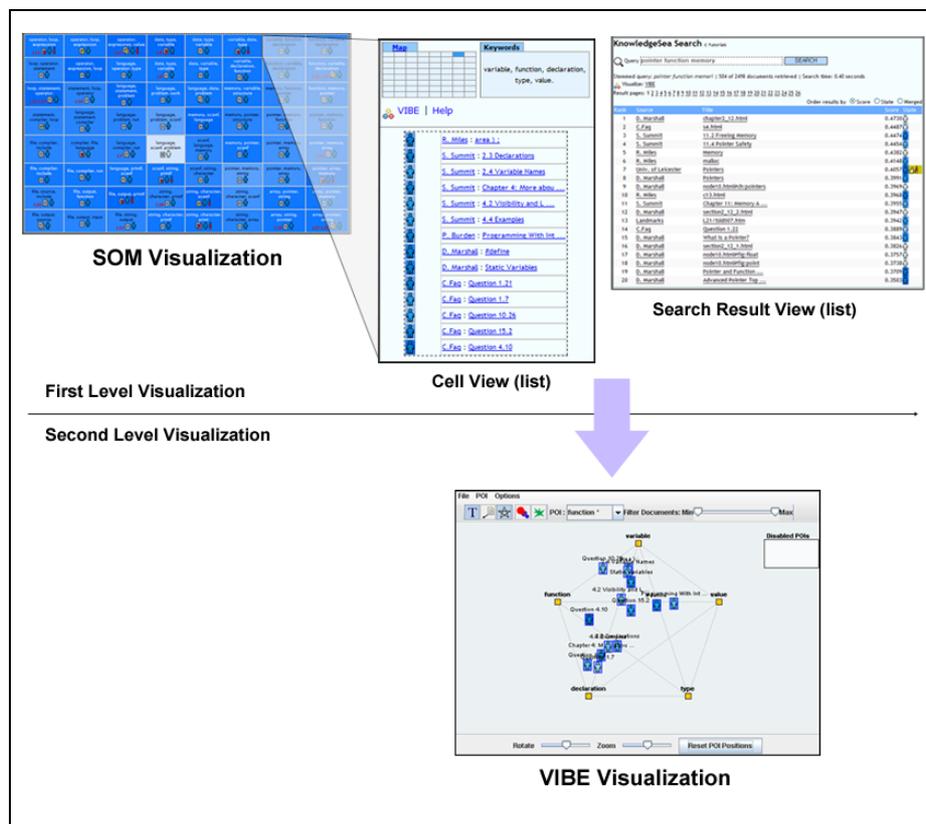
<sup>2</sup> University of Pittsburgh, Intelligent Systems Program,  
Pittsburgh, PA 15260  
rosta@cs.pitt.edu

**Abstract.** The labyrinthine abundance of educational resources on the Web has greatly expanded the challenge of helping students find, organize, and use resources that will best match their individual goals, interests, and current knowledge. Map-based navigation, using technologies such as the Self-Organizing Maps (SOM), is one solution to this growing challenge. However, as the number of documents organized by SOM increases, the number of documents within each cell becomes too large for the user to make meaningful choices, overwhelming his ability to make accurate decisions. Combining interactivity with the ability to organize a large number of documents, we have developed two-level heterogeneous maps that are augmented with social navigation support. We implemented our idea within the Knowledge Sea II system and ran a pilot study using this system in an Information Retrieval course.

## 1 Introduction

The labyrinthine abundance of educational resources on the Web has greatly expanded the challenge of helping students find, organize, and use resources that will best match their individual goals, interests, and current knowledge. Map-based navigation is one solution to this growing challenge. Our previous work (described in [4]) shows the importance of using maps to access information in open-corpus educational resources. Map-based navigation is supported with technologies such as the Self Organizing Map or *SOM* [8]. *SOM* provides resource organization by grouping and visualizing similar resources into each cell on the map. However, as the number of documents organized by *SOM* increases, the number of documents within each cell becomes too large for the user to make meaningful choices. One known remedy for this problem is to create a multi-level information map. Multi-level maps were explored by Roussinov and Chen [9]. They suggested a homogeneous, multi-level map based on *SOM* technology. With this technology, a group of cells in the original map can be expanded into a second level map. The problem with homogeneous multi-level *SOM* maps is their static nature. Unlike other kinds of 2D visualizations such as MovieFinder [1] or VIBE (Visual Information Browsing Environment) [10], which

can be interactively explored by users, SOM allows only passive exploration. With the multi-level support (multi-level SOM), it is just a set of static SOMs distributed in a hierarchy. Combining interactivity with the ability to organize a large number of documents, we have developed two-level heterogeneous maps in which the first level is formed by a SOM and the second level is created through dynamic, relevance-based visualization (Fig. 1). To further help users in selecting relevant resources, we have enhanced our own two-level maps with social navigation technology which, as we have shown in our past studies, is able to lead the users to high quality, relevant documents [4].



**Fig. 1.** Two-level visualization.

This paper presents our work on two-level maps that have been augmented with social navigation support. We explored this kind of two-level map within our Knowledge Sea II system. The Knowledge Sea II provides personalized and adaptive access to web-based educational resources such as textbooks, slides, and tutorials. Section 2 describes the two-level visualization and section 3 describes the integration of social navigation into our two-level maps. Section 4 concludes the paper and presents the future direction of this work.

## 2 Two-Level Visualization in Knowledge Sea II

Knowledge Sea II implements two-level heterogeneous visualization using SOM technology and the VIBE visualization approach. On the first level, the documents inside Knowledge Sea II are clustered into cells using SOM technology, as shown in Fig. 2. Detailed information about how SOM technology has been used to generate the map can be found in [5].

operator, expression, value L14  	data, type, variable L8  	data, type, variable  
language, operator, type  	data, type, variable L9  	data, variable, type  
language, statement, problem  	language, problem, work  	language, data, problem  
language, problem, run  	language, problem, scanf  	memory, scanf, language  
language, compiler, run L7  	language, scanf, problem  	scanf, language, memory  

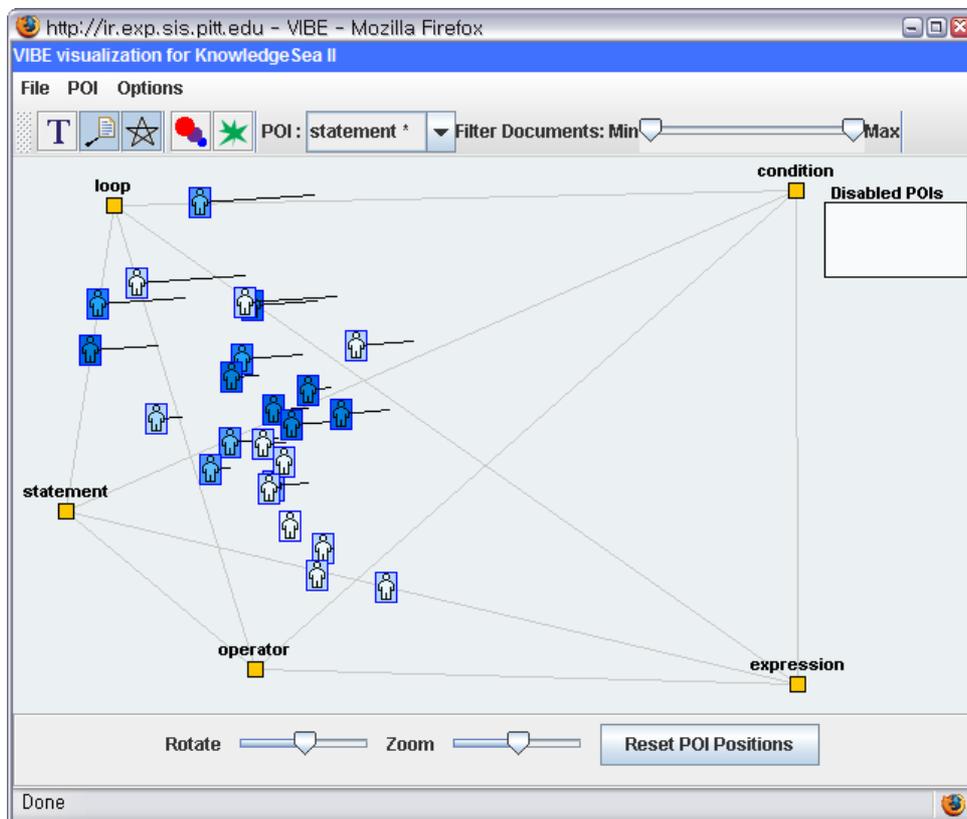
**Fig. 2.** First level: Map-based navigation generated by SOM.

On the second level, the content of each cell is presented in the visual format shown in Fig. 3 based on VIBE's relevance-based visualization. VIBE was originally developed in Molde College in Norway and the School of Information Sciences at The University of Pittsburgh [10]. VIBE uses document content analysis to present a collection of documents in two dimensions, relative to the *points of interest* (POI). By manipulating the location of the POI, a user can explore the collection and locate relevant documents.

To access information in Knowledge Sea II, users can start their own search for knowledge by using the SOM-based map. They may also perform query-based searches using the system's interactive search interface. When a user clicks on a cell, the content of the cell is presented in a list format, accompanied by VIBE visualization options. The keywords presented in the legend are the POIs for the VIBE visualization of documents inside the cell. Search results can also be visualized using VIBE. In this case, the keywords inside the search query become the POIs for VIBE. VIBE visualizes retrieved documents and query terms, so that users can easily discover relationships between the documents and the query terms.

VIBE supports various functionalities that let users easily understand the relationships between POIs (search terms or keywords in the SOM cells) and documents. First and foremost, the document positions are determined by their similarities to POIs, being placed closer if their contents are similar to POIs and further if dissimilar. In Fig. 3, we can see that the documents that are displayed as human-shaped icons are

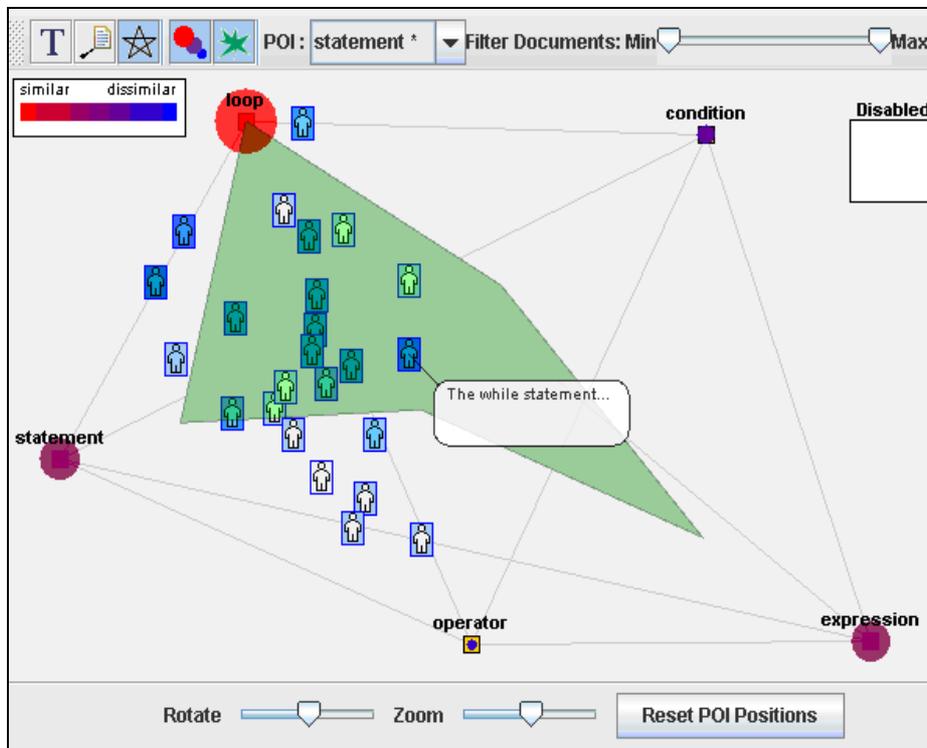
more similar to terms like “loop,” “statement,” and “operator” than the terms “condition” and “expression.” When a user drags a POI around the screen, related documents follow the move, according to their similarity to that POI. Therefore, the user can easily understand the related document by observing these movements. If one document moves a greater distance than the other documents do, when one POI is displaced, it means that the document is much more similar to that POI. Trails of the movements may optionally be displayed, as in Fig. 3. The lines attached to the document icons are trails of their movements (following the POI “loop”). Longer trail lines mean bigger movements and short or missing lines mean little or no movement of the document. Therefore, users can compare the movements of each document and thus comprehend its similarity to the POI.



**Fig. 3.** Second level: Cell content presentation using VIBE.

Additional facilities for helping users to discover relationships among the documents and POIs, beyond positional representations, are also supported. In Fig. 4, some discs are overlaid on the POIs which represent their similarity to a document entitled, “The while statement...” by changes in the disc’s sizes and color. The bigger the diameter of the disc is, the more similar the POI is to the document. The col-

ors of the discs range within a red to blue spectrum, which represent complete similarity and dissimilarity respectfully. In Fig. 4, therefore, we can first notice that the most similar POI to the current document is “loop,” since it has the biggest and brightest red disc. Secondly, we can see that two similar but not as important POIs would be “statement” and “expression,” since they have purple colored discs (somewhere between red and blue) and are medium-sized. Thirdly, we can see that the most dissimilar POI is “operator,” which has a disc slightly smaller than the one for the POI “condition.” Another display uses a green radar graph, which is created by connecting points representing the document similarity values to the POIs. From the radar graph, we can roughly estimate that the similarity between the POI “loop” and the document would be around 1.0 (on a scale of 0.0 to 1.0) and the similarity between “statement” and the document would be around 0.7.



**Fig. 4.** Similarity visualization.

Sometimes, when the number of documents to be presented is too big for the small size of a window, they are very crowded and it becomes extremely hard to distinguish each of them. Especially when the “display document titles” option is turned on, as in Fig. 5, this problem becomes more serious. Therefore, we added a filtering function for the documents. In Fig. 5, we have selected the POI “loop” and only documents with a similarity of 0.5 or more (by moving a double slider on the upper right

side of the screen). Documents with lower similarities to the selected POI than the minimum threshold of 0.5 are filtered out by being shrunk to small ghostly squares with no titles, so that they will no longer block the documents we are interested in. The maximum threshold level can be also set by the user, in which case the documents with higher similarities are filtered out.

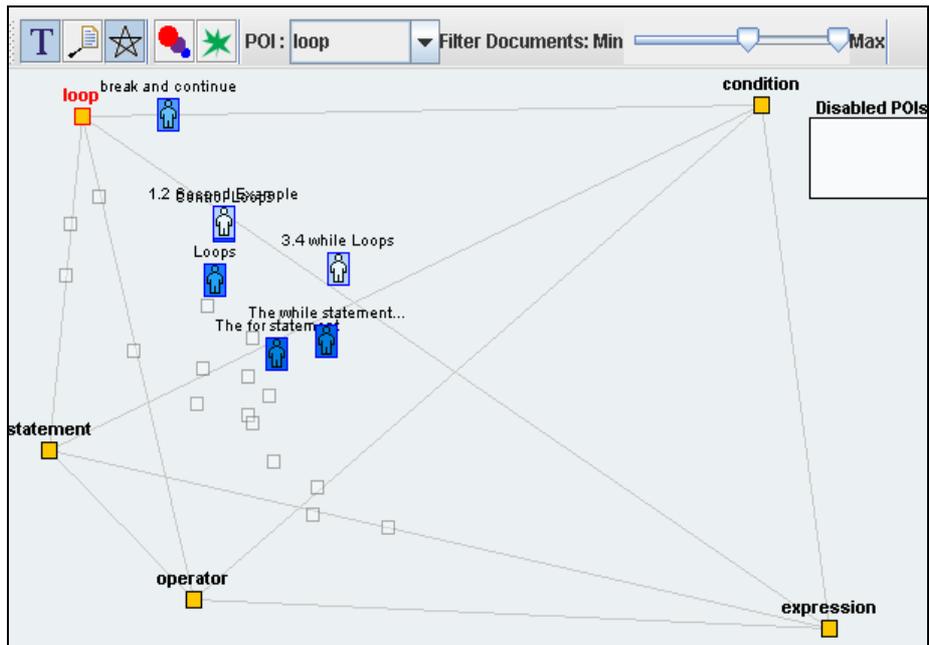


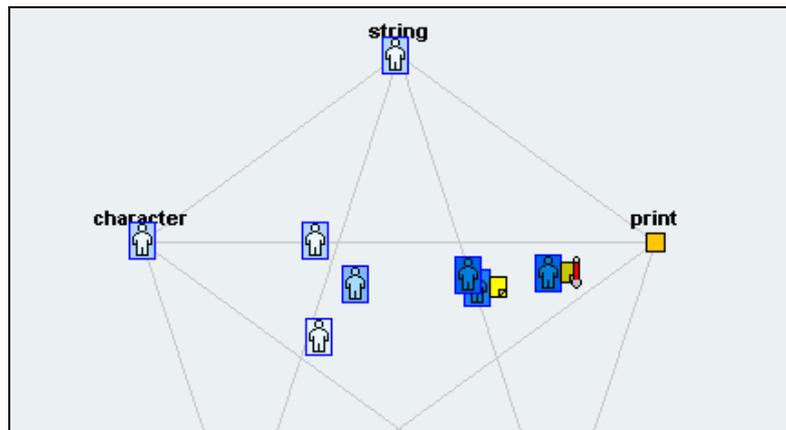
Fig. 5. Filtering documents.

### 3 Personalization through Social Navigation

We employ social navigation techniques as an alternative to content-based techniques [2] in order to support adaptive navigation in the Knowledge Sea II system. Unlike content-based techniques, which are powered by knowledge about the documents, social navigation techniques [6] are powered by the “collective wisdom” of a community of users. Knowledge Sea II offers two kinds of social navigation support: traffic-based and annotation-based. Traffic-based social navigation support is developed by tracking the users’ history of visiting certain cells, while annotation-based social navigation support is based on user annotation in the form of free-format notes or the highlighting of specific parts of a page. At the map level, group activity is represented by the density of background color. As shown in Fig. 2, degree of color intensity is used to represent increasing levels of group activity. Darker colors represent more activity. Along with group activity, individual user activity is represented by the color intensity of a human icon inside each cell. Similarly, darker colors mean

more activity. Cells containing documents with user annotation are augmented with small yellow sticky notes.

Inside the cell view, each document may be annotated with one or two icons, representing traffic-based and annotation-based social navigation support. Traffic-based navigation support is provided by the icon that shows a human figure inside a colored square. The background color of the square represents group traffic and the color of the human icon represents user traffic. The details on how the color is calculated can be found in [3]. Annotation-based navigation support is provided by another square icon with a yellow background of changing intensity that shows a sticky note icon or a thumbs-up icon inside. The background color of the square represents the magnitude of the group annotations. The thumbs-up icon indicates the presence of at least one positive annotation from the logged-on user, while a sticky note indicates the existence of a general note. The color of the foreground icons represents the density of individual notes. In addition, a thermometer icon was added to represent the “temperature” of the annotations, an overall rating given by the whole group of students. The temperature grows warmer when a page attracts more positive annotations. Our previous work presents that important pages accumulate users’ activities (visiting or annotation) and social navigation support is attractive to students, affecting their navigational decisions [3], [7].



**Fig. 6.** Social navigation support in VIBE

We integrated similar social navigation support with VIBE’s content visualization for each cell on the map (Fig. 6). Six documents displayed show different traffic and annotation information related to them. The foreground colors of human icons represent users’ traffic while their background colors represent group traffic. Darker colors mean higher traffic and lighter colors mean lower traffic. Two documents with sticky note and thermometer icons on the right side of the screen have annotations. One has lighter color and the other has darker color sticky note, which means lower and higher density of annotations respectively. The warmer thermometer icon provided means high positive annotations from users. We hypothesize that we would

observe the same beneficial effect of social navigation support when it is augmented with VIBE visualizations.

## **4 Conclusion and Future Work**

In this research, we proposed a two-level adaptive visualization technique for personalizing information access to open-corpus educational resources. We presented an approach to integrate SOM technology with another level of visualization, such as VIBE, in order to move beyond classical map-based navigation. Building on our previous work in social navigation, we incorporated social navigation techniques with two-level visualization, in order to offer strong navigation support for a large quantity of information. We ran a pilot study using the system in an Information Retrieval course. However, the system was not available for the whole semester and the collected data was not sufficient for formal evaluation. Our plan for the first step of the future direction of our work is to evaluate the effectiveness of our two-level adaptive visualization. We would like to assess the effect that social navigation with visualization has on the students' ability to access relevant online resources, and compare it with our previous results. This would mean comparing student access through VIBE visualization with our previous option, which was a simple list of resources. Specifically, we would like to look at students' access behavior for cells with large number of resources. For this purpose, the current system is tracking and recording every activity of users to a user model server. Very fine-grained information is being stored into this server: opening (with the information where it was called) or closing of the application, which document was examined by users, which POI was selected, disabled /enabled, or moved, options turned on or off (document titles, guiding lines), aid functions used (radar, disc), distortion methods used (zooming, rotating, panning). This information will help us complete our tasks described above. We expect the two-level visualization method would increase the possibility for students to access relevant information. To assess our hypothesis we track accessing method to each document and we will average access for each document through different methods. To compare the effect of social navigation and visualization, we will compare the effect of social navigation in students' navigation behavior with previous semesters where students did not have visualization option. We expect that social navigation will have stronger effect in combination with VIBE visualization. We will also conduct a lab study to closely observe the behavioral effect of providing students with VIBE visualizations during document selection.

## **Acknowledgement**

This research is supported by the National Science Foundation under Grant No. 0447083 and the National Science Foundation graduate fellowship.

## References

1. Ahlberg, C. and Shneiderman, B. Visual information seeking: Tight coupling of dynamic query filters with starfield displays. In: *Human Factors in Computing Systems*. ACM Press, New York (1994) 313-317
2. Brusilovsky, P. Adaptive hypermedia. *User Modeling and User Adapted Interaction*, Ten Year Anniversary Issue (Alfred Kobsa, ed.) 11, 1/2 (2001) 87-110
3. Brusilovsky P, Chavan G, and Farzan R (2004) Social adaptive navigation support for open corpus electronic textbooks. In De Bra P and Nejd W (eds) *Third International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems (AH'2004)*, Eindhoven, the Netherlands, August 23-26 (2004) 24-33
4. Brusilovsky, P., Farzan, R., and Ahn, J. Comprehensive personalized information access in an educational digital library. In: *Proceedings of the 5th ACM/IEEE-CS Joint Conference on Digital Libraries (2005)* 9-18
5. Brusilovsky, P. and Rizzo, R. Map-Based Horizontal Navigation in Educational Hypertext. *Journal of Digital Information* 3, 1 (2002)
6. Dieberger A., Dourish P., Höök K., Resnick P., Wexelblat A. Social Navigation -- Techniques for Building More Usable Systems, *interactions* 7, 6 (2000) 36-45
7. Farzan, R. and Brusilovsky, P. Social navigation support through annotation-based group modeling. In *Proceedings of 10th International User Modeling Conference (2005)* 463-472
8. Kohonen, T. *Self-Organizing Maps*. Springer-Verlag (1997)
9. Roussinov and Chen. A Scalable Self-organizing Map Algorithm for Textual Classification: A Neural Network Approach to Thesaurus Generation. *CC-AI, The Journal for the Integrated Study of Artificial Intelligence, Cognitive Science and Applied Epistemology* 15, 1/2 (1998) 81-111
10. Olsen, K.A., Korfhage, P.R., Sochats, K.M., Spring, M.B., and Williams, J.G. Visualization of a document collection: The vibe system. *Information Processing and Management* 29, 1 (1993) 69-81