INFORMATION VISUALIZATION FOR KNOWLEDGE REPOSITORIES: APPLICATIONS AND IMPACTS

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DEDICATION

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ABSTRACT

Information technology plays a supportive role in knowledge management. It captures and stores knowledge into knowledge repositories. At the same time, it also improves access to knowledge stored in knowledge repositories. The codification strategy in knowledge management (Hansen, et al., 1999) and the capturing functionality of information technology have made more and more knowledge repositories available. However, the utility of a knowledge repository may largely depend on how information is presented and requested through its interfaces. The interface requirement of a knowledge repository varies with the content of knowledge and the media type in which the repository stores the knowledge. The dissertation provides an example of selecting appropriate information visualization and analysis technology to facilitate effective knowledge retrieval from different types of knowledge repository. It identifies four types of knowledge repository, each of which has unique requirements for its interfaces. The dissertation applies various visualization technologies to fulfill such requirements. The interfaces developed facilitate the knowledge retrieval by helping in the specification of information needs or by supporting users' information browsing behavior. In addition, the dissertation also presents four empirical studies evaluating the systems developed. Since the lack of evaluation studies in the field of information visualization has become an issue, such empirical studies also provide examples of approaches to evaluating different aspects of an interface.

1. INTRODUCTION

Identified as an important management concept (Garner, 1999), the purpose of knowledge management (KM) is to enable organizations to capture, organize, and access their intellectual assets effectively. Information technology has been identified as playing a supportive role in the process of knowledge management. It not only converts data into knowledge and individual knowledge into organizational knowledge, but also provides connections between knowledge and people and connections between people and people (O'Leary, 1998a). Various types of technology have been utilized based on the characteristics and the location of knowledge (Hahn & Subramani, 2000). To manage knowledge residing in artifacts, an organization can use knowledge discovery techniques to extract knowledge from data, apply text-mining algorithms to convert textual information into knowledge, and utilize information representation and analysis technologies to facilitate knowledge retrieval. On the other hand, intranet and various computer mediated communication (CMC) tools have been used to enhance accessibility to knowledge that exists in the minds of individuals.

Hansen et al. (1999) recognized codification as one of the main knowledge management strategies. The term codification strategy denotes the capturing of knowledge and storing it as artifacts. Those artifacts can be indexed and retrieved. Various knowledge discovery and CMC tools have been used to capture and store knowledge. As a result, more and more knowledge repositories have become available. Although a knowledge repository plays an important role in knowledge sharing, creation, and application (Walsh &

Ungson, 1991; Stein & Zwass, 1995; Abecker, 1998), using it may cause information overload, which in turn may affect its usefulness. For instance, the Internet or Intranet can be regarded as a valuable knowledge repository, but its use also adds a burden to individuals seeking helpful information. While various information technologies can be applied to relieve the resulting overload, the usefulness of a knowledge repository depends on technology characteristics, social factors, and behavior factors. Therefore, the HCI (human computer interaction) aspect of a knowledge repository inevitably plays a crucial role in its acceptance. As a mature discipline, HCI studies the design, the implementation, and the use of an interactive information system and its impacts at different levels (Myers et al., 1996). As one sub-field in HCI, how information is presented and requested has drawn much attention. Various approaches have been proposed to support specification of information needs (Shneiderman, 1994) and to speed information assimilation and pattern detection (Robertson et. al, 1991). However, the interface requirements of a knowledge repository vary with its content and the media types in which it stores knowledge. How to select appropriate visualization and analysis techniques to improve access to knowledge stored in a knowledge repository still needs further exploration.

On the other hand, in response to the lack of evaluation in the field of information visualization (Chen & Czerwinski, 2000), two questions are usually raised regarding a visualization system, "does the visualization work?" and "do you trust your visualization?" While a visualization technology can present information graphically on a computer screen, evaluation studies are needed to validate its effectiveness (question 1) and correctness (question 2). This requires more research in task design, usability studies, and usage studies in different contexts (Chen & Czerwinski, 2000).

The dissertation identifies four types of knowledge repository, each of which has some unique requirements for its interfaces. The four types of knowledge repository include large collection of textual documents, image repository, multimedia repository, and archive of a CMC process. While the textual document has been the classical media type of knowledge storage, how to retrieve un-structured knowledge from a large collection of textual documents has always been a challenge. In addition, more and more information is available in media types other than conventional numbers and text. Interfaces of a knowledge repository thus need to support users' cross-media knowledge retrieval, which requires integration of information analysis and media processing technologies. On the other hand, the best way to manage knowledge that exists in the minds of individuals is to provide "who knows what" information. Various CMC tools not only enable people to share knowledge, their archives also serve as valuable knowledge repositories. Again, such repositories may also create information overload for individuals seeking helpful information. Information analysis and visualization techniques can help relieve information overload during knowledge retrieval.

By selecting appropriate information visualization and analysis technology to develop interfaces for a given knowledge repository, the dissertation provides an example of how visualization technologies can be applied to knowledge repositories to facilitate knowledge retrieval. In addition, the dissertation also describes four empirical studies to evaluate the interfaces that have been developed. Such empirical studies not only validate the performance of interfaces developed, but also provide examples of approaches to evaluating different aspects of an interface.

The dissertation is organized as follows. Chapter 2 elaborates the development of research questions after reviewing related literatures. It also summarizes information analysis technologies employed. Chapters 3, 4, 5, and 6 describe the applications of analysis and visualization technologies to different types of knowledge repositories. Each of these four chapters focuses on one type of knowledge repository. Summary and conclusions are provided in Chapter 7.

2. LITERATURE REVIEW AND RESEARCH FORMULATION

While capturing knowledge is the objective of a knowledge repository, effectively accessing the knowledge stored may become troublesome as its volume or diversity increases. When integrated with information analysis technologies, information visualization technologies provide an opportunity to relieve the information overload caused by the use of knowledge repositories. This chapter reviews related literature and describes the formulation of research questions of this dissertation. Four types of knowledge repositories are identified, each of which has unique requirements for its interface. The review of information visualization reveals different ways of combining information analysis and visualization technologies to present information from a knowledge repository.

2.1 Knowledge Management and Information Technology

2.1.1 What is knowledge?

Understanding the definition of knowledge is not necessary for motivating knowledge management within an organization, but it can help uncover assumptions basic to knowledge management research. Several researchers have defined knowledge by distinguishing among data, information, and knowledge (Alavi & Leidner, 2001). A commonly held hierarchical view has been used to describe the data, information, and knowledge relationship (Alter, 1996; Tobin, 1996; Van Der Spek & Spijkervet, 1997). Such a hierarchical view considers information to be interpreted data and considers knowledge to be information with instinct that can guide actions. Some researchers believe such a hierarchical view cannot effectively distinguish between knowledge and information. They believe knowledge and information to be interchangeable (Alavi & Leidner, 2001). Because knowledge results from cognitive processing triggered by incoming information, Alavi & Leidner (2001) believe that information becomes knowledge once it is processed in an individual's mind. At the same time, knowledge can also be converted to information once it is described and represented by artifacts such as text, graphics, or other forms. There are also other perspectives for viewing knowledge as: (1) a state of mind, (2) an object, (3) a process, (4) a condition of having access to information, or (5) a capability. Alavi & Leidner (2001) provide a detailed review of various knowledge perspectives.

While definitions of knowledge vary, there is only one widely cited classification of knowledge: tacit and explicit knowledge (Polanyi, 1967; Nonaka, 1994). Explicit knowledge denotes knowledge that can be expressed in symbolic form or natural language. Examples of explicit knowledge include books and various manuals. Tacit knowledge has technical and cognitive dimensions. The technical dimension refers to the "knowing how" type of informal personal skill or craft in a certain context. The cognitive dimension of tacit knowledge consists of mental models, beliefs and viewpoints. One example of tacit knowledge is an individual's being able to drive home without thinking about the route.

Another commonly used knowledge classification is the individual/collective knowledge scheme (Nonaka, 1994). Individual knowledge refers to knowledge possessed in the mind of an individual. Collective knowledge is both a composite of individual knowledge and the social process that leads to shared understanding by articulating and exchanging information among individuals (Krippendorff, 1975). Capturing collective knowledge is always more difficult than capturing individual knowledge. Collective knowledge is also called collective memory, one instance of which is organizational memory, frequently described in the literature of organization learning (Stein & Zwass, 1995).

2.1.2 Knowledge Management

The increasingly competitive global marketplace and personnel turnovers within organizations provide incentives for knowledge management, which can be facilitated by more and more advanced information technologies. Knowledge management is an interdisciplinary research area consisting of technologies, human resource management, and organizational science (O'Leary & Studer, 2001). Beckman (1999) provides a thorough review of the current state of knowledge management. To summarize previous knowledge management literature, Beckman (1999) views the research of knowledge management from six perspectives: conceptual, process, technology, organizational, management, and implementation.

- **Conceptual perspective** is concerned with defining knowledge, describing various knowledge taxonomies, and creating frameworks for knowledge management. This perspective has been discussed in section 2.1.1.

- **Process perspective** focuses on how organizations learn from previous experience and how to convert individual expertise into an organizational asset by distributing, sharing and applying knowledge. Research from this perspective usually proposes models to describe an organization learning cycle (DiBella & Nevis, 1998) or knowledge management process (Nonaka & Konno, 1998).

- **Technology perspective** studies how information technologies can be applied to facilitate knowledge management. A more detailed review on research from this perspective is provided in section 2.1.3.

- **Organizational perspective** investigates the interaction between knowledge management and organization structure. Research from this perspective discusses an appropriate organization structure for knowledge management (Liebowitz & Beckman, 1998), the role of knowledge management in organizations (Davenport & Prusak, 1998), the responsibilities of a chief knowledge officer (Davenport & Prusak, 1998), and organizational culture that fosters knowledge management (Zand, 1997)

- **Management perspective** is concerned with measures of intellectual assets (Edvinsson, 1997; Benkman, 1998) and motivation and reward of knowledge sharing within an organization (Zand, 1997; Davenport & Prusak, 1998)

- **Implementation perspective** analyzes success factors of knowledge management (DiBella & Nevis, 1998), implementation of infrastructure, and knowledge management strategy.

2.1.3 The Role of Technology in Knowledge Management

The role of information technology is to capture knowledge, to enhance access to the knowledge captured, and to generate or to help generate new knowledge. As an emerging discipline, knowledge discovery has been used to capture knowledge from numerical and textual information. Most knowledge discovery tools employ AI (artificial intelligence) or statistics techniques to identify patterns from data in numerical or textual media type. To capture knowledge residing in the minds of individuals, especially tacit knowledge, various computer mediated communication (CMC) or collaboration tools have been developed to support cross-space and cross-time information sharing. While such CMC tools provide a context in which individuals can articulate their tacit knowledge, the archives they produce also serve as valuable knowledge repositories that can be searched and browsed. O'Leary (1998a) calls such knowledge capturing converting. He believes the capturing process converts data into knowledge, text into knowledge, and individual knowledge into group or organization knowledge.

The conventional codification strategy (Hansen et al., 1999) and the capturing functionality of technology inevitably result in various knowledge repositories. Those repositories will be useless unless users can retrieve knowledge from them effectively. Information analysis and visualization technologies can add value to a knowledge repository by providing help in users' knowledge retrieval. The application of information analysis and visualization technologies usually consists of three levels:

1. **Information Representation** understands the semantics of information stored in a knowledge repository. Based on the media type in which information is stored, various technologies can be employed including automatic indexing (Salton, 1989), image processing, voice recognition and so on.

2. **Information Analysis** applies various clustering algorithms to categorize information (Chen et al., 1996), generates an ontology to integrate different knowledge reposition (O'Leary, 1998b), applies a visualization method to indicate expert (Zhu & Chen, 2001), and utilizes a diversity of intelligent agents to push related information to users.

3. **Information Presentation** uses information visualization and human computer interaction technologies to facilitate users' searching and browsing behavior. A detailed review of various visualization techniques is provided in section 2.2,

In addition to enhancing access to knowledge stored in a knowledge repository, information analysis and visualization technologies also play an important role in knowledge creation. Nonaka (1994) identifies four processes of knowledge creation: ***socialization***, ***externalization***, ***combination***, and ***internalization***. ***Socialization*** involves the creation of new tacit knowledge from other people's tacit knowledge through social interaction and observation. ***Externalization*** refers to creating new explicit knowledge by articulating and presenting tacit knowledge, and this process can be supported by computer mediated communication tools. The other two processes can benefit from the application of information analysis and visualization technologies. The ***combination*** process creates new explicit knowledge by synthesizing, categorizing, and integrating existing explicit knowledge. Information analysis and visualization technologies can facilitate this process. For instance, categorizing a knowledge repository results in a yellow page of concepts that indicates where in the repository the knowledge resides. Such meta-knowledge proves to be as important as knowledge itself (Andreu & Ciborra, 1997). The application of technology can also facilitate the ***combination*** process by understanding the semantics of terminology (Chen & Lynch, 1992) and by identifying experts in certain area (Zhu & Chen, 2001). The ***internalization*** process refers to the generation of new tacit knowledge through observation and processing incoming information. Information analysis and visualization technologies improve access to existing explicit knowledge, which in turn encourages the creation of new tacit knowledge in the minds of individuals (Alavi & Leidner, 2001).

In summary, KMS facilitates knowledge management by capturing knowledge, by improving access to knowledge, and by generating new knowledge. It facilitates the knowledge creation, storage/retrieval, and sharing within an organization. Tools of knowledge discovery, information analysis, and visualization are employed to manage knowledge residing in artifacts or symbolic forms, while communication/collaboration tools are utilized to share knowledge existing in the minds of individuals. The literature review reveals the importance of applying information analysis and visualization technology in knowledge management.

2.1.4 Knowledge Repository

According to Liebowitz & Beckman (1998), "*A knowledge repository is an online, computer-based storehouse of expertise, knowledge, experience, and documentation about a particular domain of expertise. In creating a knowledge repository, knowledge is collected, summarized, and integrated across sources.*" Based on source, a knowledge repository is either internal or external (Davenport et al., 1998). A knowledge repository may also be structured or unstructured (Davenport et al., 1998; Hahn & Subramani, 2000).

In the literature of organization learning, knowledge repositories are viewed as organizational memory systems. Organizational memory plays vital roles in the acquisition, preservation, identification, distribution, and utilization of organizational knowledge (Walsh & Ungson, 1991; Stein & Zwass, 1995; Abecker, 1998). Various types of organizational memory that have been recognized include team/group memory (Nunamaker et al., 1991b), design rationale memory (Reddy, 1993; Klein, 1993), topic memory (Ackerman, 1994), document memory (Berline. & Grunin, 1993), and electronic community memory (Schatz, 1992).

However, the usefulness of a knowledge repository may largely depend on the extent to which its interfaces help its users find what they want. While most knowledge repositories have stored knowledge in textual documents, multimedia knowledge repositories provide a challenge to the knowledge retrieval process. In addition, as diversity and scale increase, the usage of a knowledge repository inevitably causes information overload, which provides a chance to apply information analysis and information visualization techniques to enhance the accessibility of stored knowledge.

2.2 Information Visualization

The above literature review suggests the importance of information visualization in knowledge management. This section reviews technologies developed in the field of information visualization. As a sub-field of human computer interaction (HCI), information visualization is "the use of computer-supported, interactive, visual representations of abstract data to amplify cognition" (Card et al., 1999). Visualization research takes advantage of the fact that human eyes can perceive various visual cues (i.e., color, shape, texture) in a parallel manner. Studies of Bertin (1983) and Tufte (1983) established the cognitive foundations for visualization research. Larkin and Simon (1987) furthered the understanding of visual aids by pointing out that they can relieve cognitive load by grouping related things, by using location to group information that has a common single element, and by supporting large numbers of perceptual inferences. Because of such abilities to facilitate the construction of mental representation and therby to save cognitive resources, various visualization systems have been developed to relieve information glut resulting from both Internet and easy information creation.

This section briefly discusses two related aspects: visual representation methods and user-interface interaction.

2.2.1 Visual Representation Methods

One important type of abstract information that has drawn intensive attention is the textual document. In both the Internet and the digital library, a majority of information is in the textual format (Card et al., 1999). Of the two applications of the textual document visualization, one is content representation of a single document and the other is an overview providing over a collection of textual documents. Shneiderman (1996) proposed seven types of representation methods including the 1D, 2D, 3D, multi-dimension, tree, network, and temporal approaches. He provided a detailed description of the characteristics of each approach, but this section briefly reviews only the development of textual visualization in his seven representation approaches. The following review compares the seven representation approaches on the basis of metaphor they use and the type of information they represent.

- The **1D** approach represents abstract information as 1D objects and displays these on the screen in a linear (Eric et al, 1992; Hearst, 1995) or a circular (Salton et al., 1995) manner. 1D representation has been applied to display either the content of a single document (Hearst 1995; Salton et al., 1995) or the overview of a collection of documents (Eric et al., 1992). In a 1D representation, colors are used to represent some attributes of each visual object. For instance, colors indicate type of document in the SeeSoft system (Eric et al., 1992), while in the Tilebar (Hearst, 1995) they depict the location in a document of terms specified by a users. In addition, the second axis on the screen also plays a role in the 1D visualization, presenting the characteristic of each visual object. For instance, the SeeSoft system piles up documents in the x-axis and uses y-axis to visualize lines in each document.

- A **2D** approach represents information as two-dimensional objects that it lays out on the screen according to the values of the two dimensions. Visualization systems based on 2D output of a self-organizing map (SOM) (Kohonen, 1995) belong to this category (Lin et al., 1991; Chen et al., 1996). Such systems display categories created over a large collection of textual documents, with the layout of each category based on its location in the two-dimensional output of the SOM. In addition, spatial proximity on the interface also represents the semantic proximity of the categories created. The challenge presented by this approach is to help users deal with the large number of categories created when the scale of the textual data is large.
- A **3D** approach represents information as 3D objects. One example is the WebBook system (Card, et al., 1996) that folds web pages into a three-dimensional book.
- The **multi-dimension** approach represents information as multi-dimensional objects and projects them into a three-dimensional or two-dimensional space. Usually this type of approach represents textual documents as a set of key terms and identifies the theme of a textual collection. A projection algorithm such as multi-dimension scaling (MDS) is used to lay out the document clusters or themes identified into a two-dimensional or three-dimensional space. For instance, the two interfaces presented in Wise et al. (1995) both belong to this category. The Galaxy interface projects multi-dimensional representation of individual documents in a two-dimensional space,

while the ThemeScape interface adopts a three-dimensional landscape to visualize clusters of documents and their relationships with certain topics. Another type of the multi-dimension representation is the glyph representation that uses graphical objects or symbols to represent data through visual parameters that are spatial (positions x or y), retinal (color and size), or temporal (Chernoff, 1973).

- The **tree** approach is usually used to represent hierarchical relationships. The most common example is an indented text list. Example tree structure systems include the Tree-Map (Johnson & Shneiderman, 1991), the Con Tree system (Robertson et al., 1991), and the Hyperbolic Tree (Lamping & Rao, 1995). One crucial challenge to this approach is that the number of nodes grows exponentially as the number of tree levels increases. As a result, different layout algorithms have been applied to the visualization of a large-scale hierarchy. For instance, the Tree-Map (Johnson & Shneiderman, 1991) allocates space according to attributes of nodes, while the Con Tree (Robertson et al., 1991) takes advantage of the 3D visual structure to pack more nodes on the screen. The Hyperbolic Tree (Lamping & Rao, 1995), on the other hand, projects sub-trees on a hyperbolic plane and puts the plane into the range of display. In addition, most interfaces provide interaction that enables users to manipulate visual objects directly in such a way as to permit navigating the entire hierarchy with relatively low cognitive load.

- The **network** representation method is often applied when a simple tree structure is insufficient to represent complex relationships existing among text documents.

Complexity may stem from citations among academic papers (Mackinlay et al. 1995) or from the fact that textual documents are distributed over and linked by the Internet (Andrews, 1995). While various network visualizations have been created to represent citation relationships (Mackinlay et al., 1995) or to display the World Wide Web (Andrews, 1995), the most difficult aspect of the network approach is the challenge of how to provide meaningful interface of complex relationships without losing any information (Card et al., 1999).

- The **temporal** approach visualizes information based on the temporal order. Visual objects are usually listed along one axis according to the time when they occurred, while the other axis may be used to display the attributes of each temporal object (Eric et al., 1992; Robertson, et al., 1993). For instance, the Perspective Wall (Robertson, et al., 1993) lists objects along the x-axis and presents the attributes along the y-axis. In addition, to deal with the "small-screen problem," when a large amount information must be put onto a small screen (Robertson, et al., 1993), the Perspective Wall integrates a distortion technique called Bifocal Display (Spence & Apperley, 1982) into its interface to fold information that is not under investigation.

In summary, seven types of representation methods may be employed to turn the abstract textual documents into objects that can be visualized on a computer screen. However, this does not mean that a visualization system can apply only one method at one time. For instance, the multi-level ET map created by Chen et al. (1998a) combines both 2D and the tree structure, where a large set of Web Sites are partitioned into a hierarchical categories based on their content. While the entire hierarchy is organized in a tree structure, each node in the tree is a two-dimensional SOM, on which the sub-categories are graphically displayed.

In addition, in order to present meaningful representation, a representation method needs to have a precise information analysis technique at its back end. For instance, the TileBar system (Hearst, 1995) employs the Wavelength analysis algorithm to segment a document, while the ThemeScape system (Wise et al., 1995) uses clustering algorithm multi-dimension scaling (MDS) to cluster and lay out documents on the screen. In order to make the repository of documents more manageable, the integration of scalable analysis algorithms becomes extremely crucial, especially when the amount of information is large (Chen et al., 1998a).

The "small screen problem" (Robertson et al., 1993) is common to representation methods in any type. Since the representation method alone is insufficient to create an intuitive interface, it needs to be integrated with various types of user-interface interaction. Recent advances in the hardware and software allow quick user-interface-interaction, and various combinations of representation methods and the interface functionalities have been employed. For instance, the Con Tree (Robertson et al., 1991) applies 3D animation to provide direct manipulation of visual objects, while Lamping & Rao (1995) integrate hyperbolic projection with the fish-eye view technique to visualize a large-scale hierarchy.

2.2.2 Interface Functionality

While visual representation turns abstract information into visual objects, the interface functionality research focuses on the user-interface interaction. Quick interaction between an interface and its users not only allows direct manipulation of the visual objects displayed without mental rotation, but also allows users to select what to display and what not to display (Card et al., 1999). In addition, such interaction also enables users to specify their information needs graphically (Shneiderman, 1994). Shneiderman (1996) summarizes six types of interface functionality: overview, zoom, filtering, detail on demand, relate, and history. Different techniques have been developed to facilitate different types of interactions and this subsection briefly reviews the two types of approaches usually selected when the scale of information displayed is large. These approaches are overview + detail and the focus + context approaches (Card et al., 1999).

The overview + detail approach provides multiple views with the first view being the overview so that users can gain the knowledge of the overall pattern. In this approach, only details about parts of users' interests will be displayed. Usually the overview and the detail view can be displayed at the same time or separately. When the detail view is needed, two types of zooming are involved (Card et al., 1999). Spatial zooming is the process of enlarging selected visual objects spatially just to obtain a close look, whereas semantic zooming provides more content about a selected visual object by changing its appearance. For instance, in the Pad++ system (Bederson & Hollan, 1994), a visualization systems that applies the semantic zooming, provides more details for a region selected as a user zooms in and the appearance of the origin selected region is changed.

The focus + context technique dynamically provides detail (focus) and overview (context) on the same view. One example is the 3D perception approach adopted by systems like Information Landscape (Andrews, 1995) and Con Tree (Robertson et al., 1991), where visual objects at the front are bigger than those at the back while the overview is provided. Another focus + context technique is the fisheye view (Furnas, 1986), a distortion technique acting like a wide-angle lens to amplify the part of the focus. The objective is to provide surrounding information with reduced detail at the same time details are provided for the region of interest. In any focus + context approach, users can change the region of focus dynamically. One example system that applies the fisheye technique is the Hyperbolic Tree (Lamping & Rao, 1995), where users can scrutinize the focus area and scan the surrounding nodes for a big picture. Other focus + context techniques include filtering, highlighting, and selective aggregation (card et al., 1999).

In summary, the overview + detail and the focus + context are two types of interactions provided by a visualization system to help users deal when large-scale information is presented. They may have their own advantages and disadvantages under different circumstances.

2.3 Research Formulation and Dissertation Structure

Given the importance of a knowledge repository and its potential to cause overload, applying information analysis and visualization algorithms to facilitate knowledge retrieval becomes more and more urgent. However, a knowledge repository may be structured or unstructured (Hahn & Subramani, 2000) and may also be text-based or multimedia. Different repository types pose different requirements on how information should be presented and requested on their interfaces. How to fulfill those requirements through applying information visualization and analysis technologies needs more exploration. This section identifies four types of knowledge repositories whose information can be represented and requested through interfaces in a more intuitive way if visualization and analysis technologies are applied.

- *Textual documents*

Structured knowledge repository are repositories that can be stored in a database. Examples include numerical transactional data and fully indexed and categorized textual documents. While textual document has been the classic way to store knowledge, manual indexing and categorizing have become extremely tedious and costly as amount of information increases. While search engine techniques facilitate users' searching behaviors, providing hierarchical subject categories proves to be an effective way to support browsing behaviors (Marchionini, 1987; Marchionini 1988; Carmel et al., 1992; Chen et al., 1998a). How to generate and present hierarchical subject categories automatically deserves further exploration. In addition, as indicated in Chen et al.

(1998a), users can be confused by hierarchical subject categories that have been generated automatically. The reason for this is incongruity between users' expectation and the way the hierarchy is organized. Therefore, automatically creating hierarchical subject categories over a collection of documents is insufficient unless the hierarchy generated matches users' expectation during the process of browsing. Chapter 3 explores this issue by proposing a prototype system that integrates an expert's domain knowledge into the generation of hierarchical subject categories. This chapter also estimates the consistency between the categories generated and users' expectations.

- *Image Repository*

More and more information is being stored in other than conventional numerical or textual media types. Literature in the fields of both knowledge management (Beckman, 1999) and HCI (Myers et al., 1996) acknowledges the challenge of dealing with multimedia information. An important and common media type used to store knowledge is image. Various image retrieval systems have been developed to support image retrieval (Pentland et al., 1994; Flickner et al., 1995; Ramsey et al., 1999). All those systems represent an image by its low-level features such as color, texture, or shape. Such approach addresses the scalability problem caused of the conventional manual annotation approach. But, still poses several challenges. One challenge is how to help users in specifying their information needs. Users are not experts in low level features and they feel awkward when trying to specify a query in terms of low level features. Users may feel more comfortable specifying a query as "find a image that contains farmland and forest." How to convert such high level queries into low level features therefore becomes an issue. In addition, another challenge is how to define a similarity measure associated with low-level features that is consistent with human's perception of similarity. Chapter 4 deals with those issues by summarizing an image retrieval system (Ramsey et al., 1999) and describing an empirical study that investigated whether the similarity measure selected and the automatic image categorization were consistent with human perceptions.

- *Multimedia knowledge repository*

A knowledge repository may also contain information stored in more than one media type. Therefore, in addition to dealing with information stored in different media types, facilitating cross-media knowledge retrieval is also important. Chapter 5 presents a prototype system that supports information browsing a cross textual, numerical, and imagery media types. However, as more information is presented, the screen becomes more crowded. To deal with the "small screen" problem (Robertson et al., 1993), Chapter 5 employs three dimensional (3D) interface to increase information density on a computer screen. Given the lack of supporting evidence for 3D interfaces in previous studies (Kulmer & Groop, 1990; Pilon & Friedman, 1998; Swan & Allen, 1998), Chapter 5 also presents an empirical study to validate the effectiveness and efficiency of 3D interfaces.

- *Archive of a computer mediated communication*

Unlike other types of knowledge repositories, the archive of a computer mediated communication process captures and stores knowledge residing in the minds of participants. To improve access to such knowledge, different technologies to organize the content of an archive have been proposed (Nunamaker et al, 1991; Ackerman, 1994; Konstan et al., 1997; Chen et al. 1998b; Van Dyke at al., 1999). However, in addition to the shared knowledge, an archive also contains information that is equally valuable for knowledge management, which is how people behave during communication. Examples include how active people are, wherther they like their community, and who is the most active person in a certain area. This information is helpful for individuals who are looking for an appropriate community in which to share knowledge and may be helpful in identifying experts in a certain area. Although technologies called social visualization do exist to present such information (Donath et al., 1999; Xiong & Donath, 1999), there is no system that provides summaries of both content discussed and participants' behavior. Inspired by the work of Xiong & Donath (1999), Chapter 6 presents a social visualization method developed to depict certain aspects of participants' behavior. Such representation is combined with information analysis techniques to provide both content and behavior summaries. To validate the visualization method, Chapter 6 also presents an empirical study that evaluates the effectiveness and efficiency of graphical interfaces. That study adopted the "de-featuring" (Morse & Lewis, 2000) approach which eliminates other features of a system and evaluates only the visualization component.

2.4 Overview of Information Visualization and Analysis Technologies Selected

To facilitate both browsing and specification of information needs, information visualization technology not only presents information on a screen in a user-friendly way, but also provides an intuitive user interface interaction functionality to assist users in navigating through various interfaces. Such facilitation is necessary because it is always impossible to place everything on a computer screen at the same time. Given many choices of existing techniques, careful selection of information visualization technologies based on the characteristics of a knowledge repository has significant impact on the effectiveness of knowledge retrieval from this repository. On the other hand, visualization cannot work alone and must have information analysis technologies underneath to achieve the scalability. Therefore, it is important to choose appropriate analysis techniques to accommodate the needs posed by different types of knowledge repository.

This dissertation demonstrates examples of how to facilitate knowledge retrieval from repository of a large collection of documents, an image repository, a multimedia repository, and the archive of a computer mediated computer mediated communication. The first three of these deal with explicit knowledge residing in artifacts and symbolic forms, while the last records the knowledge shared and participants' behavior. At the information representation level, AZNP (Arizona Noun Phraser) was used to represent information in the textual media types, while Gabor filter technique (Gabor, 1946) was employed to represent imagery information. At the categorization level, the dissertation chooses Kohonen's self-organizing map (SOM) (Kohonen, 1995). Its two-dimensional (2D) output also makes SOM a good candidate for visualization. SOM thus has been used as a categorizing tool and a visualization tool in this dissertation. Furthermore, to present people's behavior during a CMC process, the dissertation developed a social representation method to depict such information. The rest of this section provides further elaboration of the technologies selected.

2.4.1 Information Representation

2.4.1.1 Representation of Textual Documents

Indexing is the process of representing a document automatically with a vector of terms (Salton, 1989). The indexing tool used consists of two parts. The first operation is to use a noun-phrasing tool to identify relevant noun phrases. The natural language processing noun-phrasing technique has been used in information retrieval to capture a richer linguistic representation of document content (Anick & Vaithyanathan, 1997). Allowing multi-word (or multi-phrase) matching (Girardi & Ibrahim, 1993), such an approach has potential to improve precision over other document indexing techniques. Tolle & Chen (2000) compared the performance of different noun phrasing tools including MIT's Chopper and NPtool, a commercially available noun-phrase detector (Voutilainen, 1997) with Arizona Noun Phraser. In their study they used several tools to extract medical related noun phrases from a collection of cancer-related documents. Arizona Noun Phraser was found to have higher precision than the other noun phrasing tools they used.

The second operation was to select a subset of the phrases extracted to represent a document. The indexing tool selected phrases according to phrase frequency (number of times a phrase occurs in a document) and document frequency (number of documents in which a phrase occurs).

2.4.1.2 Representation of Imagery Information

The traditional algorithm of textual annotation represents an image based on its author, date, and content. This approach, however, fails to capture the complete content of an image and requires manual effort to define and enter the necessary annotation. To counteract the non-scalability of this approach, effective algorithms for image feature extraction and image representation have been developed, as evidenced by several recent prototypes such as the Photobook system at MIT (Pentland et al.,, 1994) and by commercial systems such as IBM's QBIC system (Flickner et al., 1995). A variety of algorithms can be employed to extract low-level features in image retrieval systems. For instance, QBIC calculates the texture features of an image according to its coarseness, contrast, and directionality. Photobook consists of three parts: the Appearance Photobook, the Shape Photobook, and the Texture Photobook. In the texture Photobook, Wold-based representations are used to extract the texture features of an image. In the Los Alamos National Lab's CANDID Project, Laws' texture energy maps are applied to extract textural features from pulmonary CT images (Kelly & Cannon, 1994). Manjunath and Ma (1996) present a prototype system for the Alexandria Digital Library Project, where they use Gabor filters to extract texture features of an aerial photo. The selection of an algorithm for image representation varies with the image type. For instance, an algorithm may work well with medical images but may not be appropriate for geographical images. Using aerial photos as a testbed, this dissertation employs Gabor filters as its image representation algorithm and Euclidean distance as the similarity measure in the feature space. Gabor filters were first proposed by Gabor (1946) to analyze one-dimensional (1D) signals such as audio signals, and were extended into 2D by Daugman (1980). As indicated in (Manjunath and Ma, 1996), Gabor filters perform well in representing aerial photos. Zhu & Chen (2000) also indicates that Gabor-filter-extracted features and associated similarity measure can map the human perception of aerial photo similarity

2.4.2 Information Categorization

Compared with several neural network algorithms used in previous research (Lippmann, 1987), a variant of the Kohonen's self-organizing maps (SOM) appears to be the most promising algorithm for organizing large volumes of information. As an information categorization and visualization tool, SOM was first proposed by Kohonen, who based his neural network on the associative neural properties of the brain (Kohonen, 1995). The network consists of an input layer and an output layer. The number of the input nodes

Table 2.1 Description of SOM Algorithm

- **Present each document or image in order**: Represent each document or image by a vector of N features and present to the system.
- **Compute distances to all nodes**: Compute distance d_j between the input and each output node j.
- **Select winning node j* and update weights to node j* and neighbors**: Select winning node j* as that output node with minimum d_j. Update weights for node j* and its neighbors to reduce their distances (between input nodes and output nodes).
- **Label regions in map**: After the network is trained through repeated presentation of all inputs, submit unit input vectors of single terms to the trained network and assign the winning node the name of input feature. Neighboring nodes which contain the same feature then form a concept or topic region. The resulting map thus represents regions of important terms or image patterns (the more important a concept, the larger a region) and the assignment of similar documents or images to each region.
- **Apply the above steps recursively for large regions**: For each map region which contains more than k (e.g., 100) documents or images, conduct a recursive procedure of generating another self-organizing map until each region contains no more than k documents or images.

equates with the number of attributes associated with the input. After all of the input is processed, the result is a spatial representation of the input data, organized into clusters of similar regions. Table 2.1 provides a detailed description of the SOM algorithm. SOM is defined as a mapping from a high-dimensional input space into a two-dimensional array of output nodes, where special proximity represents semantic proximity. In addition, its 2-dimensional output makes SOM an ideal candidate for information visualization. Several recent studies adopted the SOM approach to textual analysis. Examples are the DISCERN (Distributed Script Processing and Episodic Memory Network) developed by Mikkulainen (1993) as a natural language processing system, the WEBSOM system developed by Kohonen's group for newsgroup classification (Honkela, 1996), and the multi-layered SOM system developed by the Arizona Artificial Intelligence Group for Internet web page categorization (Chen et al., 1996). Their work suggests a high applicability of the SOM approach to large-scale classification.

2.4.3 Social Visualization

Social visualization research represents human behavior graphically. Systems such as Loom (Donath et al., 1999) and PeopleGarden (Xiong & Donath, 1999), for instance, provide graphical summaries on who starts a discussion, who talks with whom, how long a person stays, and how lively a discussion is. Chat Circles (Donath et al., 1999) aims to facilitate synchronous conversation in an online chat room, where each participant is assigned one circle. The size of the circle indicates the freshness of a posting. Users can only "hear" from or "talk" to others in their vicinity. They can also move their circles around to find an appropriate subgroup to talk with. The representation method developed in this dissertation is described in detail in Chapter 6.

3. CREATING HIERARCHICAL SUBJECT HEADING OVER LARGE COLLECTION OF TEXTUAL DOCUMENTS

3.1 Background

Identified as valuable external knowledge repositories, various online collections of textual documents provide domain knowledge, market changes, breakthroughs in technology, and new trends in management. One effective way to access knowledge stored in this type of repository is information browsing. Browsing behavior is "characterized by the absence of planning" (Liebscher & Marchionini, 1988) and is used as "an alternative to the complex Boolean search strategy." (Marchionini, 1987) Providing hierarchical subject categories has been proven to be an efficient facilitator for browsing behavior (Marchionini, 1987; Marchionini 1988; Carmel et al., 1992; Chen et al., 1998a). For instance, MEDLINE, the largest and most widely used medical bibliographic database in the world, uses this approach. Created by the United States National Library of Medicine (NLM), MEDLINE utilizes the vocabulary of the Medical Subject Headings (MeSH) in manually indexing its textual documents and organizes MeSH terms into 15 hierarchies called "MeSH Tree Structures" (Lowe & Barnett, 1994).

However, the manual approach currently employed may cause difficulty in updating subject categories as the amount of information increases. For instance, manually processing articles from 33 journals (Lowe & Barnett, 1994), MEDLINE updates its MeSH trees only on a yearly basis, which may make the newest emerging concepts or categories unavailable to users in a timely fashion. In addition, the manual process of creating subject categories and associating textual documents with them is in itself tedious and time-consuming (Chen et al., 1998a). Although different machine learning technologies have been used to generate subject categories, users frequently get lost during browsing because of inconsistency between users' expectations and the way in which the categories are organized.

Furthermore, presenting subject categories in a user-friendly way poses still another challenge. Drabenstott & Weller (1996) found that hierarchy-based alphabetic subject headings became unmanageable as the number of categories increased. Providing an intuitive graphical interface can address this problem efficiently, but the abstract nature of content-based categories makes them difficult to present (Hearst & Karadi 1997). Examples of interfaces developed to present subject hierarchies include the Cat Cone Tree (Robertson et al., 1993), the hyperbolic tree (Lamping et al., 1995), the hierarchical ET map (Chen et al., 1998a), and hierarchical axes (Shneiderman et al., 2000). Although they provide graphical representations of a subject hierarchy, few of the studies incorporate an information analysis technique at the backend.

Therefore, this chapter addresses following research questions:

- *How to automatically generate hierarchical categories from a collection of documents that is consistent with users' conceptual model?*
- *How to display a large- scale subject hierarchy?*

This chapter describes an automatic approach to creating and visualizing subject categories in the domain of cancer-related research. The system, called CancerMap, uses CANCERLIT, a bibliographic database, as its testbed. CANCERLIT was chosen as testbed not only because it contains citations and abstracts from over 4,000 different sources including biomedical journals, proceedings, books, reports, and doctoral theses, but also because health care is so information-intensive that access to domain knowledge plays a crucial role. Conducting parallel computing through a super computer, the CancerMap automatically generates at its backend the content-based subject categories within it. To address the problem of inconsistency between users' mental models and the hierarchical category generated, the CancerMap integrates the domain knowledge of an expert into the process of category generation. It also combines the text-based alphabetic approach with graphical visualization to presents subject categories at its front-end.

To validate the performance of combining the expert's domain knowledge with the automatic categorization algorithm, this chapter describes an empirical study that assessed the quality of subject categories generated. The research question was:

- *Is a subject hierarchy generated automatically consistent with its users' expectations during the browsing process?*

3.2 CANCERMAP: Facilitating Information Browsing over the Domain of Cancer-Related Research

CancerMap is a prototype system designed to facilitate information browsing over the domain of cancer-related research. The input data to CancerMap consisted of 591895 cancer-related documents obtained from CANCERLIT. Applying techniques such as automatic indexing and neural networks, CancerMap generated a subject hierarchy that contained 18120 categories. The CancerMap also combined a text-based alphabetic display with a graphical approach to represent the subject categories generated. This section provides a detailed description of the generation process and the representation approach.

3.2.1 Category Generation

Figure 3.1 summarizes the process of automatic category generation. The two types of information analysis techniques used were *indexing* and a *clustering algorithm*. The third part of the generation process was *expert intervention* that integrated an expert's domain knowledge with information analysis. The *visualization tool* in Figure 3.1 will be discussed in next section 3.2.2.

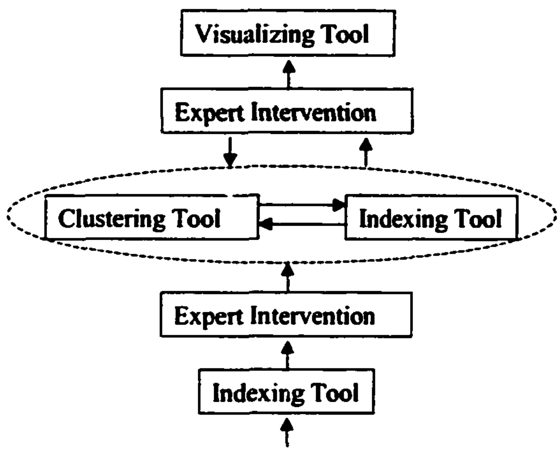


Figure 3.1 The Process of CancerMap Generation

- *Indexing* is the process of representing a document automatically with a vector of terms (Salton, 1989). CancerMap used Arizona Noun Phraser to represent the content of a document. The indexing tool has been reviewed in detail in Chapter 2. Figure 3.1 shows the two places at which the indexing tool is applied. First it extracted relevant noun phrases and selected a subset of phrases to represent each document in the entire collection. Second it re-selected phrases for a subset of documents from which sub-categories were generated.

- *Clustering* is the assignment of items to groups based on semantic association. CancerMap selected SOM as its categorization tool. Chapter 2 provides the justification for the selection and presents the detailed description of the algorithm. During the creation of CancerMap, SOM was applied repeatedly to generate hierarchical subject categories in the way described in Chen et al. (1998a).

- *Expert intervention* incorporates an expert's domain knowledge into the process of generating meaningful categories. Although SOM is capable of categorizing, and thus facilitating the browsing of internet web pages, the conceptual model it suggests is unfamiliar to many users (Chen et al., 1998a), creating inconsistency between the subject categories generated and a user's expectation. To address this problem, CancerMap integrated expert knowledge into the process of applying SOM. The expert employed in this process had more than three years of experience as a medical librarian. As displayed in Figure 3.1, this expert intervened at two places in the entire process. After each document had been represented by a set of noun phrases, the expert removed phrases such as "mice, nude" that she thought would not contribute to generating meaningful subject categories. The expert edited the results of SOM by removing inappropriate category labels assigned when the categories were generated Those label phrases thus were removed from the list of terms that were used to represent a document before the categorization process was resumed.

The resulting SOM map appeared to be promising. Subject categories such as "Skin Neoplasm, " "Breast Cancer, "and "Liver Neoplasm" appeared as the first-level labels, and the sub-categories under each category seems to be related to the top label. To further validate the consistency between the conceptual model that was generated and the mental models of users, an empirical study was conducted and is presented in section 3.

3.2.2 The Interface Of CancerMap

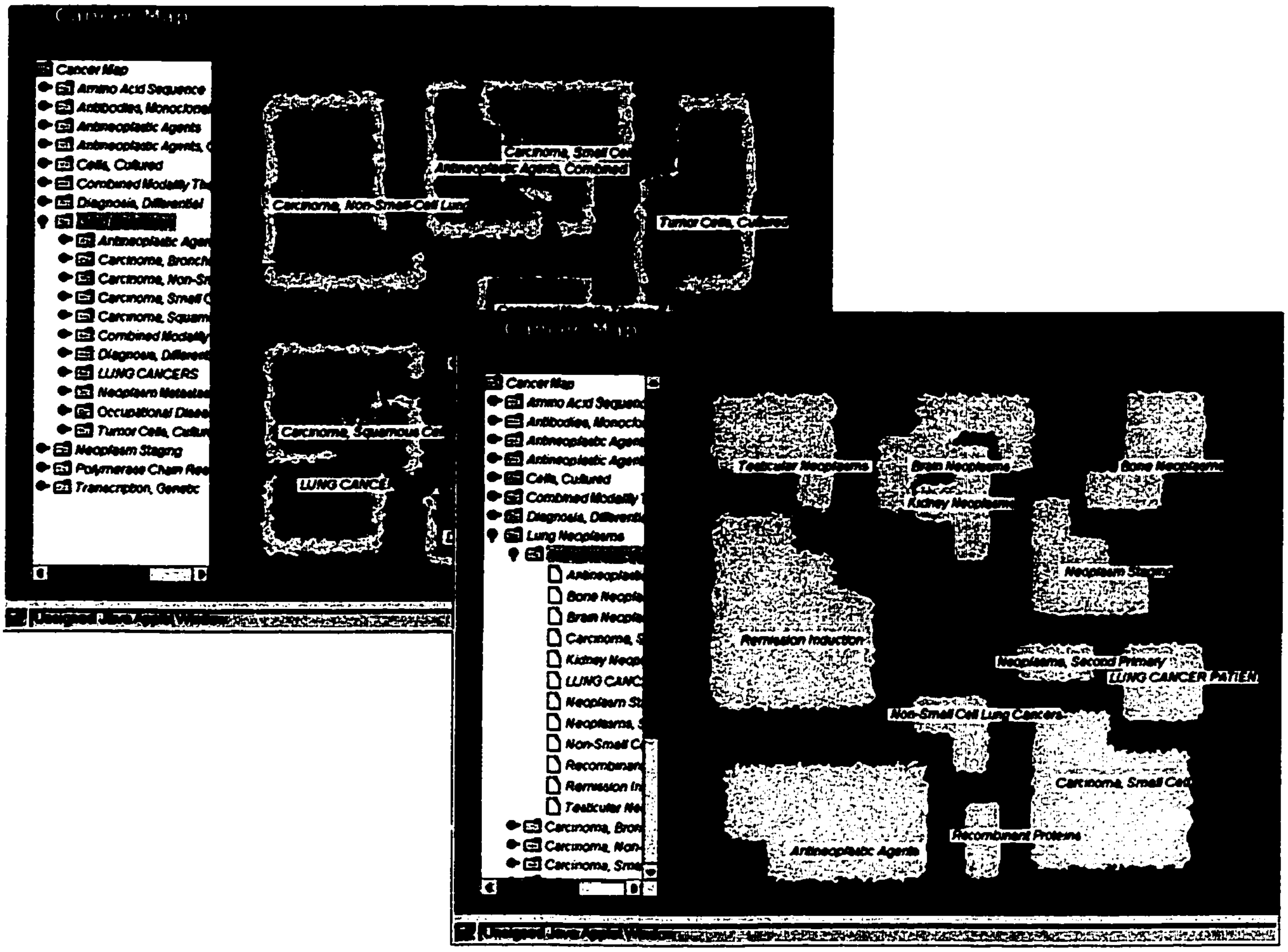


Figure 3.2 The Interface of the CancerMap

The graphical nature of SOM output qualifies it to be a good technique for visualizing subject categories. One advantage of such an interface is that spatial proximity between categories corresponds with their semantic proximity. However, the evaluation of SOM in (Chen et al., 1998a) indicated that users tended to get lost when browsing multi-level SOM maps and continued to prefer to use a conventional text-based alphabetic hierarchy.

On the other hand, limitations of an alphabetic display have been recognized (Holley and Killheffer, 1982; Massicotte,1988; Drabenstott and Weller, 1996). The main disadvantage of such a display is that the interface itself becomes increasingly difficult to utilize as the hierarchy grows.

The interface of the CancerMap system integrates both representations. Figure 2 displays the CancerMap interface, which consists of two panels. The left panel is "Windows Explorer like" and presents an alphabetic display of the hierarchy generated, while the right panel is the graphical display of the SOM output. On the left panel, a user can click on any category of interest and the system will display its sub-categories. At the same time, those sub-categories are also displayed on the right panel, where spatial proximity equals the semantic proximity. For instance, in figure 3.2, when the user indicated interest in "Lung Neoplasms", the system displayed its sub-categories in both panels. The user then clicked on one of the sub-categories named "Antineoplastic Agents, Combined" on either the right or the left panel. As a result, the system presented its sub-categories on both the left and the right panels. Again, the left panel listed the sub-categories in alphabetic order beneath the label clicked, while on the right panel semantically close sub-categories were displayed close to each other.

3.3 The Empirical Study

The CancerMap system integrates an expert's domain knowledge with the SOM algorithm to generate meaningful subject categories and combines a conventional alphabetic display of the hierarchy alongside the graphical representation of the SOM output. Until validation of the system's performance took place, no claim for its usefulness could be made. Therefore an empirical study was designed to estimate the quality of the subject hierarchy generated by the CancerMap system. The empirical study defined its research question as follows:

Can the approach employed by the CancerMap system generate hierarchical subject categories that are meaningful to human subjects?

The experiment compared the subject categories generated by the CancerMap with subtrees of the "MeSH Tree Structures" generated manually by the MEDLINE. One of the sub-trees of the MeSH hierarchy that starts with "Neoplasm" contains all the subject headings that are related to cancer research. Having examined the CancerMap subject categories and the MeSH hierarchy, we found that the subject hierarchy generated by the CancerMap system was comparable to sub-trees in the MeSH hierarchy "Neoplasm by Site" and "Neoplastic Process." Table 3.1 lists the first-level labels of the CancerMap and those from the MeSH sub-trees under the "Neoplasm by site" and "Neoplastic Process." Six overlap labels were found among the first-level labels of the CancerMap and MeSH sub-trees, while sixteen first-level labels on the CancerMap appeared as sub-categories under five first-level labels of MeSH sub-trees. For instance, first-level labels of CancerMap such as "Liver Neoplasms," "Stomach Neoplasms," and "Colonic Neoplasms" were sub-categories under the "Digestive System Neoplasms," one of the first-level labels of the MeSH sub-trees. The following are some interesting statistics:

- 20 of the 37 labels generated by SOM were found in MeSH sub-trees starting with "Neoplasms by site."
- 2 of the 37 labels generated by SOM were found in the MeSH sub-tree starting with "Neoplastic Process."
- 4 of the 16 first-level labels of the "Neoplasms by site" sub-tree were found in the CancerMap first-level labels.
- 2 of the 8 first-level labels of the "Neoplastic Process" sub-tree were found in the CancerMap first-level labels.

Table 3.1 First-level Labels from the MeSH Sub-Tree and the CancerMap

(The labels in ***bold and italic font*** are overlap or partial overlap labels between the CancerMap and the MeSH su-btrees)

MeSH Sub-Trees	CancerMap	Overlap
Anaplasia	Structure-Activity Relationship	*Bone Neoplasms*
Cocarcinogenesis	DNA-Binding Proteins	*Breast Neoplasms*
Neoplasm Invasiveness	Cloning, Molecular	*Head and Neck Neoplasms*
Neoplasm Metastasis	Bone Marrow	*Skin Neoplasms*
Neoplasm Regression, Spontaneous	Monoclonal Antibodies	*Cell Transformation, Neoplastic*
Neoplasm, Residual	Cell Survival	*Neoplasm Recurrence, Local*
Abdominal Neoplasms	Lymphocyte Transformation	
Anal Gland Neoplasms	DNA, Neoplasm	
Eye Neoplasms	Lymphoma, Non-Hodgkin's	
Hematologic Neoplasms	Acquired Immunodeficiency Syndrome	
Pelvic Neoplasms	Neoplasms, Experimental	
Soft Tissue Neoplasms	Pituitary Neoplasms	
Splenic Neoplasms	Cell Cycle	
Digestive System Neoplasms	*Esophageal Neoplasms*	
	Colorectal Neoplasms	
	Stomach Neoplasms	
	Colonic Neoplasms	
	Liver Neoplasms	
	Pancreatic Neoplasms	
Endocrine Gland Neoplasms	***Ovarian Neoplasms***	
	Adrenal Gland Neoplasms	
Nervous System Neoplasms	***Brain Neoplasms***	
Thoracic Neoplasms	***Lung Neoplasms***	
Urogenital Neoplasms	***Prostatic Neoplasms***	
	Cervix Neoplasms	
	Kidney Neoplasms	
	Bladder Neoplasms	
	DNA Damage	
	Bone Marrow Transplantation	
	TUMOR CELLS	
	Tumor Markers, Biological	

3.3.1 Hypothesis Generation

It was observed that the MeSH sub-trees always categorized text documents according to one aspect of cancer research. For instance, the "Neoplasms by site" sub-tree always categorizes documents based on the part of the human body where the cancer occurred. As a result, users could find categories "Stomach Neoplasms" and "Liver Neoplasms" under the category "Digestive System Neoplasms." However, this approach might restrict users' browsing activity. For instance, after finding the "Digestive System Neoplasms," a user would not be able to find a category such as "the cause of the digestive system neoplasms" or "the prevention of the digestive system neoplasms."

On the other hand, the CancerMap categorizes text documents based on semantic relationships among the documents, which may create more comprehensive categories than one-aspect categorization does. However, observations indicate that level-confusion may arise from such an approach and a category and its sub-categories both may appear at the same level in the CancerMap.

Because of level-confusion, several first-level categories in the CancerMap usually were sub-categories of one of the top categories in MeSH sub-trees, while at lower levels, MeSH sub-categories were more and more limited by one-aspect categorization. Accordingly, hypothesis were developed as follows:

- H1: CancerMap and MeSH sub-trees will have comparable performance in both *precision* and *recall* at the top level.

- H2: At the second and lower levels, the CancerMap will exhibit no significant difference from the MeSH sub-trees in *precision.*

- H3: At the second and lower levels, the SOM will have better performance in *recall* than MeSH sub-trees.

The concepts of precision and recall used in this paper will be explained in detail in sub-section 3.3.3

3.3.2 Tasks Design

A set of tasks was designed to evaluate the consistency between the categories generated automatically and those expected by users during their browsing process. The consistency between the MeSH sub-trees and users' expectation was also investigated. The goal was to compare the performance of the CancerMap with that of MeSH sub-trees.

To evaluate the ***first-level labels***, the task was as follows:

1. Ask a human subject to generate a list of possible sub-categories that he/she expects to see under the category of "Neoplasms."

2. Present the lists of first-level labels generated by MeSH sub-trees and CancerMap to the subject, asking him/her to modify the list he/she has generated. During the experiment, subjects did not know from which source (the CancerMap or MeSH sub-trees) suggested labels had come.

3. Use the list generated by the subject to evaluate the first-level labels of the MeSH sub-trees and CancerMap.

At the first level, there were six overlapping labels between the CancerMap and MeSH sub-trees. Three tasks were designed for each human subject in order to compare the performances of the CancerMap and MeSH sub-trees at the ***second-level***. For each task, the subject was to repeat the process used for the first-level evaluation. Again, subjects did not know the source of suggested label terms.

1. We randomly selected one of the 6 *overlapping* labels at the first-level and asked a subject to evaluate its sub-labels. The subject was to generate his/her own desired list and modify it by reading the labels generated by the MeSH sub-trees and the CancerMap.

2. We randomly selected one of the *non-overlapping* first-level labels from MeSH sub-trees and asked a subject to evaluate its sub-labels. The subject was to generate his/her own list and modify it by reading the labels generated by the MeSH sub-tree.

3. We randomly selected one of the *non-overlapping* first-level labels from the CancerMap and asked a subject to evaluate its sub-labels. The subject was to generate his/her own desired list and modify it by reading the labels generated by the CancerMap.

At the ***third-level*** evaluation, subjects conducted the sub-label evaluation in the same manner as in the upper level evaluations. Tasks are as follows:

- We randomly selected one second-level label from MeSH sub-trees and asked a subject to evaluate its sub-labels.
- We randomly selected one second-level label from the CancerMap and asked a subject to evaluate its sub-labels.

The evaluation was terminated at the third-level because most MeSH hierarchies stop at the third-level.

3.3.3 Objective Measures

Cluster recall and *cluster precision* as defined in (Roussinov & Chen, 1999) were used as the objective measures for all the tasks. *Cluster precision* indicates the accuracy of the categories generated by a system, while *cluster recall* represents how many related categories have been captured by the system. According to (Janes, 1994), there are two types of relevance. Objective relevance denotes the accuracy of the categories generated by a system, whereas subjective relevance denotes a subject's perception of the accuracy of the categories created. In this study, we selected the subjective measure, because only when the categories generated are consistent with users' expectations can they be helpful in facilitating users' browsing behavior. Therefore, both the cluster precision and cluster recall results obtained in this study refer to perceived precision and perceived recall.

Following are the measures used to evaluate the performance of MeSH sub-trees and the CancerMap:

- *CancerMap Cluster Precision* = number of categories generated by the CancerMap that were also selected by a subject ÷ number of subject categories generated by the CancerMap
- *CancerMap Cluster Recall* = Number of categories generated by the CancerMap that were also selected by a subject ÷ number of subject categories generated by the subject
- *MeSH Cluster Precision* = number of categories generated by the MeSH sub-trees that were also selected by a subject ÷ number of subject categories generated by the MeSH sub-trees
- *MeSH Cluster Recall* = Number of categories generated by the MeSH sub-trees that were also selected by a subject ÷ number of subject categories generated by the subject

3.4 EXPERIMENT RESULTS

Eighteen senior Ph.D. students, researchers and faculty members from the Arizona Cancer Center participated in this study. Most of them reported being familiar with MeSH tree structure. During the evaluation process, subjects were encouraged to think aloud. Every subject finished the first-level evaluation. At the second and the third levels, some subjects quitted because they said the categories were not in their research areas.

Due to level-confusion, several first-level categories on the CancerMap were sub-categories of one first-level category of the MeSH sub-trees. We counted those CancerMap categories as one first-level category. As a result, the number of first-level categories on the CancerMap was reduced. However, the experiment results still indicated that the first-level of the CancerMap performed significantly better than the MeSH sub-trees in *perceived cluster recall* (p = 0.049). There was no significant difference in *perceived cluster precision* (p = 0.591) between the two.

Table 3.2 Summary of the Experiment Results (C: CancerMap, M: MeSH sub-trees)

	First-level	**Level 2 (Overlap)**	**Level 2 (non-overlap)**	**Level 3**
Recall Comparison	C : 0.557	C: 0.765	C: 0.859	C: 0.839
	M: 0.466	M: 0.113	M: 0.466	M: 0.459
	P = 0.049	**P = 0.00**	**P = 0.000**	**P = 0.003**
Precision Comparison	C: 0.926	C: 0.826	C: 0.829	C: 0.863
	M: 0.956	M: 0.608	M: 0.904	M: 0.917
	P = 0.591	**P = 0.104**	**P = 0.459**	**P = 0.808**

Similar results were found in the second and third-level comparisons. Table 3.2 summarizes the experiment results

As displayed in Table 3.2, *the CancerMap was comparable to MeSH sub-trees in perceived cluster precision at each level and was significantly better in perceived cluster recall at all levels.*

Table 3.3 Sub-Categories under the Label of "Head and Neck Neoplasms"

Labels in ***bold and italic*** font are considered to be bad labels by this subject

MeSH Sub-Tree	CancerMap	Subject
Esophageal Neoplasms	Oral cavity	Epidemiology
Eye Neoplasms	Squamous Cell Carcinomas	Screening
Facial Neoplasms	Facial Neoplasms	pathology
Mouth Neoplasms	Mouth Neoplasms	genetic
Otorhinolaryngologic Neoplasms	Radiation Therapy	infection
Paratyroid Neoplasms	***Treatment of Head***	Risk factor
Skull Neoplasms	Neoplasms, multiplre Primary	diagnosis
Tracheal Neoplasms	Surgery, Plastic	prevention
	Radiation Injuries	potency
	Neck Tumors	hormones
	Neoplasm Invasiveness	immunology
	Laryngeal Neoplasms	
	Neck Surgery	
	Lymphangioma, Cystic	
	Neck Cancer Patient	
	Neck Squamous Cell	
	Tumor Cells, Cultureed	
	Thyroid Neoplasms	
	Soft Tissue Neoplasms	
	Neck Regions	

During the entire process of the empirical study, it was observed that the manually created subject hierarchy was restricted by its one-aspect categorization, while the major complaint about the CancerMap was its level-confusion. Taking the label "Head and Neck Neoplasms" as an example (Table 3.3), one subject would have likeed to have had "risk factors," "prognosis," "diagnosis," "prevention," and "survival" as its sub-labels. Since the MeSH sub-trees categorized text documents only based on part of body where the cancer occurs in this subtree, only categories such as "Eye Neoplasms," "Facial Neoplasms," or "Mouth Neoplasms" can be found under the "Head and the Neck Neoplasms." Such a one-aspect categorization may restrict users' browsing activity, whereas CancerMap provides more comprehensive categories. However, a subject complained that some sub-categories of a category should have been at a higher level. As displayed in Table 3.3, CancerMap puts "Neck Regions" under the "Head and Neck Neoplasms" as its sub-category.

3.5 SUMMARY AND CONCLUSiON

CancerMap integrates expert knowledge with information analysis techniques to generate meaningful subject hierarchies in the domain of cancer-related research. In addition, the system also combines graphical visualization and a conventional alphabetic hierarchy to present the subject hierarchy created. An empirical study compared the performances of CancerMap and MeSH sub-trees, a manually generated subject hierarchy. The study found that CancerMap performed significantly better in *perceived cluster recall* than MeSH sub-trees while it had comparable performance in *perceived cluster precision*. It was found that the one-aspect categorization employed by manual creation might have restricted users' browsing activity but that the level-confusion of CancerMap may have decreased its precision. Overall results of the empirical study demonstrate that the approach employed by CancerMap generated a meaningful subject hierarchy to facilitate browsing.

4. INTEGRATION OF INFORMATION ANALYSIS AND IMAGE PROCESSING TECHNOLOGIES IN IMAGE RETRIVEAL

4.1 Objectives

More and more knowledge repositories store their information in media other than textual documents. As images become more widely used as a medium in which to store knowledge, accessing stored knowledge requires the integration of image processing and information retrieval techniques. To counteract the non-scalability of traditional textual annotation, effective algorithms for image feature extraction and image representation have been developed in the field of image processing (Pentland et al., 1994; Flickner et al., 1995). Such techniques include representing an image by its low-level features such as color, texture or shape and identifying objects such as face, farmland, or airport from an image. To facilitate image retrieval from an image repository, it is necessary to define a similarity measure over the low-level features of an image. However, an image retrieval system cannot be effective unless such a similarity measure matches its users' perception of similarity. Similar investigation is also needed for object identification to ensure that the algorithm does identify objects in the way consistent with human perception.

Most research in image retrieval compares several potential algorithms by running them on data sets from the Brodatz library (Picard & Kabir, 1993). Research has rarely evaluated the performance of an algorithm against that of human subjects. To address this weakness, this chapter describes an interactive experiment to validate the performance of a geographical image retrieval system: SOM-AIR that integrates the algorithm created by the Alexandra Digital Library project (Manjuanth & Ma, 1996; Ma & Manjuanth, 1998) for feature extraction with a classification technique called self-organizing map (SOM) (Kohonen, 1995) to support image searching and image browsing.

4.2 Background

4.2.1 Image Retrieval System

An image retrieval system requires the incorporation of both image representation and information retrieval techniques. The traditional algorithm for representing an image is based on its author, date, and content. However, this approach is unable to capture the complete contents of an image and requires manual effort to define and enter the necessary annotation. Another approach, searching images based on their low-level features, has therefore been introduced and offers a promising research alternative.

Another important factor that affects an image retrieval system is its retrieval model. Most existing image retrieval systems are based on pattern recognition techniques (Huang et al., 1996). The image retrieval process of these systems assumes that users must have complete knowledge of the low-level features of an image to map the pattern they perceive. This assumption, however, is not true under most circumstances. In addition, users may perceive patterns on the same objects differently and, consequently, may map the same objects to different queries. An efficient image retrieval system needs to incorporate an algorithm that will translate high-level image queries provided by users into low-level visual features (Picard & Kabir, 1993)

4.2.2 SOM-AIR: An Image Retrieval System Based on Self-organizing Map

The system retrieves images based on texture pattern. The system's clickable image interface enables users to specify their queries without specific knowledge of texture. The current system supports three functionalities: similarity analysis, region segmentation, and image categorization (Ramsey et al., 1999).

4.2.2.1 Feature Extraction

Automatic feature extraction is representation of an image by its low-level features. Based on the work of Manjunath & Ma (1996), the SOM-AIR system selects Gabor filters (Gabor, 1846) as image representation algorithm. The justification for such selection and the description of Gabor filters are provided in Chapter 2. The system divides one image into small tiles, each of which has 128 × 128 pixels. Tiles are the smallest units in the SOM-AIR system and are represented by their Gabor features (Ma & Manjuanth, 1998). The system constructs a feature vector of length 60 to represent each tile and stores all the feature vectors in a feature database.

4.2.2.2 Define Similarity Measure

Taking a user's query and finding the most similar tiles is called similarity analysis. Users expect an image retrieval system to return a set of images that match their queries. The SOM-AIR system chose to use Euclidean distance in the texture feature space as the similarity measure because it is commonly employed in existing image systems and

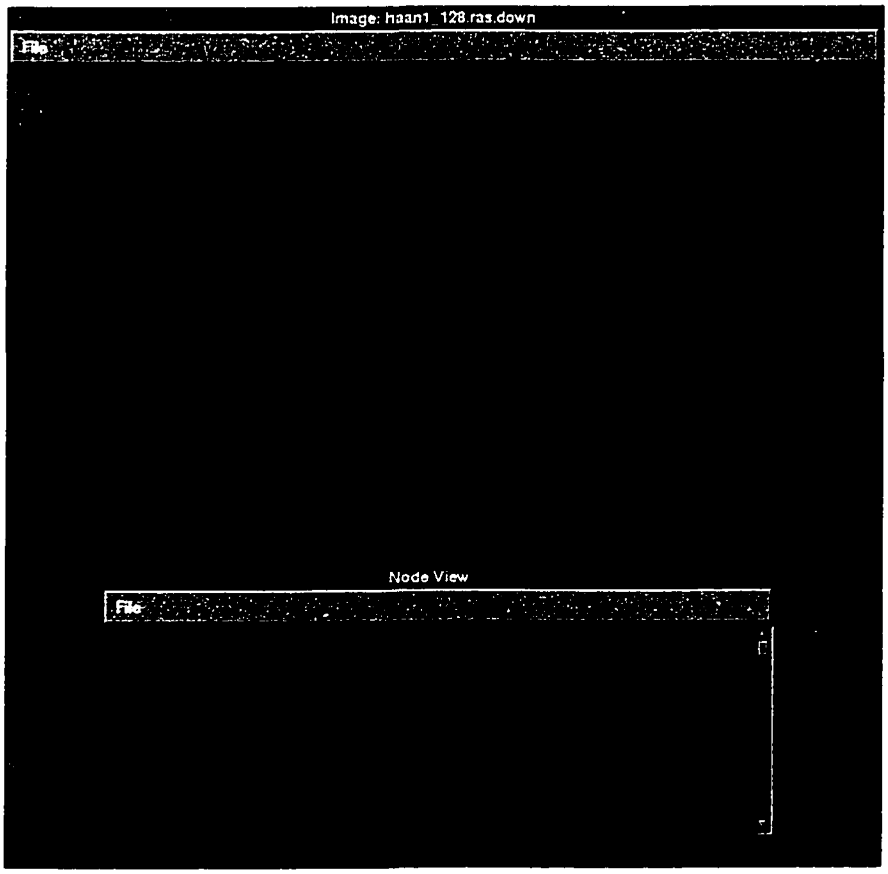


Figure 4.1 Similarity Analysis.

A user can browse the whole image provided by the interface and click on a tile of interest. The system then pops up another window called the result window. This window is titled in "Node View" and displays tiles similar to the clicked tile. At the same time, in order to indicate locations of those tiles in the original image, the system highlights the clicked tile in red, and the other similar tiles in blue in both the original image and the result window.

information retrieval systems. The system considers two image tiles to be similar if they have relatively small values of Euclidean distance. As a result, when a user specifies a specific texture pattern (e.g., orchard), the system calculates the Euclidean distances between this tile and all the other tiles. The system then sorts all the other tiles in ascending order according to their distances and returns the top 10 tiles as the ones most similar to the one referenced. The images to which these chosen tiles belong can also be displayed on the screen. Figure 4.1 presents the interface of this functionality.

4.2.2.3 Image Segmentation

The goal of image segmentation is to distinguish "objects" with large geographic features (e.g., airports, dams) and to support more specific queries such as " Find images that have airport." The SOM-AIR system partitions one image into nearly 6000 tiles and accomplishes the task of region segmentation by grouping adjacent similar tiles. The detailed description of the entire process can be found in Manjuanth & Ma (1996).

Based on the feature vectors of its tile elements, the system calculates a feature vector for each of the regions created. Users can specify their queries in terms of regions and the system can retrieve similar regions and the corresponding images. Figure 4.2 is an example of image segmentation.

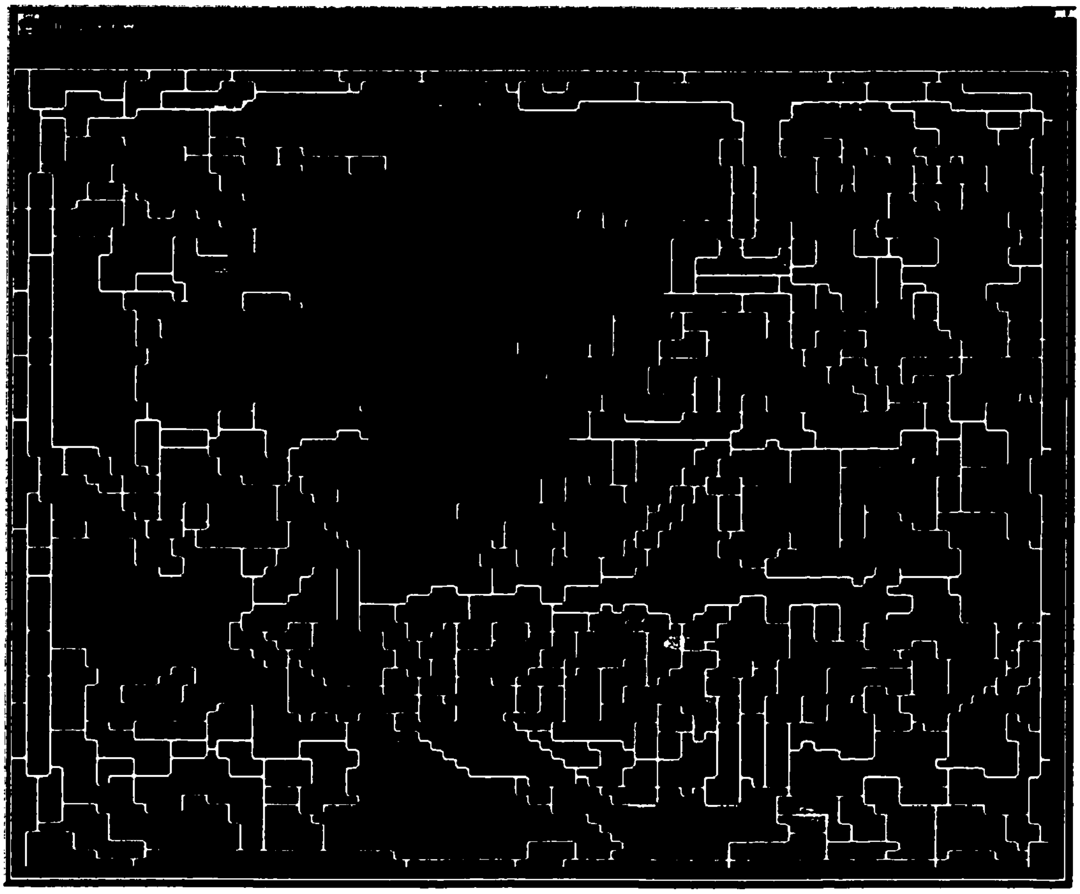


Figure 4.2 Region Segmentation.

The whole image in this figure contains 6400 x 6400 tiles. The system forms the regions by drawing lines that conform to the boundaries between tiles. One region represents a large geographical feature. For instance, the region highlighted in red is farm land, while the regions highlighted in green represent roads. Users can click on a region of interest, such as roads or vegetation, and the system will respond by displaying all similar regions

4.2.2.4 Image Categorization

SOM-AIR system uses Kohonen's Self-organizing Map (SOM) (Kohonen, 1995) to categorize the tiles of an image and visualize the categories created. Users can browse the map created and find the desired texture. After clicking on the category of interest, all the tiles belonging to this category and corresponding images can be browsed.

SOM is defined as a mapping from an input space onto a two-dimensional array of output nodes, each of which is connected with an input vector via variable scalar weights. In SOM-AIR system, an image is divided into tiles, and each tile is represented by its

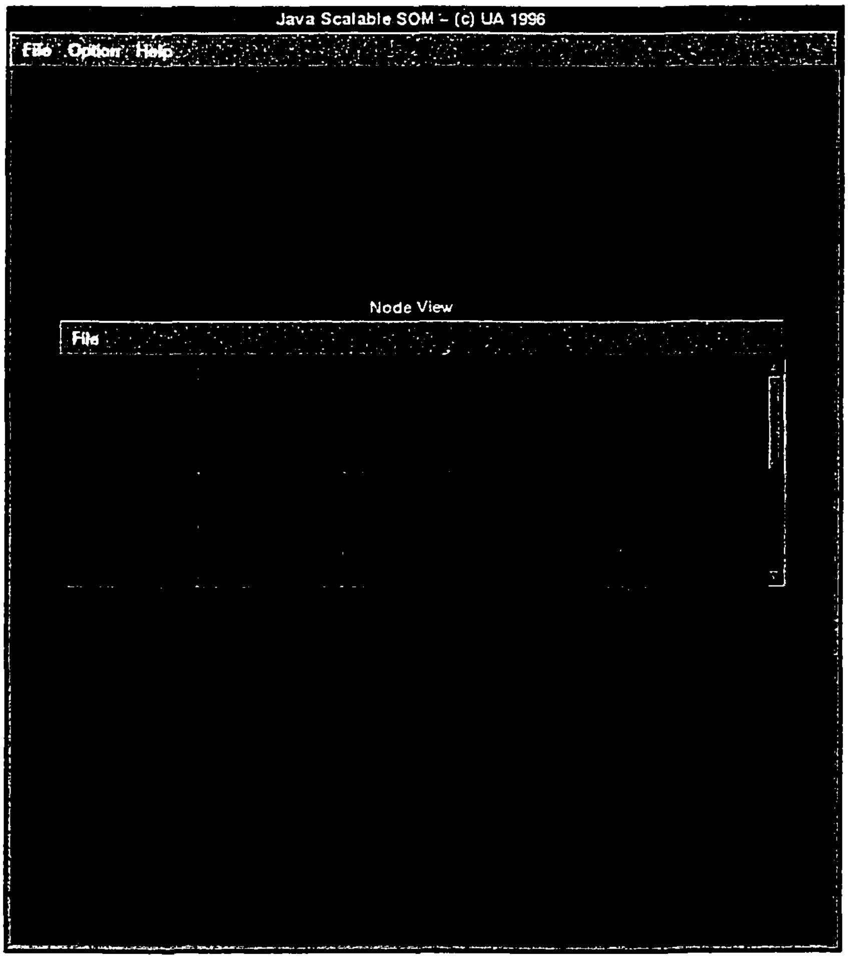


Figure 4.3 **Image Categorization.**

This is the 2-dimensional display of a SOM with 100 (10 × 10) output nodes, each of which is represented by its representative tile. Output nodes with the same representative tile are considered to be in the same category. When a user clicks on a representative tile, the system pops up another window titled "Node View" and displays all the tiles belonging to that category in this window. Since we use the image tile itself as the label of each category, users can easily find a desired category and browse all the image tiles of interest by clicking on the representative tile.

feature vector. Tiles are the unit input in for the SOM algorithm. A detailed description of the SOM algorithm is provided in Chapter 2.

The SOM map created can be considered to be a graphical categorization of the images. Figure 4.3 presents the interface of the image categorization.

4.3 Research Question and Experiment Design

4.3.1 Research Questions

The SOM-AIR system gives rise to several research questions:

- *To what extent do extracted features and corresponding similarity measures map a human's perceived similarity?*
- *Does the segmentation method distinguish objects that could be distinguished by a normal person?*
- *Does applying SOM to the feature vectors produce better results than manual indexing?*

In order to address these questions, three experiments were designed and conducted. To address the quality of the similarity analysis of the system, the first experiment involved comparing the similar tiles retrieved by the system with similar tiles chosen by human subjects. The second experiment compared segmentation results of the system with those of human subjects. The third experiment addressed the effectiveness of the adopted SOM in image categorization. Each of these experiments involved 10 subjects and 10 different images. Every image consisted of 12 × 16(192) tiles. Thirty human subjects were involved in experiments; most of them were graduate and undergraduate students in the Department of Management Information Systems at the University of Arizona (UA). The others were graduate students from other UA departments. In each comparison, both the system and human subjects performed the same tasks. An expert who had had three years of experience in analyzing remote sensing pictures evaluated both sets of results.

4.3.2 Experiment 1: Similarity Analysis

Ten images were selected, from each of which 6 tiles were randomly selected as reference tiles. A subject was assigned one image and its corresponding reference tiles. For each reference tile, the subject was asked to evaluate every tile on the image and assign a score, from 0 to 10, based on its similarity to the reference tile. Subjects were asked to judge similarity according to the content of tiles and assign a score based on their own visual perceptions of coverage, layout and texture orientation. An interface was designed and implemented for this part of the experiment (Figure 4.4).

The interface consisted of 4 components, the Image Panel, the Reference Panel, the Results Panel, and the Control Panel. The entire process of the first part of the experiment was as follows. A subject chose a reference tile by clicking on one of the tiles on the Reference Panel. This tile became the current referenced tile and was highlighted in red. After selecting a reference tile, the subject could choose one or more image tiles from the image by clicking on image tiles on the Image Panel. The selected image tiles were highlighted in red and were displayed in the Results Panel. By clicking on the scroll bar on the Control Panel, the subject could assign to the image tile or tiles selected a score based on the similarity between the current reference tile and the tiles selected. He/She then could click on the "OK" button on the Control Panel to finish this assignment. As a result, the tiles on the Results Panel were removed and the corresponding tiles on the Image Panel were highlighted in green

Figure 4.4 Interface for Similarity Analysis.

The interface consists of 4 components, the Image Panel, the Reference Panel, the Results Panel, and the Control Panel. The Image Panel displays an image of 12 × 16 (192) tiles, while the reference panel presents the 6 reference tiles and shows the current reference tile highlighted in red. Tiles on the Image Panel being inspected are also highlighted in red and are displayed on the Results Panel. In this figure, the subject is examining 11 image tiles and there are 4 tiles on the Image Panel that have been assigned scores corresponding to the current reference tile. The buttons "check" and "recover" are used to check how many tiles have been assigned a score corresponding to current referenced tile. "ok" button is used to finalize the assigning of a score to the image tile under inspection and the "save" button is used to save the results.

4.3.3 Experiment 2: Region Segmentation

A different group of 10 subjects participated in the second part of the experiment. The same images were used as in the first part and subjects were asked to draw lines around areas in the image that they considered similar. For instance, if an area was predominately orchard, it was to be enclosed as one area, while an area of buildings was to be enclosed as a different area. The only restriction was that in drawing the boundaries of the regions subjects had to use tile boundary lines. The restriction was established in

Figure 4.5 **Interface for Region Segmentation.**

The region being inspected has a boundary color of blue. The subject can include or exclude an adjacent tile by clicking on it. He can use the "ok" button to finalize his decision about this region. The region with a boundary color of red indicates that this is a created region. The "check", "recover", and " save" buttons on the Control Panel have similar functionalitv to those in the first oart of the exoeriment order to make the results comparable to those of computers. The interface for this part of the experiment is presented in figure 4.5

4.3.4 Experiment 3: Image Categorization

The third part of the experiment continued to use the same set of images, but a different group of 10 human subjects participated. A human subject worked with one image that had been categorized by using the SOM algorithm. For every image, the label tiles of created categories were regarded as representative tiles. Those system-selected representative tiles were used as suggested categories and human subjects were asked to put every tile on the image into a category.

Figure 4.6 presents the interface for this part of the experiment, which resembles that for the first part of the experiment. A subject could select a current representative tile and have some image tiles brought up on the Results Panel by clicking on the Image Panel. The image tiles selected could then be assigned to the category represented by the current representative tile by clicking the "OK" button on the Control Panel. After such assignment, tiles on the Results Panel were removed and the corresponding tiles on the Image Panel were highlighted in the same color as the current representative tile. The subject could then change the current representative tile and repeat the whole process until all tiles on the Image Panel had been assigned to a category. The "Check", "Recover" and "Save" buttons on the Control Panel functioned as they did in the first part. Subjects took 40-50 minutes to finish this task.

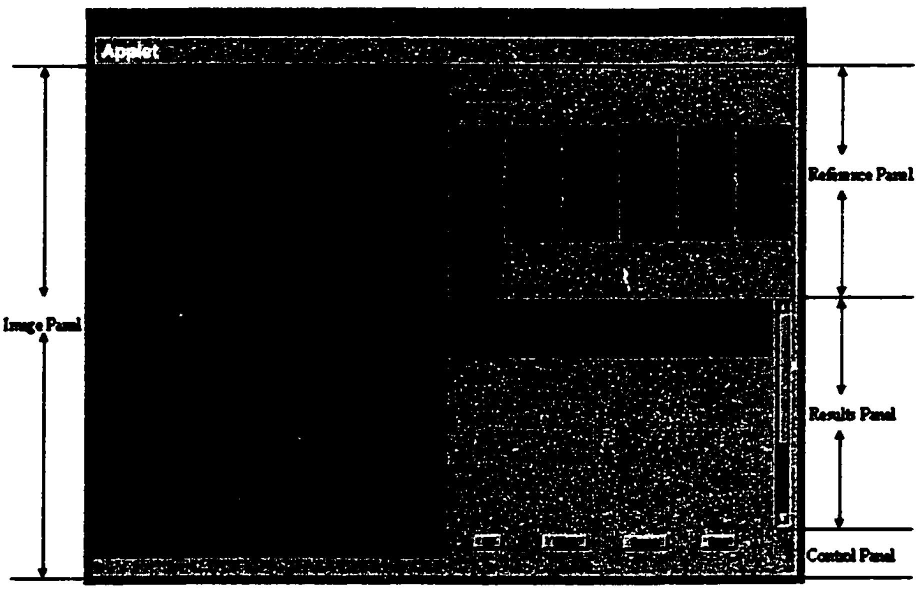


Figure 4.6 **Interface for Image Categorization.**

The interface has 4 components: the Image Panel, the Reference Panel, the Results Panel, and the Control Panel. The Image Panel displays an image, while the Reference Panel presents 13 representative tiles, each of which suggests a category. The current representative tile is highlighted in its own color, while image tiles being inspected are highlighted in the same color and are displayed on the Results Panel.

4.4 Experiment Procedure and Results

Human perception of image texture is subjective (Huang et al., 1996); different persons or the same person at a different time may have different perception criteria. Therefore the evaluation of the system incorporated the concept of relevance. This study experiment considered objective relevance of the system to be an indication of the relationship of an image tile to a query specified by a user (Janes, 1994). The experiment relied on an expert to evaluate the performances of the system and the human subjects. Comparing the performance of the system with those of the human subjects can help to determine how useful the SOM-AIR system would be in helping a non-expert user in image retrieval. The evaluation study used two measures, *precision* and *recall*. Precision represented the relevance of the retrieved information, while recall indicated how much of the relevant information in the database was retrieved (Salton & McGill, 1983). Each the experiment had its own method of calculating *precision* and *recall*.

4.4.1 Similarity Analysis

The SOM-AIR system determines the similarity between image tiles based on Euclidean distances in their feature space. A threshold of Euclidean distance was decided and an image tile was considered to be similar to a reference tile when the Euclidean distance between them was shorter than that threshold value. This threshold was determined during the pilot study by the experimenter's visual judgment. A threshold value was also set for the scores assigned by human subjects. Janes (1991) conducted an experiment to study humans' perception of relevance. During his experiment, in which human subjects were asked to give a "break point" on a continuum of relevance from 0 relevance to complete relevance, he found that the break points assigned by human subjects exhibited a wide range. However, the mean value of the break point remained at around 50 on a scale of 100. Therefore, we considered an image tile to be similar to the reference tile if human subjects assigned it a score higher than or equal to 6. Meanwhile, the expert selected all the similar image tiles corresponding to every reference tile. The experiment used the measures of *subjective recall* and *subjective precision* to evaluate the performance of human subjects and applied *system recall* and *system precision* to represent the performance of the SOM-AIR system. These measures were defined as follows:

- *Subject recall,* reflected the percentage of total number of tiles similar to those retrieved by the expert that were located by the subjects.
- *System recall* reflected the percentage of the total number of similar tiles retrieved by the expert that were located by the system.
- *Subject precision* reflected the percentage of the number of similar tiles selected by the subjects that were considered to be similar by the expert.
- *System precision* reflected the percentage of the number of tiles retrieved by the system as similar that were considered to be similar by the expert.

When results were compared, the system exhibited no significant difference from human subjects in precision, but it performed less well than human subjects in recall.

Ten subjects worked on 10 different images, from each of which we randomly selected 6 tiles as reference tiles to this image. We asked subjects to assign every image tile a score based on their similarity to the corresponding reference tile. This process was repeated for every reference tile on the interface. Because of limited time and cognitive resources, 9 subjects finished 4 reference tiles and only one subject finished 5. We obtained 41 finished reference tiles at the end of the experiment. Using the previously described threshold, *subject recall*, *subject precision*, *system recall*, and *system precision* were calculated for a finished reference tile. There were 41 evaluations each from subjects and the system. Minitab statistical software was used to perform a one-way analysis on each comparison (Figure 4.7), using the value of P to indicate the significance and setting the threshold value of P at 10%. At P>10% there was no significant difference between the computer results and those of human subjects, while at P<10% there was a significant difference. The P value (P=0.343) of precision indicated that the results were not significant; while the results of recall (P=0.004) indicated that the SOM-AIR system performed worse in recall than human subjects.

For a given referenced tile, the average number of similar tiles retrieved by human subjects was larger than the average of those retrieved by system

Although the system did relatively poorly in recall, we do not view this as a major weakness. When people retrieve images from a database, they usually are interested in finding the first N images that are most similar to a query image. Under these circumstances, precision is more important than recall. It was found that for a given

```
Analysis of Variance of Recall (Similarity)
Source  DF   SS      MS      F     P
Factor   1  0.4316  0.4316  8.80  0.004
Error   81  3.9729  0.0490
Total   82  4.4044
                         Individual 95% CIs For Mean
                         Based on Pooled StDev
Level    N   Mean    StDev  -------+---------+---------+--------
System  42  0.6575  0.2418  (------*------)
Subject 41  0.8018  0.1985                    (------*------)
                            -------+---------+---------+--------
Pooled StDev = 0.2215            0.640     0.720     0.800

Analysis of Variance of Precision (Similarity)
Source  DF   SS      MS      F     P
Factor   1  0.0630  0.0630  0.91  0.343
Error   81  5.6206  0.0694
Total   82  5.6836
                         Individual 95% CIs For Mean
                         Based on Pooled StDev
Level    N   Mean    StDev  ---+---------+---------+---------+--
System  42  0.4749  0.2527       (-----------*-----------)
Subject 41  0.4198  0.2740  (-----------*-----------)
                            ---+---------+---------+---------+--
Pooled StDev = 0.2634        0.360     0.420     0.480     0.540
```

Figure 4.7 Recall and Precision Comparisons for Similarity Analysis

referenced tile, the average number of similar tiles retrieved by human subjects was 68, while the SOM-AIR system retrieved only 28. This fact could explain why the system exhibited relatively poor recall. Therefore, it was concluded that the system's recall could be improved by allowing a lower threshold of similarity measures.

An interesting result of this research was the lack of duplication in the top 5 similar tiles suggested by the system and by human subjects.

When the system and human subjects were asked to find the 5 tiles most similar to a referenced tile, their results were likely to be different. Apparently the measure of Euclidean distance can match the human perception of similarity only to a certain extent; it needs to be combined with other similarity measures to simulate human perception. This finding is consistent with the results of Manjuanth & Ma (1996), whose research also indicates that nearest-neighbor searching fails to retrieve some other more relevant patterns.

Both the system and human subjects did well in retrieving tiles with distinguishable texture, but had difficulty in retrieving image tiles that could not be distinguished by texture alone.

Another interesting finding is that both the system and human subjects did well in retrieving image tiles of orchard, which has obviously distinguishable texture (subject recall=96.9%, system recall=57.9%, subject precision=42.5%, and system precision=100%), but both the human subjects and the system, especially the system, had difficulty in retrieving the pure water tiles (subject recall=80%, system recall=37.5%, subject precision=27%, and system precision=17.6%). We found that water tiles had the same homogeneous texture as soil or forest tiles. The SOM-AIR system certainly had difficulty in distinguishing these because it represents image in terms of texture features. Human subjects had the same problem. Although they used contrast information in comparing an image tile with its background, their decision was more affected by texture, resulting in their retrieving pure soil tiles as similar to pure water tiles, which had similar gray scale and texture. This indicates that, under some circumstances, texture alone is insufficient to represent image.

4.4.2 Region Segmentation

In this part of the experiment, the measures of recall and precision were defined as follows:

- *Subject recall,* reflected the percentage of total number of image tiles the expert grouped with a tile that had been grouped with that tile by subjects.
- *System recall,* reflected the percentage of total number of image tiles the expert grouped with a tile that had been grouped with that tile by the system.
- *Subject precision,* represented the percentage of number of image tiles subjects grouped with one tile that had been grouped with that tile by the expert.
- *System precision,* represented the percentage of the number of image tiles the system grouped with one tile that had been grouped with that tile by the expert.

```
Analysis of Variance of Recall (Segmentation)
Source   DF     SS       MS      F      P
Factor    1   5.5284   5.5284  55.73  0.000
Error  3838 380.7327   0.0992
Total  3839 386.2611
                        Individual 95% CIs For Mean
                        Based on Pooled StDev
Level     N    Mean   StDev  ---------+---------+---------+------
System  1920  0.5248  0.2931  (---*---)
Subject 1920  0.6007  0.3354                      (---*---)
                             ---------+---------+---------+------
Pooled StDev =  0.3150           0.540     0.570     0.600

Analysis of Variance of Precision (Segmentation)
Source   DF     SS       MS       F      P
Factor    1  17.1459  17.1459  174.20  0.000
Error  3838 377.7571   0.0984
Total  3839 394.9030
                        Individual 95% CIs For Mean
                        Based on Pooled StDev
Level     N    Mean   StDev  ------+---------+---------+---------+
System  1920  0.5352  0.3025  (--*--)
Subject 1920  0.6689  0.3246                       (--*--)
                             ------+---------+---------+---------+
```

Figure 4.8 Recall and Precision Comparisons for Region Segmentation

The system did worse than humans on both recall and precision

The subject recall, subject precision, system recall, and the system precision were calculated for each tile, which resulted in 1920 (192 × 10) evaluations at the end of the experiment. Figure 4.8 illustrates Minitab's one-way ANOVA test for recall and precision. This experiment continued to use P=10% as the threshold of significance and it was found that the system did worse in both recall (P =0.00) and precision (P=0.00).

Most differences between selections by human subjects and those by the system occurred in connection with tiles having undistinguishable texture or more than one type of texture.

Most of the differences between human subjects' and the system's selections occurred on image tiles that contained more than one land surface type. For instance, if one tile was mainly occupied by orchard but included a small road, human subjects probably grouped it with adjacent orchard tiles, while the SOM-AIR system would regard it as another region. Once again, in the experiment, both subjects and the SOM-AIR system had problems similar to those experienced in the first part. They both grouped adjacent tiles that had similar texture and gray scale but belonged to different land surface types.

4.4.3 Image Categorization

In this experiment, the definitions of recall and precision were as follows:

- *Subject recall* represented the percentage of total number of image tiles assigned to a category by the expert that had been assigned to this category by subjects.
- *System recall* represented the percentage of total number of image tiles assigned to a category by the expert that had been assigned to this category by the system.
- *Subject precision* reflected the percentage of total number of image tiles assigned to a category that had been assigned to this category by the expert.
- *System precision* reflected the percentage of total number of image tiles assigned to a category that had been assigned to that category by the expert.

The system did at least as well as human subjects in image categorization.

After calculating the subject recall, subject precision, system recall, and system precision for each category suggested, 127 evaluations were obtained at the end of the experiment. Comparisons of recall and precision are presented in Figure 4.9. There were no statistically significant differences between human subjects and the system in recall (P=0.562) or precision (0.760).

```
Analysis of Variance of Recall (Categorization)
Source   DF     SS      MS      F     P
Factor    1    0.039   0.039   0.34  0.562
Error   252   29.287   0.116
Total   253   29.327
                        Individual 95% CIs For Mean
                        Based on Pooled StDev
Level     N    Mean    StDev   -------+---------+---------+-------
System  127   0.4160   0.3335     (------------*------------)
Subject 127   0.3912   0.3482  (------------*------------)
                               -------+---------+---------+-------
Pooled StDev =  0.3409               0.360     0.400     0.440

Analysis of Variance of Precision (Categorization)
Source   DF     SS       MS      F     P
Factor    1   0.0069   0.0069   0.09  0.760
Error   252  18.7535   0.0744
Total   253  18.7604
                        Individual 95% CIs For Mean
                        Based on Pooled StDev
Level     N    Mean    StDev   --+---------+---------+---------+--
System  127   0.3358   0.2336  (------------*------------)
Subject 127   0.3462   0.3071     (------------*------------)
                               --+---------+---------+---------+--
Pooled StDev =  0.2728          0.300     0.330     0.360     0.390
```

Figure 4.9 Recall and Precision Comparisons for Image Categorization

The system was inclined to produce too many categories, and representative tiles sometimes were not really representative.

Most of the subjects complained that there were too many suggested categories and some of the representative tiles were similar to each other. This probably was due to the small size of the input data set to the SOM in this experiment. As a matter of fact, the SOM-AIR system used hundreds of thousands of image tiles as the input data for the SOM. A set of 192 tiles was too small for the SOM algorithm, but we discovered it was impossible to increase the image size in the experiment. During the pilot studies, it was learned that, even though the interface provided relieved human subjects of the need to manage tiles, they still could not accomplish a task having too many tiles due to limited cognitive resources. The pilot study also found that when the number of tiles exceeded 200, most subjects either gave up on the task or assigned tiles to categories randomly because of cognitive overload. Therefore, it was encouraging that the SOM-AIR system could perform at a level comparable with that of human subjects, based on such a limited input size.

4.5 Conclusions

When performing the task of similarity analysis, the system did as well as human subjects in precision, but did worse in recall. While completing region segmentation, the system did worse than human subjects. The experiment found that the system did at least as well as human subjects in completing the task of image categorization. As a result, the SOM-AIR system is believed to be able to do as well as humans in image analysis and categorization. This is especially true for surface types with distinguishable texture. The SOM-AIR system addresses two issues in the image retrieval field. It successfully integrates image processing techniques such as the Gabor filter with information analysis algorithms like the SOM. The system created is scalable and has performance comparable to that of a normal person. On the other hand, the system addresses a troublesome aspect of traditional retrieval models, which require users to have complete knowledge of the low-level features of an image. The system enables users to specify their queries by clicking on images and translates their high-level queries into low-level features.

5. USING 3D INTERFACES TO DELIVER MULTIMEDIA GEO-REFERENCED INFORMATION

5.1 Background

Chapters 3 and 4 having discussed knowledge retrieval from knowledge repositories in textual and imagery media types, this chapter turns to a discussion of information visualization technology aimed at improving access to knowledge from a multimedia knowledge repository. The system described provides an example of provision of support to cross-media information browsing. Using geographical information as testbed, the system utilizes both realistic and abstract maps to deliver spatial knowledge sought by users of GIS (geographical information systems). The combination of realistic and abstract graphics has been proven valuable for linking "where" and "what", two important concepts in GIS research (Monmonier, 1992). However, a computer screen may become more and more crowded as more information is available. For instance, previously developed GIS systems use several windows for information in different media types (Larson, 1996; Smith, 1996; Zhu et al., 1999) and the number of windows increases as the number of media types increases. The entire computer screen can become unmanageable when users have to jump back and forth among several windows. The ability to pack more information on a computer screen makes a 3D interface a promising candidate to address this "small screen" problem (Robertson et al., 1993). This approach has been applied in the construction of 3D cone Tree (Robertson et al., 1991) that displays a hierarchical relationships. The system described in this chapter provides an example of incorporating information from different media types on the same window by utilizing a 3D interface technique.

Most previous studies do not provide supportive evidence for using a 3D interface (Kulmer & Groop, 1990; Pilon & Friedman, 1998; Swan & Allen, 1998). Those studies, however, use only static interface and provide no interaction between human subjects and the stimuli. Human subjects therefore have used a 3D interface from only one perspective, inevitably giving rise to the "hidden object" problem. On the other hand, the system developed for this dissertation provides interactive animation so that users are able to manipulate visual objects directly. This makes it necessary to examine the comparative effectiveness and efficiency of the 3D system and its 2D counterpart in delivering spatial knowledge when interactive animation is available. By designing an empirical study for the comparison, this chapter is also intended to contribute to the area of evaluation of visualization, which recently has drawn more and more attention (Chen & Czerwinski, 2000).

5.2 Related Work and Research Issue

Geo-referenced information was selected as the testbed because the use of GIS has been proven to have a positive impact on decision-making (Murphy 1995; Robey & Sahay 1996; Dennis & Carte 1998). In addition, diversity of geographical information media makes it an appropriate candidate for research in cross-media information browsing.

5.2.1 Existing Systems

As indicated in DiBiase et al., (1992), graphical interfaces usually belong to one of two categories: the realistic or the abstract. The spatial dimensions in a realistic graphic correspond with those of the object depicted, while spatial dimensions in an abstract graphic represent non-spatial data. A GIS system usually utilizes both types of graphics to link the two most important concepts in geographical information, "where" and "what." While cartography research studies various techniques for presenting a geographical map, a variety of GIS systems focus on how to help users specify their information needs. For instance, the GKRS system described in Chen et al. (1998c) and Zhu et al. (1999) supports concept-based cross-media searching behavior. The Alexandra Digital Library (ADL) project has developed a system that enables users to specify their queries over a map. These systems use multiple windows to display information of different media types and users have to jump back and forth among windows to obtain information. Such processes may become unmanageable as the number of windows increases.

On the other hand, using a 3D interface is one way to pack more information on the screen. Advanced hardware technology and specialized 3D software fortunately have made it more and more rapidly to accomplish 3D transformations, hidden-surface removal, and surface models. Researchers and software developers have invented several 3D designs, including the Cone Tree (Hearst & Karadi, 1997; Roberston et al., 1991), Hyperbolic Tree (Lamping et al., 1995), the WebBook (Card et al., 1996), Information

Cube (Feiner & Beshers, 1990), and information landscape (Chalmers et al., 1996). However, as more and more 3D prototype systems have been developed to visualize large-scale information, little work has been done to incorporate this technique into GIS research.

5.2.2 Spatial Knowledge

MacEachren (1991) cited the work of Golledge & Stimson (1987) and listed three types of spatial knowledge that users can acquire from a geographical information visualization system: declarative knowledge, procedural knowledge, and configurational knowledge. Declarative knowledge, which calls for the lowest level of cognitive development, denotes knowledge about places and their attributes (i.e., place name and location). Procedural knowledge, considered to be at a higher level than declarative knowledge, is characterized by awareness of how to get from one place to another place and is also called routing knowledge. At the highest level of cognitive processing is configurational knowledge, which refers to the spatial relationships among places and knowledge of geographical patterns. While the effectiveness of a particular interface varies with the type of knowledge, there is little current research comparing the effectiveness and efficiency of 2D and 3D approaches in conveying all three types of spatial knowledge.

5.2.3 Previous 3D-2D Comparison studies

Most geographical information visualization (GIV) systems involve describing terrain surfaces, which requires a realistic map to provide information about both location and elevation. Even though a 3D terrain description is considered to be more similar to a real earth surface than a 2D description, its biggest disadvantage is the problem of hidden objects. Kumler and Groop (1990) found that a 2D terrain-depiction method, continuous tone shading, performed better in facilitating static map reading than a 3D depiction did. Research in cognitive psychology had obtained similar results when abstract graphics were used. For instance, Pilon & Friedman (1998) indicated that search among 2D objects is more efficient than search among 3D objects because of the complexity of 3D objects. In addition, Swan & Allan (1998) conducted an experiment to evaluate the user interface of their textual document retrieval system. They compared the usefulness of the 2D and 3D interfaces in facilitating textual information retrieval. Again, their study found no evidence to support the effectiveness of the 3D interface.

One limitation of the cited studies is that only static 3D interfaces were provided to subjects and there was no interaction between subjects and the interface. Providing a single point of view inevitably causes the hidden-object effect. As indicated by Moellering (1980), a 3D terrain-description can increase map understanding when multiple perspectives are provided. However, Goldberg et al. (1992) argued that providing several perspectives of 3D depiction might increase a user's cognitive load because having to rotate the map mentally can be difficult for human subjects. In addition, that research found more than one type of mental rotation to be involved when human subjects read a series of 3D depictions. On the other hand, researchers in the information visualization field have indicated that interactive animation enables users to have sole control of the rotation of 3D subjects, which can effectively shift the cognitive processing to the perceptual process (Robertson et al., 1993). One important example that applies this theory is the 3D Cone Tree system (Hearst & Karadi, 1997; Robertson et al., 1991), which visualizes the structures of a large collection of text documents by using abstract graphics. However, little user study has been conducted regarding the effectiveness and efficiency of a 3D interface with interactive animation.

Another limitation of previous evaluation studies is their focus on only the delivery of declarative and configurational knowledge, using either realistic graphics (Goldberg et al., 1992; Kumler & Groop, 1990) or abstract data (Pilon & Friedman, 1998; Swan & Allan, 1998). Most studies have indicated that a static 2D interface was more efficient than a static 3D interface in conveying these two types of knowledge. On the other hand, Elvins et al. (1998) found that people's ability to find their way was enhanced by using 3D landmarks. However, few studies have compared the effectiveness of 3D and 2D interfaces in delivering routing knowledge.

In summary, there has been very little research comparing the relative effectiveness and efficiency of 3D and 2D interfaces in both realistic and abstract types. In addition, most comparisons provide only a single perspective on a 3D interface, introducing the possibility of a hidden-objects effect. Some other studies provided human subjects with a series of multiple perspectives of a 3D object. However, since human subjects had no control over the rotation, the mental rotation required for this approach still may have increased the cognitive load. Furthermore, their research attention focuses only on the declarative and configurational knowledge. Little comparison with routing knowledge has been done.

5.2.4 Research Formulation

Support of knowledge access from a multimedia knowledge repository requires organization of information in various media types on a computer screen. Previous GIS systems used one window for each media type (Larson, 1996; Smith, 1996; Zhu et al., 1999). Such display can become unmanageable as the number of windows increases, but emerging 3D techniques provide a chance to increase information density and thus to decrease the number of windows. This chapter develops its first research question as follows:

- *How to apply 3D interface and information analysis techniques to support cross-media information browsing?*

The system developed also provides interactive animation that enables users to manipulate visual objects on the screen directly without mental rotation. This provides a new setting for further exploration into the differences between 3D and 2D interfaces. Most previous comparison studies used a static interface with which human subjects had no interaction. Therefore, the second research question of this chapter is as follows.

- *Can a 3D interface with interactive animation produce a performance level at least comparable to that of its 2D counterpart?*

5.3 The 3D Prototype system: Cross Media Information Browsing

The data used by the 3D system includes aerial photos, Digital Elevation Model (DEM) data, Geographical Name Information Systems (GNIS), and geo-referenced textual documents. The interface of the 3D-system had 2 parts, a 3D aerial photo (Figure 5.1) and a 3D semantic map (Figure 5.2). The 3D aerial photo depicts elevation changes of a landscape according to the DEM data. Because this map employs a three-dimensional coordinate system, the X and Y coordinates of each point on the map show its spatial location on the land surface and the Z coordinate suggests its elevation. The system places the aerial photo on the surface of the landscape to visualize land-surface type such as building, street, sea, and mountain. Red dots on the 3D aerial photo indicate the locations of places named in the GNIS. The 3D aerial photo thus integrates three different types of geo-referenced information based on the X and Y coordinates. Therefore, the 3D aerial photo incorporates information in the numerical, textual, and imagery media types in the same window.

While the 3D aerial photo displays spatial information, the 3D semantic map presents non-spatial information in the same topological format. The textual documents describe the geographical attributes (i.e., ground water) of different places. The documents were categorized by using the self-organizing map (SOM) (Kohonen, 1995; Chen et al., 1998) for creation of the semantic map. In addition to clustering similar documents into the same category and labeling each category with a keyword, the 3D semantic map also utilized the graphical SOM output to present the categories of the textual documents. The

Figure 5.1 3D Aerial Photo

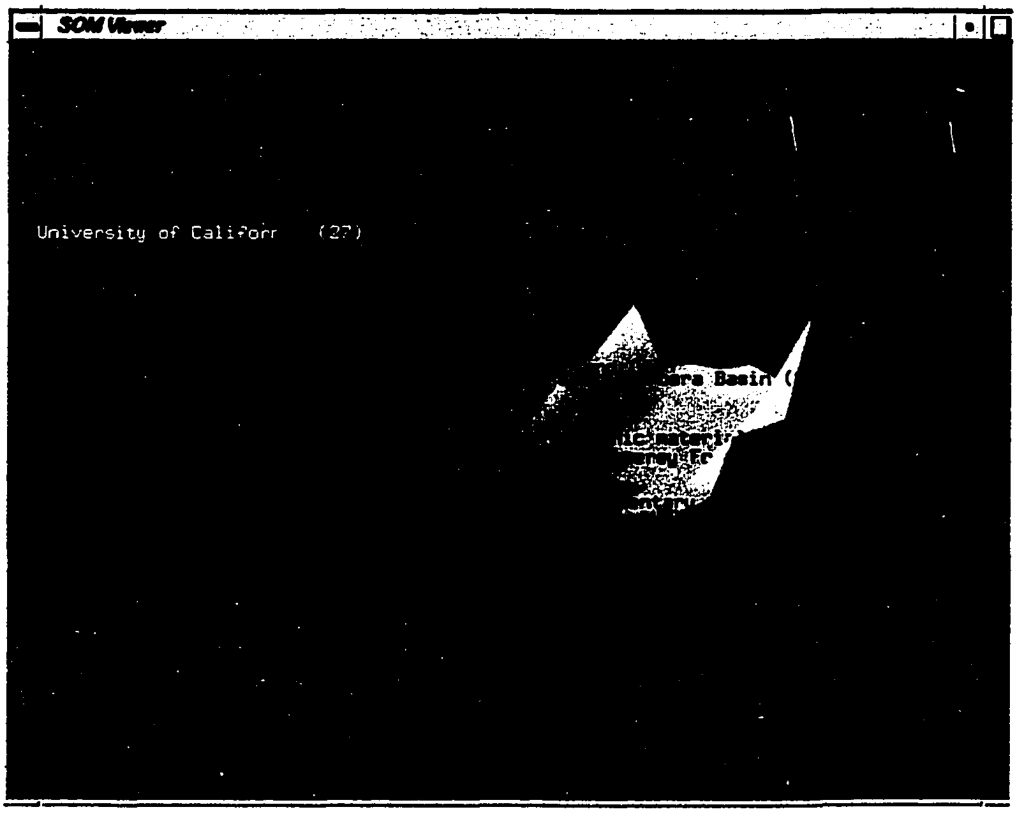


Figure 5.2 3D Semantic Map

X and Y coordinates of each category represent its location on the SOM, while the Z coordinate exhibits the number of documents belonging to each node. Each category has its own color and the label of each category includes the keyword and a number indicating the number of documents within the category.

The 3D-system enables users to rotate and to zoom in/out on both the aerial photo and the semantic map. In order to identify a place of interest, a user can display place names by positioning the mouse cursor on the red dots of the 3D aerial photo. He/she can also click on one of the red dots, prompting the system to display near the dot on the aerial photo a text label indicating the place name and the number of textual documents related to this place. At the same time, the categories that contain those documents are highlighted on the semantic map. Alternatively, the user can also start with the semantic map. Upon clicking on a category of interest, the system highlights the category clicked. At the same time the red dots on the 3D aerial photo are highlighted in yellow and a text label is displayed near each dot. Having a 3D aerial photo and a semantic map available, a user can jump back and forth between the two frames of the interface. This maneuver by the user can achieve familiarity with a new environment without literally having to be there.

Instead of providing buttons on the interface, the system enables users to manipulate the object within a window by dragging the mouse or using the keyboard. For instance, dragging the mouse from left to right rotates the object from west to east along the Y axis and dragging the mouse from up to down leads to the rotation from up to down along the X axis. A user can also move the object up, down, left, and right by striking designated keys on the keyboard. By interacting with the interface, a user can obtain multiple perspectives of a visual object. Thus to avoid the hidden objects effect, users using 3D interface may rotate the visual object to obtain an appropriate angle of view.

5.4 Empirical Study

5.4.1 Benchmark System

In order to conduct the comparison study, a 2D system was developed. It was similar to the 3D-system except that each map was 2-dimensional. In order to deliver as much information as a 3D aerial photo, the 2D aerial photo (Figure 5.3) needed to be supplemented by a 2D elevation map (Figure 5.4). The aerial photo suggests the land surface type, while the elevation map indicates elevation changes within the area. The elevation map utilized colors instead of Z coordinates to represent the elevation of each point on the map according to a color scheme indicator displayed with the map. Moreover, because the semantic map was the same as a 3D semantic map without Z dimension, the number of documents associated with each category was indicated only by its label. The 2D-system also provides a functionality to enable users to move among the maps and to manipulate the view angles.

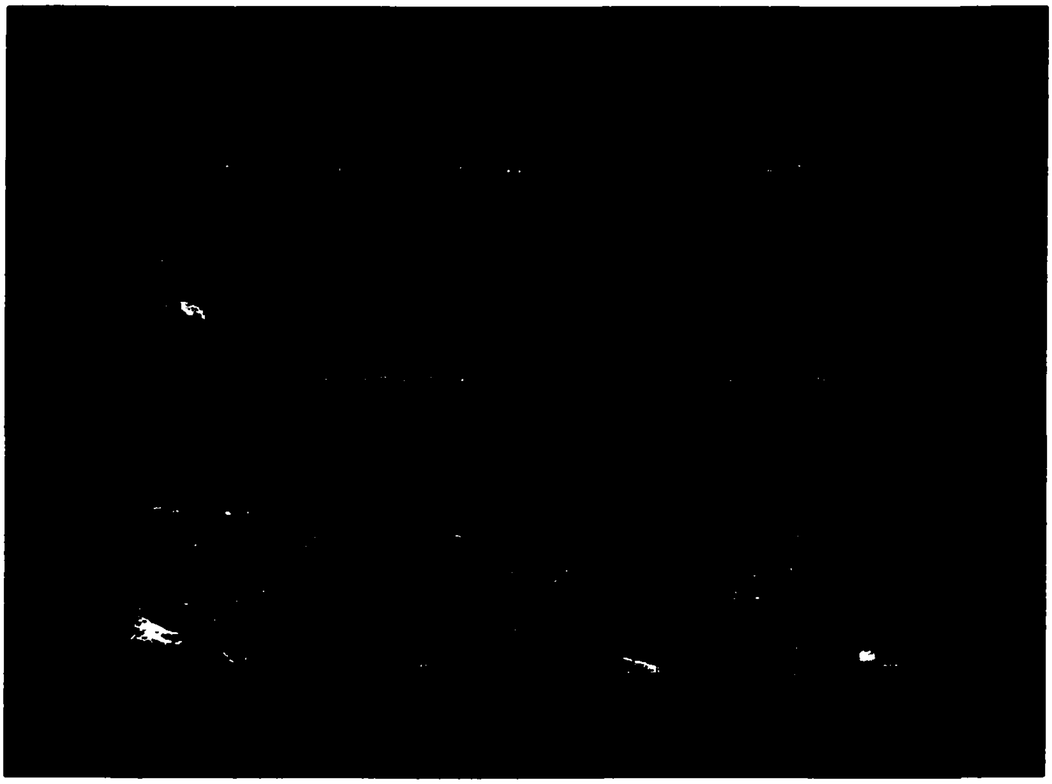


Figure 5.3 2D Aerial Photo

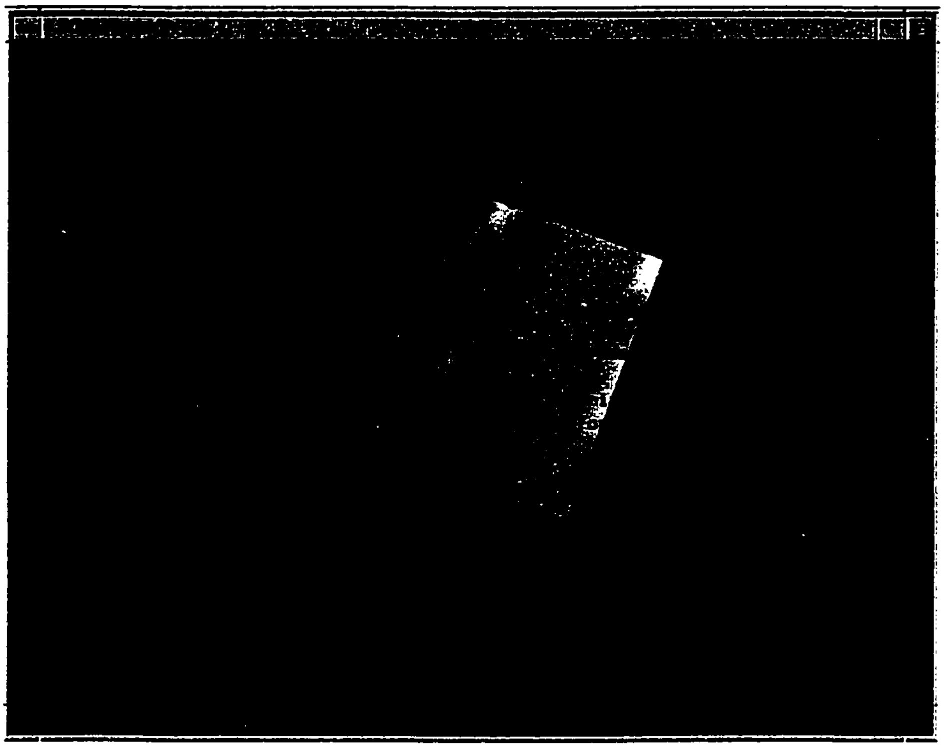


Figure 5.4 2D Semantic Map

Figure 5.5 2D Elevation Map

5.4.2 Hypothesis Development

Most studies have found a static 2D interface to be more effective and efficient in presenting declarative and configurational knowledge. Based on the fact that providing interactive animation can convert a user's cognitive process to a perspective process (Robertson et al., 1993), the empirical study developed its hypothesis as follows:

- With the assistance of interactive animation, a 3D aerial photo (realistic graphic) is <u>at least as effective and efficient</u> as a 2D aerial photo in conveying declarative and configurational knowledge

- With the assistance of interactive animation, a 3D aerial photo is more effective and efficient in conveying procedural (or routing) knowledge than a 2D aerial photo

- With the assistance of interactive animation, a 3D semantic map (abstract graphic) is at least as effective and efficient as a 2D semantic map in delivering declarative and configurational knowledge

- With the assistance of interactive animation, a 3D system (realistic + abstract) is as effective and efficient in conveying declarative and configurational knowledge as a 2D interface

5.4.3 Experiment Process

The experiment designed seven tasks to evaluate how well an aerial photo, a semantic map, and combined use of an aerial photo and a semantic map presented various types of spatial knowledge (Table 5.1). The task types were selected according to those used by previous studies in cognitive psychology and interface evaluation. Identification has been proposed by previous studies to be an elementary task types needed to evaluate a graphical interface (Wehrend & Lewis, 1990; Zhou & Feiner, 1998). This type of task requires subjects to find certain visual objects based on certain attributes. We thus selected the identification task to evaluate the delivery of declarative spatial knowledge (tasks 1, 3, and 5). A common map reading task, estimating relative surface values, has

Table 5.1 Task Design

	Description	**Interface Type**	**Spatial Knowledge Type**
Task 1	Please use the aerial photo to locate a place named University of California at Santa Barbara (UCSB).	Realistic	Declarative
Task 2	There are two roads displayed on the aerial photo. According to your visual judgment, which road will take a shorter time for you to drive? • Road a • Road b • Either road Please explain your answer	Realistic	Routing
Task 3	Which category or categories do not have any documents? Please find their locations on the semantic map	Abstract	Declarative
Task 4	Looking at the semantic map, which category, the "geophysical surveys" or the "Santa Barbara", has more documents?	Abstract	Configurational
Task 5	Does the place named UCSB have documents about ground water?	Combination of realistic and abstract	Declarative
Task 6	How many places on the interface have documents about ground water?	Combination of realistic and abstract	Configurational
Task 7	Among the places that have documents about ground water, how many are in the urban area?	Realistic	Configurational

also been used to evaluate the delivery of configurational spatial knowledge (tasks 4, 6, and 7). On the other hand, distance estimation was used to measure the delivery of routing-knowledge (task 2), because it has been demonstrated by research in cognitive psychology to be an appropriate measure for routing knowledge (Hirtle & Heidorn, 1987). In addition to selecting task types based on previous studies, we also designed tasks according to the geographical information provided by the system: land surface information, surface elevation information, text documents about places, and place locations and names.

Since each task required human subjects to find an answer (right or wrong), *task completion* was used as the measure of effectiveness. The system was to be considered effective if users could accomplish the tasks by using it. To measure efficiency, we employed *time to task* as the measure.

Sixty graduate and undergraduate students participated in this experiment. According to previous studies, subjects' individual differences such as map reading skill, spatial competence and familiarity with the computer may have an impact on their performance (Streeter & Vitello, 1986). To minimize this impact, we divided subjects randomly into two groups, with one group working on the 3D system and the other on the 2D system. The entire procedure was as follows. A written introduction was first provided to show how to use the system. The subjects then took as long as they wished to familiarize themselves with the system. Each subject was required to accomplish the seven tasks one by one and was informed that looking ahead during the experiment was not allowed. We recorded the time that it took for a subject to finish each task and his/her response to that task. Subjects were encouraged to think aloud during the entire process.

In addition, how each subject interacted with the interface was also recorded. The system provides several ways to manipulate the visual objects displayed, including moving up/down, moving left/right, zooming in/out, rotating along the Y axis, and rotating along the Z axis. One interaction score was added to a task for a subject if he/she used an interaction feature to manipulate a visual object on the interface. For instance, in order to accomplish task 7, a subject zoomed in the aerial photo to get a close look and moved the visual object from left to right to find the desired location. We assigned an interaction score of 2 to task 7 for this subject. At the end of the empirical study, we found that 3D subjects had significantly higher overall interaction scores than 2D subjects (p=0.067). This result indicates that 3D subjects were more inclined to interact with the interfaces provided, perhaps the hidden-objects effect might have encouraged 3D subjects to change their angles of view in order to obtain a suitable perspective for each task. On the other hand, 2D subjects appeared to have more difficulty than 3D subjects when they had to interact with interfaces in order to acquire correct answers for certain tasks.

5.4.4 Results Analysis

Table 5.2 provides a summary of results for each task, from which we found that *the 3D aerial photo was significantly more effective and efficient than the 2D aerial photo in delivering routing knowledge, while the system of 3D aerial photo + 3D semantic map had significant higher effectiveness and efficiency than its 2D counterpart in conveying configurational spatial knowledge*. The rest of this section discusses detailed results task by task.

- *Aerial photo, declarative knowledge (task 1)*

All human subjects were able to find the location of the University of California at Santa Barbara (UCSB). The 3D and 2D aerial photos thus appeared to have identical effectiveness. There was no significant difference in efficiency between the 2D and 3D aerial photos ($p=0.817$)

- *Aerial photo, routing knowledge (task 2)*

We assigned a score of 1 when a subject gave the right answer and a score of 0 when a subject's answer was wrong. Every subject using the 3D interface had no problem with estimating actual driving distance. On the other hand, even with the assistance of the 2D elevation map, most subjects working with the 2D interface still failed to take into consideration the elevation change. In addition, since the two roads looked identical on the interface, most subjects took longer to finish the task because they tried to figure out whether this was a trick question. The results indicate that the 3D aerial photo was significantly more effective ($p = 0.000$) and efficient ($p = 0.002$) in facilitating the routing knowledge acquisition process.

Table 5.2 Experiment Results

	Interface Type	Spatial Knowledge Type	Results	
			Effectiveness	Efficiency
Task 1	Aerial photo (Realistic)	Declarative	Identical	No difference (p=0.817)
Task 2	Aerial photo (Realistic)	Routing	**3D is better (p=0.000)**	**3D is better (p=0.002)**
Task 3	Semantic map (Abstract)	Declarative	No difference (p=0.679)	No difference (p=0.402)
Task 4	Semantic map (Abstract)	Configurational	No difference (p=0.321)	No difference (p=0.240)
Task 5	realistic + abstract	Declarative	No difference (p=0.155)	No difference (p=0.218)
Task 6	realistic + abstract	Configurational	**3D is better (p=0.025)**	**3D is better (p=0.024)**
Task 7	Aerial photo (Realistic)	Configurational	No difference (p=0.389)	No difference (p=0.186)

- *Semantic map, declarative knowledge (task 3)*

This task required subjects not only to find those categories that had no documents, but also to highlight them on the semantic map. The interface was designed to require a subject to place the mouse cursor on the colored part of the category in order to highlight the category. In other words, if a subject pointed the mouse cursor on the label of a category, the category would not be highlighted. The score of each subject was calculated as the percentage of categories selected by a subject that were desired categories.

No significant difference in effectiveness ($p = 0.679$) and efficiency ($p = 0.402$) for the delivery of declarative knowledge was detected. We observed that hidden objects seemed to be the main reason for 3D human subjects failing to recognize all categories. However, human subjects working with the 2D interface did not identify all categories, perhaps because label-overlap on the 2D semantic map may have made it more difficult to associate a text label with its corresponding color. This could help to explain the slightly higher efficiency of the 3D semantic map observed for this task.

- *Semantic map, configurational knowledge (task 4)*

Again, for this task we recorded a score of 1 if the subject gave the right answer and a score of 0 otherwise. We required subjects not only to find the category having more documents than the other but also to highlight which two categories they needed to compare. As in task 3, label overlap caused some difficulty for subjects who used the 2D interface, but for this task there was no significant difference in effectiveness ($p = 0.321$) or efficiency ($p = 0.240$) between 3D and 2D semantic maps.

- *Aerial photo and semantic map, declarative knowledge (task 5)*

This task required subjects to use both an aerial photo and a semantic map. They could start with the aerial photo, click on UCSB, and then check the map to see if the category of "ground water" was highlighted. Alternatively, they could start with the semantic map, click on the category of "ground water", and then find out whether the UCSB was highlighted on the aerial photo. We observed that most subjects started with the aerial photo, probably because they had located the UCSB on the aerial photo in task 1.

However, subjects working with the 2D interface had difficulty associating text labels with their corresponding color parts on the semantic map. Therefore, some subjects who started with the semantic map clicked on the wrong category and obtained incorrect answers. In addition, label-overlap caused more problems for the 2D users. Overall, there was no significant difference in effectiveness ($p = 0.155$) or efficiency ($p = 0.218$).

- *Aerial photo and semantic map, configurational knowledge (task 6)*

As in task 5, a subject needed to use both the semantic map and the aerial photo to accomplish this task. We recorded the score for each subject by calculating the percentage of correct locations the subject identified. Again, hidden objects caused some difficulties for 3D users, while text label-overlap prevented 2D users from obtaining correct answers. We found the 3D system to be significantly more effective ($p = 0.025$) and efficient ($p = 0.024$) in this task. This may have stemmed from the two major problems of the 2D system: the difficulty of associating text labels with their color parts on the semantic map and text-label overlap on both the semantic map and the aerial photo. 2D users appeared to be more likely to click on the wrong category on the semantic map and had more difficulty in counting highlighted locations on the aerial photo.

- *Aerial photo, configurational knowledge (task 7)*

For this task we recorded the results by calculating what percentage of locations selected by subjects as urban locations actually were in the urban area. In this task, a subject had to use interactions such as zooming in/out, rotation, and moving in order to obtain the correct answer. We also found that 3D users appeared to have less difficulty in manipulating the objects in the interface, probably because more user interaction with the 3D system already had been observed in previous tasks. Therefore, although results indicated no significant difference in effectiveness ($p = 0.389$) and efficiency ($p = 0.186$) between the use of 3D and the 2D aerial photos, we found the 3D system was slightly more effective and efficient in facilitating the completion of this task.

5.5 Summary and conclusion

The system described in this chapter provides an example of incorporating information of different media types on the same window by using 3D interface techniques. Combining the realistic and abstract graphics, the system was shown to facilitate users' spatial knowledge acquisition.

On the other hand, this chapter also presents an experiment that compared the effectiveness and efficiency of 3D and 2D interfaces in facilitating human spatial knowledge acquisition. The experiment demonstrated that *with the assistance of interactive animation, a 3D aerial photo was more effective and efficient than a 2D aerial photo in conveying routing knowledge, whereas a 3D aerial photo + 3D semantic map system (realistic + abstract interfaces) was more effective and efficient in presenting configurational knowledge.* We list other results from this experiment as follows:

- With the assistance of interactive animation, a 3D aerial photo (realistic graphic) was at least as effective and efficient as a 2D aerial photo in conveying declarative and configurational knowledge.

- With the assistance of interactive animation, a 3D semantic map (abstract graphic) was at least as effective and efficient as a 2D semantic map in delivering declarative and configurational knowledge.
- With the assistance of interactive animation, a 3D system (realistic + abstract) was as effective and efficient in conveying declarative knowledge as a 2D system.

The experiment indicates that 3D users had more interactions with the interface than did 2D users. The 2D interface presented a problem of text-label overlap and its users had difficulty in associating text labels with analogous color parts on the 2D semantic map. On the other hand, even with assistance of interactive animation, hidden subjects remained the main impediment to spatial knowledge delivery, perhaps because manipulation of objects on the interface may still add extra cognitive load. Despite the hidden-subject problem, the results nevertheless support the conclusion that, with the assistance of interactive animation, a 3D interface is a promising approach to visualizing spatial knowledge.

6. VISUALIZING THE PROCESS OF A COMPUTER-MEDIATED COMMUNICATION

6.1 Objectives

The archive of computer mediated communication (CMC) has been demonstrated to be a valuable knowledge repository that captures unstructured knowledge dispersed among individuals (Hahn & Subramani, 2000). The crucial role of the CMC memory stems not only from the fact that inter-personal communication enabled by a CMC system results in knowledge sharing and transfer (Sachs, 1995), but also from the increasing importance of CMC in maintaining a virtual community that facilitates the organizational learning process (Sproull & Kiesler, 1991). While a CMC process documents knowledge shared, it also records the behavior of its participants and their attitude toward the virtual community facilitated by the CMC (Sproull & Kiesler, 1991; Weisband et al., 1995). Empirical studies indicate not only that reviewing the record of a communication enhances individual learning (Fussell et al., 1998), but also that working with a community appears to be an effective way to share organizational knowledge (Davenport & Prusak, 1998). On the other hand, research on organizational communication shows that a person's identification with a community is based on both the contents discussed within the community and the behaviors of other participants (Lea & Spears, 1992). Therefore, to facilitate an organizational learning process, a CMC organizational memory system needs to help users be aware of both the content discussed and the other members' behaviors. Such help becomes especially important when users are overloaded by the large amount information stored in archives of various CMC systems (Hiltz et al., 1986). However, most CMC systems organize content either by mediating the way in which participants communicate with each other (Nunamaker et al, 1991; Ackerman, 1994), or by applying such information analysis techniques as automatic indexing, categorization, or collaborative filtering (Konstan et al., 1997; Chen et al. 1998b; Van Dyke at al., 1999). Very few CMC systems provide users with help in understanding both the content discussed through a CMC process and the behaviors of other participants in the communication process.

Nevertheless, various technologies to promote a user's awareness of other participants' behaviors do exist. For instance, the Netscape Messenger, a popular Email handling tool, has a user interface that enables users to organize their messages based on thread, sender, or date. Different formats for message display may suggest how active a community is (indicated by the number of message per thread) and participants' attitude toward a community (indicated by how many messages a person posts and how long he/she stays). In addition, various social visualization techniques have been developed to provide graphical representation and summary of how participants behave during a CMC process. Examples include Loom (Donath et al., 1999), Chat Circles (Donath et al., 1999), and PeopleGarden (Xiong & Donath, 1999). However, how to integrate these techniques appropriately into a CMC organization memory system has become an issue. Moreover, because users interact intimately only with the user interface of an information system

(Frank, 1993), the interface type inevitably has a significant impact on the user's communication behaviors (Subramani & Hahn, 2000), perception of other participants (Burgoon et al., 1999), or decision making process (Vessey, 1991; Dennis & Carte, 1998). Few empirical studies have evaluated the impacts of graphical interfaces created by social visualization techniques on users' behavior, perception, and decision-making process.

Viewing the archive of a CMC process as a valuable knowledge repository, this chapter presents a two-phase research to address the issues described above. The first phase proposes and implements a prototype system that integrates a social visualization technique with various information analysis technologies to graphically summarize both the content and behaviors of an online discussion group. Simple information acquisition and evaluation tasks have been identified as elementary tasks of a decision making process (Vessey, 1991; Vessey & Galletta, 1991; Dennis & Carte, 1998). The second phase employs the "de-featuring" approach used by previous interface evaluation studies (Morse & Lewis, 2000) to evaluate how the graphical interface developed in the first phase research affects users' information acquisition and evaluation processes

6.2 Related Work and Research Question Development

6.2.1 Computer Mediated Communication

Most empirical studies of CMC have focused on the interaction among information technology, individual behavior, group characteristics, and organizational structure.

These studies indicate that CMC not only provides incentives for participants to share knowledge (Sproull & Kiesler, 1991) but also creates a common context in which its participants convert their tacit knowledge into explicit knowledge (Nonaka & Konno, 1998). At the same time, CMC participants also project their personal styles, previous experiences and social norms into their computer mediated communication (Weisband et al., 1995). The attitude of participants toward the community is related to the volume of messages they send (Sproull & Kiesler, 1991). In addition, the person who posts more answers or participates more in discussion of certain topics than other individuals may be regarded as the expert in that area (Ahuja & Carley, 1998). He/she might not be the most knowledgeable individual on that subject but is probably willing to help. Knowing who and where experts are is another type of valuable organizational knowledge. The archive of a CMC process therefore contains rich information about both knowledge shared and behavior of participants.

6.2.2 Organizational Memory

From the perspective of organization learning, a knowledge repository is regarded as an organizational memory system. With the objectives of connecting people with knowledge and connecting people with people (Ackerman 1994; O'Leary 1998a), a variety of prototypes of organizational memory systems have been proposed. Most organizational memory systems focus on organizing the content of data (Grief & Sarin, 1987), artifacts, documents (Berlin & Grunin, 1993), discussions (Nunamaker et al., 1991), and topics (Ackerman, 1994) shared among people. At the same time, the introduction of the

Internet has led to the proliferation of CMC, various information analysis technologies have been developed to index, categorize, and filter the content of discussions. For instance, Chen et al. (1998b) employed an algorithm called self-organizing map (Kohonen, 1995) to automatically identify sub-topics of discussions, while Van Dyke et al. (1999) extracted keywords from the content of a discussion to help users automatically find desired online discussion groups

6.2.3 Social Visualization

The objective of visualization techniques is to convert abstract information into visual objects that can be displayed. The fact that a human brain can process various visual cues (i.e. color, texture, shape, and position) in a parallel manner provides the theoretical foundation for visualization research. Social visualization research, on the other hand, focuses on representing human behavior graphically. For instance, systems such as Loom (Donath et al., 1999) and PeopleGarden (Xiong & Donath, 1999) provide graphical summaries on who starts a discussion, who talks with whom, how long a person stays, and how lively a discussion is. Chat Circles (Donath et al., 1999) aims to facilitate synchronous conversation in an online chat room. Users can only "hear" from or "talk" to others in their vicinity. They can also move themselves around to find an appropriate subgroup to talk with. However, the impact on users of these innovative graphical representations is not yet known.

6.2.4 Research Question Development

The archive of a CMC process has been demonstrated to be a valuable resource in knowledge management. The archive contains knowledge shared and information about how participants behave during discussions. Both types of information are essential to users attempting to locate experts and wishing to identify an appropriate community with which to share knowledge. Most CMC systems focus only on organizing the content of discussion; whereas research on social visualization develops techniques to depict human behaviors during CMC, leaving unanswered such questions as how to incorporate a social visualization technique into an organizational memory system and how users react to graphical representations.

Review of previous studies reveals the importance of the following types of information in knowledge management.

- Sub-topic identification (O'Leary, 1998b)
- Temporal change of each sub-topic (O'Leary, 1998b)
- Interaction status (Xiong & Donath, 1999)
- Expert identification
- Participants' attitude toward a community (Xiong & Donath, 1999)

These five types of information can be extracted automatically from the archive of a CMC process by applying appropriate information analysis algorithms and social visualization techniques. Therefore, one research question addressed in this chapter is:

- *How can information analysis and social visualization techniques be integrated to extract the five types of information from the archive of a CMC process and to present them in a meaningful way?*

As part of a communication tool, the graphical interface developed is expected to affect the behavior pattern of a computer mediated community (Subramani & Hahn, 2000). On the other hand, according to Cognitive Fit Theory (Vessey, 1991), decision-makers develop mental representation of their tasks and adopt their decision making process based on the presentation of task-related information. Therefore interface types may also have an impact on decision-making process (Vessey, 1991; Dennis & Carte, 1998). Simple information acquisition and evaluation have been identified as elementary tasks of a decision making process (Vessey, 1991; Vessey & Galletta, 1991; Dennis & Carte, 1998). Viewing the archive of a CMC as a valuable organizational memory resource, this chapter plans to address the second research question:

- *How do the graphical representations created affect the process of users' information acquisition and evaluation process?*

6.3 Communication-Garden Systems

6.3.1 System Architecture and Technology Selection

To address the first research question, a system called Communication-Garden Systems has been developed. This system utilizes an electronic discussion forum as its testbed, because the online discussion forum has been a popular format for sharing knowledge and forming a community. In order to provide the five types of information to users in a meaningful way, the system architecture displayed in Figure 6.1 was designed.

The back end of the system has four processors: *Pre-processor, Categorizer, Thread Visualizer,* and *People Visualizer.* Each processor applies one type of information

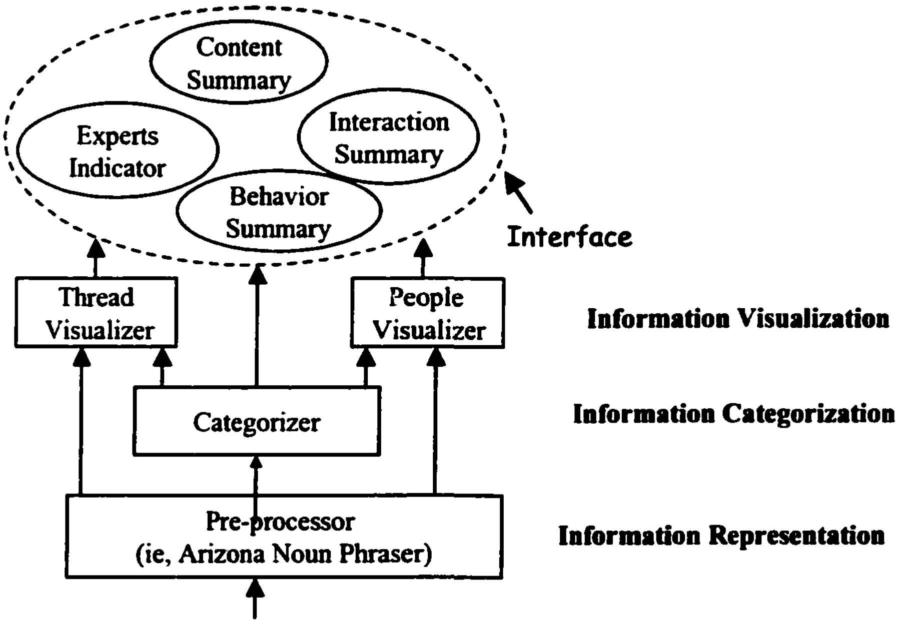


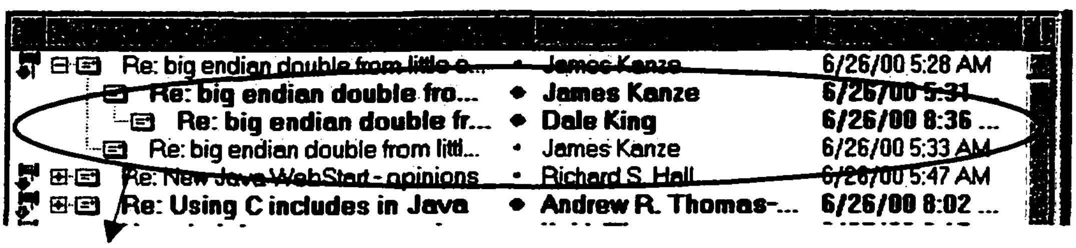
Figure 6.1 The Architecture of the Communication-Garden System

analysis or visualization algorithm to process the content or behavior information contained in the archive data.

- *Pre-processor* automatically represents a document with a vector of terms (Salton, 1989). Because the natural language processing (NLP) noun phrasing technique has been used in information retrieval to capture a richer linguistic representation of document content (Anick and Vaithyanathan 1997), the Communication-Garden system selected one of the available NLP noun phrase tools, Arizona Noun Phraser (AZNP) to represent the content of the input data. AZNP has been found to have better performance in identifying key noun phrases than other NLP noun phrase tools (Tolle & Chen, 2000). While the discussion in an electronic forum is thread based, the *Pre-processor* regards messages within one thread as a unit and represents each unit with key phrases identified by the AZNP.

- *Categorizer* categorizes the content and identifies sub-topics that have emerged in the CMC process. The output of the *Pre-processor* is the input to the *Categorizer*. The self-organizing map (SOM) (Kohonen, 1995) was selected, because it has been used by Chen et al. (1998b) to categorize and identify sub-topics from messages generated by electronic meeting systems.

- *Thread Visualizer* is a floral representation that graphically depicts the liveliness of a thread. A thread is a set of messages sharing the same title and sent by different persons (Figure 6.2.). It usually starts with one message followed by response messages from other participants. This representation idea is inspired by the flower representation developed by Xiong & Donath (1999). As displayed in Figure 6.3, each thread is represented as a flower. The number of petals of a flower equals the number of messages posted for that thread, while the number of leaves represents the number of persons who participate in the discussion of this thread. In addition, the height of a flower indicates how long the thread lasts. Such a graphical representation is consistent with the normal mental models of users. If a CMC process is full of tall blooming flowers, the community is active and participants are more likely to exchange feedback.



One thread with four messages and two participants

Figure 6.3 Text-Based Representation of a Thread

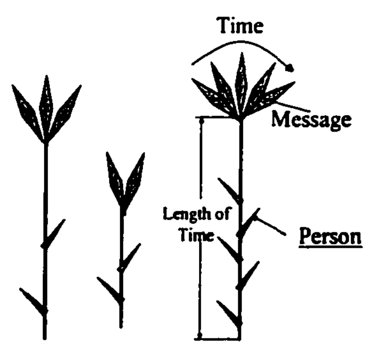


Figure 6.4 Thread Representation

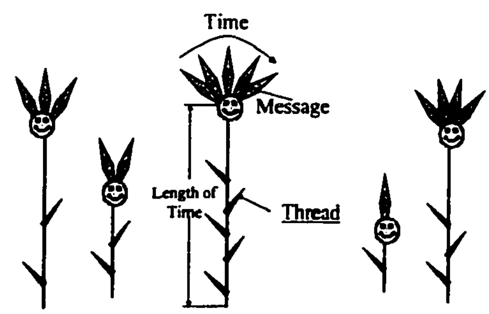


Figure 6.2 People Representation

- *People Visualizer* employs the same flower representation and is displayed in Figure 6.4. One flower represents a person, while the number of petals equals the number of messages that person has posted. The number of leaves indicates the number of threads in which that person has participated, and the height of the flower indicates how long the person has stayed in the community. In order to distinguish between a person flower and a thread flower as previously described, an icon face is put on each person flower. Therefore, a community is a popular community if it contains many tall blooming flowers.

6.3.2 System Description

Figures 6.5, 6.6, 6.7, 6.8 present a three-panel interface proposed. The left-hand panel in each of these figures is the Display-panel, presenting a detailed graphical display of a particular representation, while the upper-right panel serves as an Overview, providing a thumbprint of the detailed display. A user can select a portion of interest on the Overview, prompting the interface to display the selected part in detail on the Display-panel. At the top of both the Display-panel and the Overview are four tabs. Clicking on one of these will bring up one of the four types of the interface: *Content Summary* (Figure 6.5), *Interaction Summary* (Figure 6.6), *Expert Indicator* (Figure 6.7), and *Behavior Summary* (Figure 6.8). Each type presents one graphical representation displaying a certain aspect of a CMC process on both the Display-panel and the Overview. In addition, *Content Summary, Interaction Summary, and Expert Indicator* divide their display-panels into sub-gardens based on the output of the *Categorizer*. Thus each sub-garden represents one subtopic. A *Content Summary* describes the temporal change of each sub-topic, whereas *Interaction Summary* depicts the liveliness of discussion within each sub-topic. *Expert Indicator* uses person flowers to help users locate the active persons in each sub-topic and the *Behavior Summary* describes the behavior of each participant during the entire CMC process. A user may obtain from the *Behavior Summary* valuable information such as the attitude of the participants toward the community (indicated by the number of messages each person posts and the length of time each person stays in the community). The lower-right panel is the Message panel, which displays the messages of interest that a user has selected from the Display-panel.

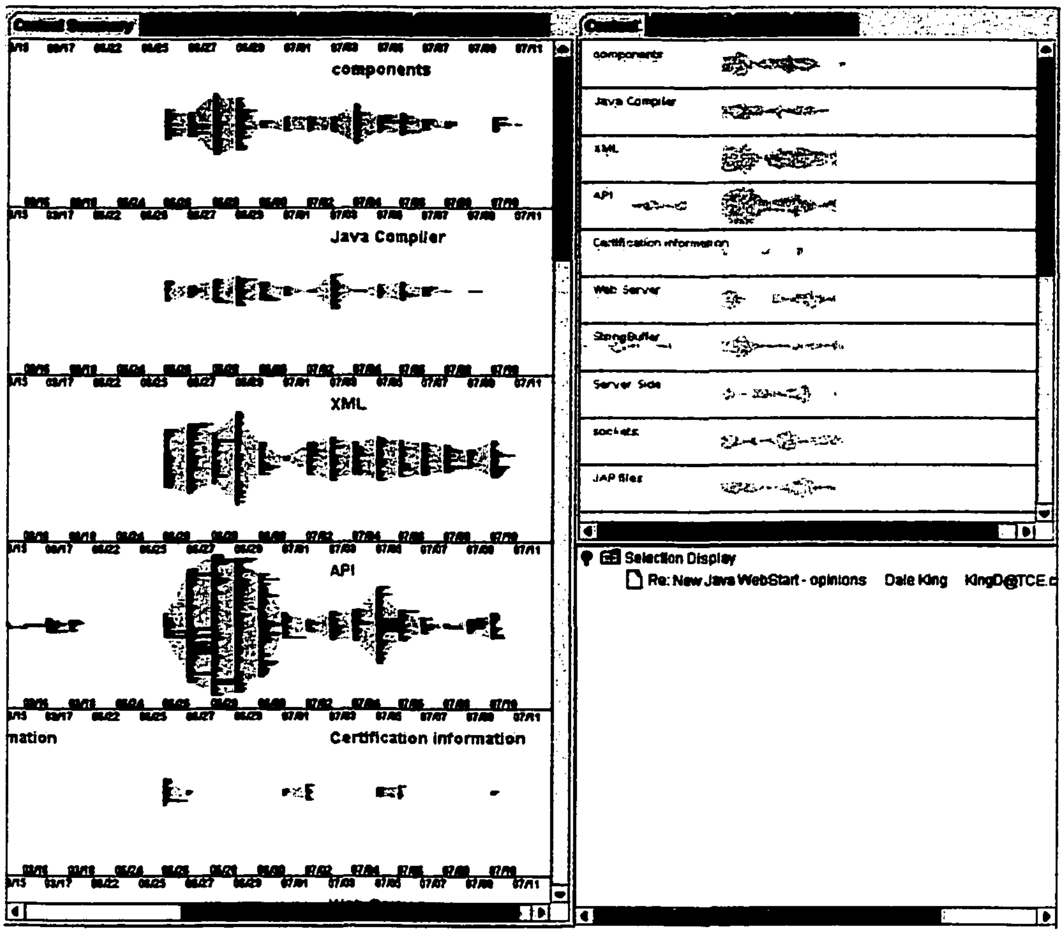


Figure 6.5 Content Summary

Description of the display-panel:

- The x-axis represents time
- Categories generated by the SOM are laid vertically
- Each green line represents one message
- The thickness of each sub-topic indicates its activity on a particular day

The length in the x-dimension of each sub-topic = time duration of that sub-topic

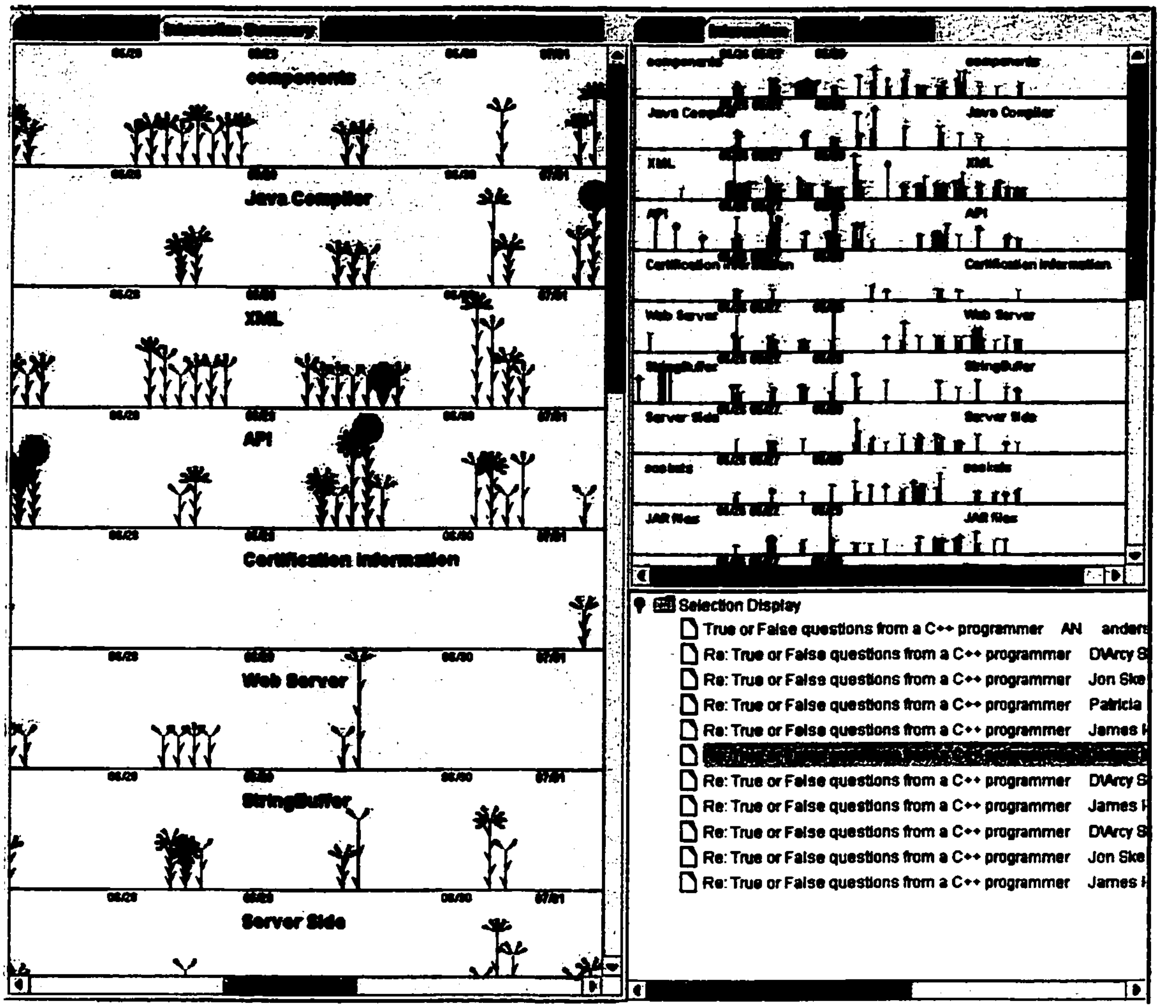


Figure 6.6 Interaction Summary

Description of the display-panel:

- The panel is divided into sub-gardens based on the SOM output. Each sub-garden is a sub-topic
- Each flower is one **thread**
  - # of petals = # of messages posted for this thread
  - # of leaves = # of participants in this thread

Height of flowers = the time duration of this thread

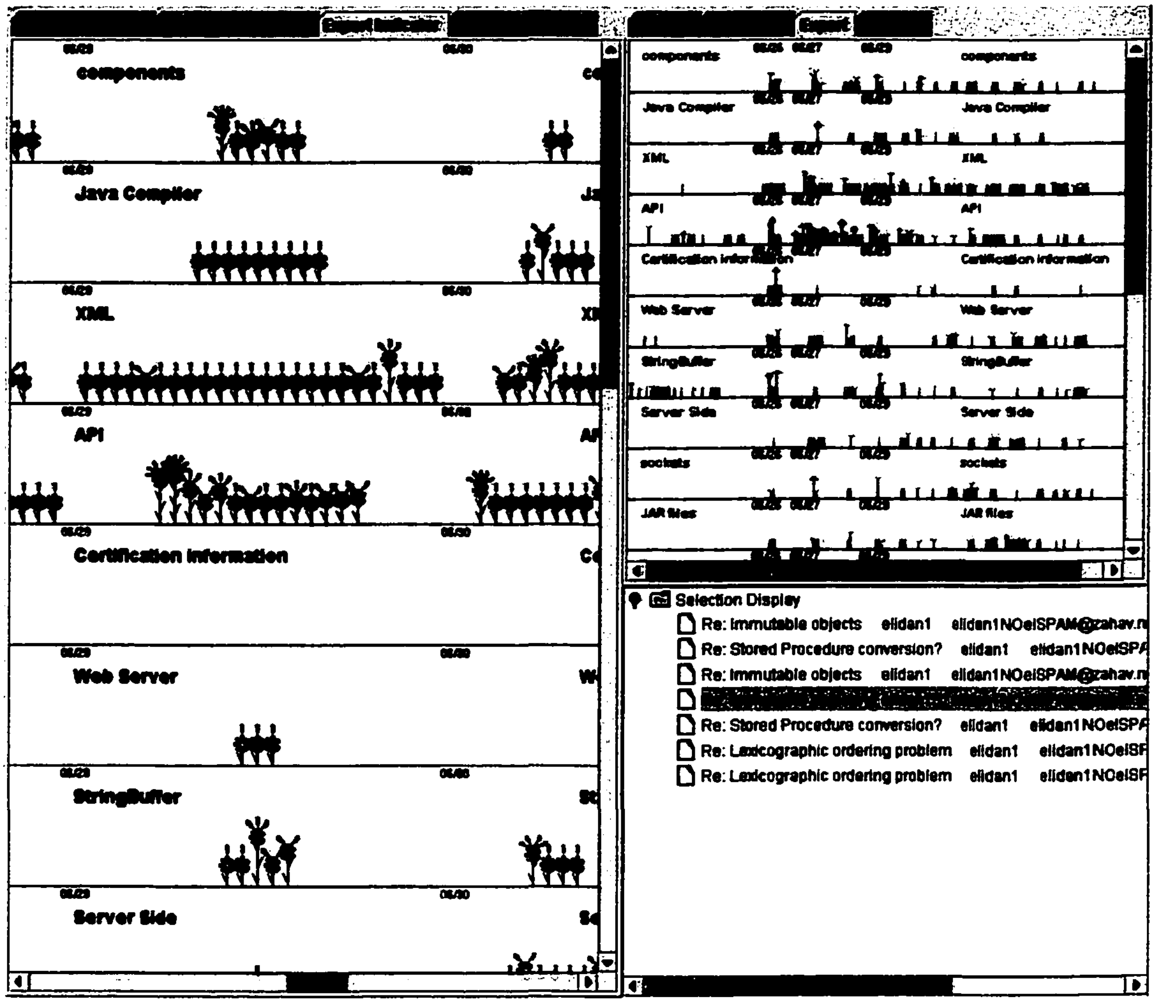


Figure 6.7 Expert Indicator

Description of the display-panel:

- The interface is divided into sub-gardens based on the SOM output. Each sub-garden is a sub-topic
- Each flower is one **<u>Person</u>**
    - # of petals = # of messages posted by this person for this sub-topic
    - # of leaves = # thread participated by this person in the subtopic

Height of flowers = How long this person stayed in this sub-topic

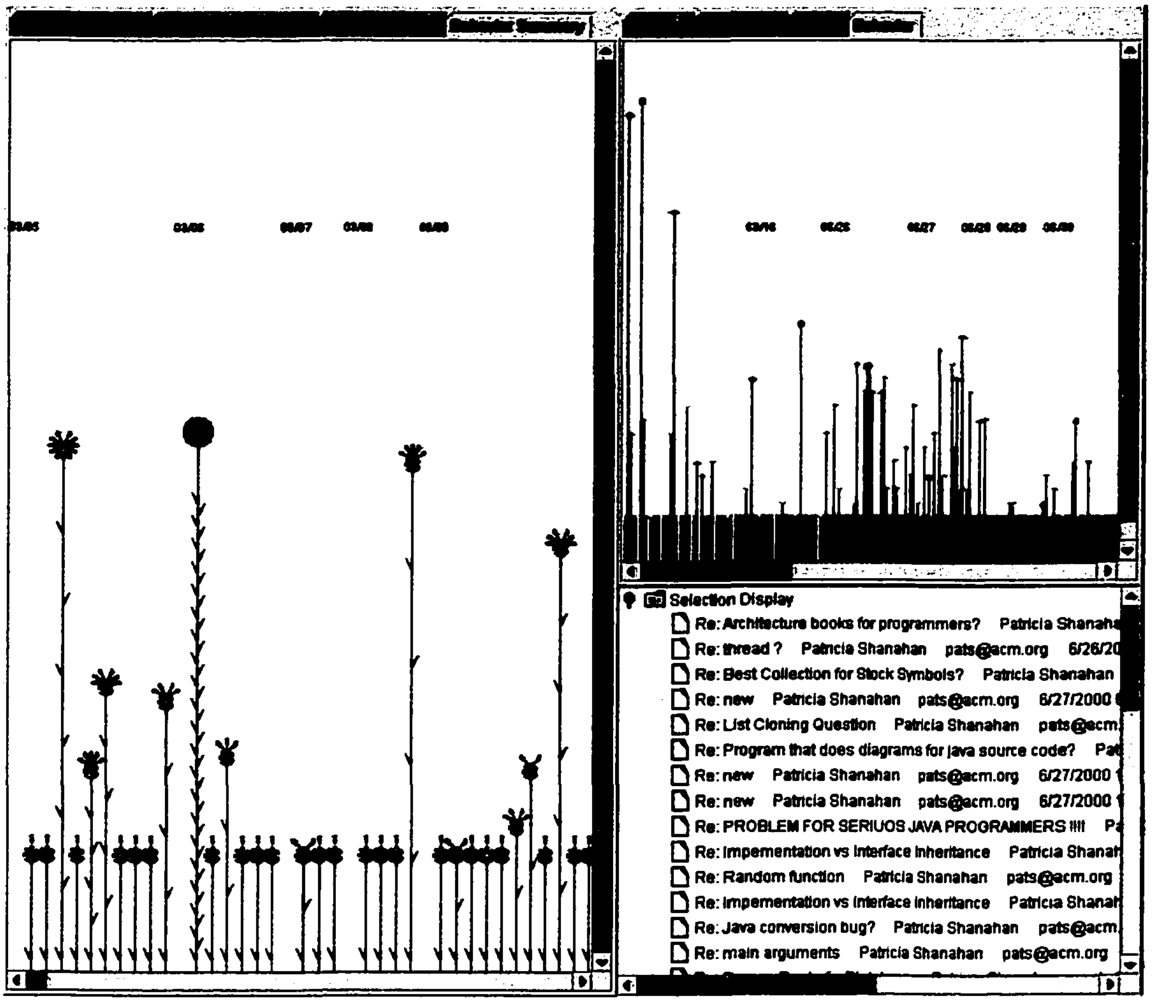


Figure 6.8 Behavior Summary

Description of the display-panel:

- The entire community is one garden
- Each flower is one **<u>Person</u>**
    - # of pedals = # of messages posted by this person in this community
    - # of leaves = # thread this person participated in this community

Height of flowers = How long this person stayed in this community

6.4 Empirical Study

In order to understand how the graphical interfaces generated affect the process of human information acquisition and evaluation, the use of the graphical interface was compared with that of the Netscape Messenger, a popular e-mail handling tool. Its interface is text-based and allows users to sort messages by thread or by sender, making the two interfaces

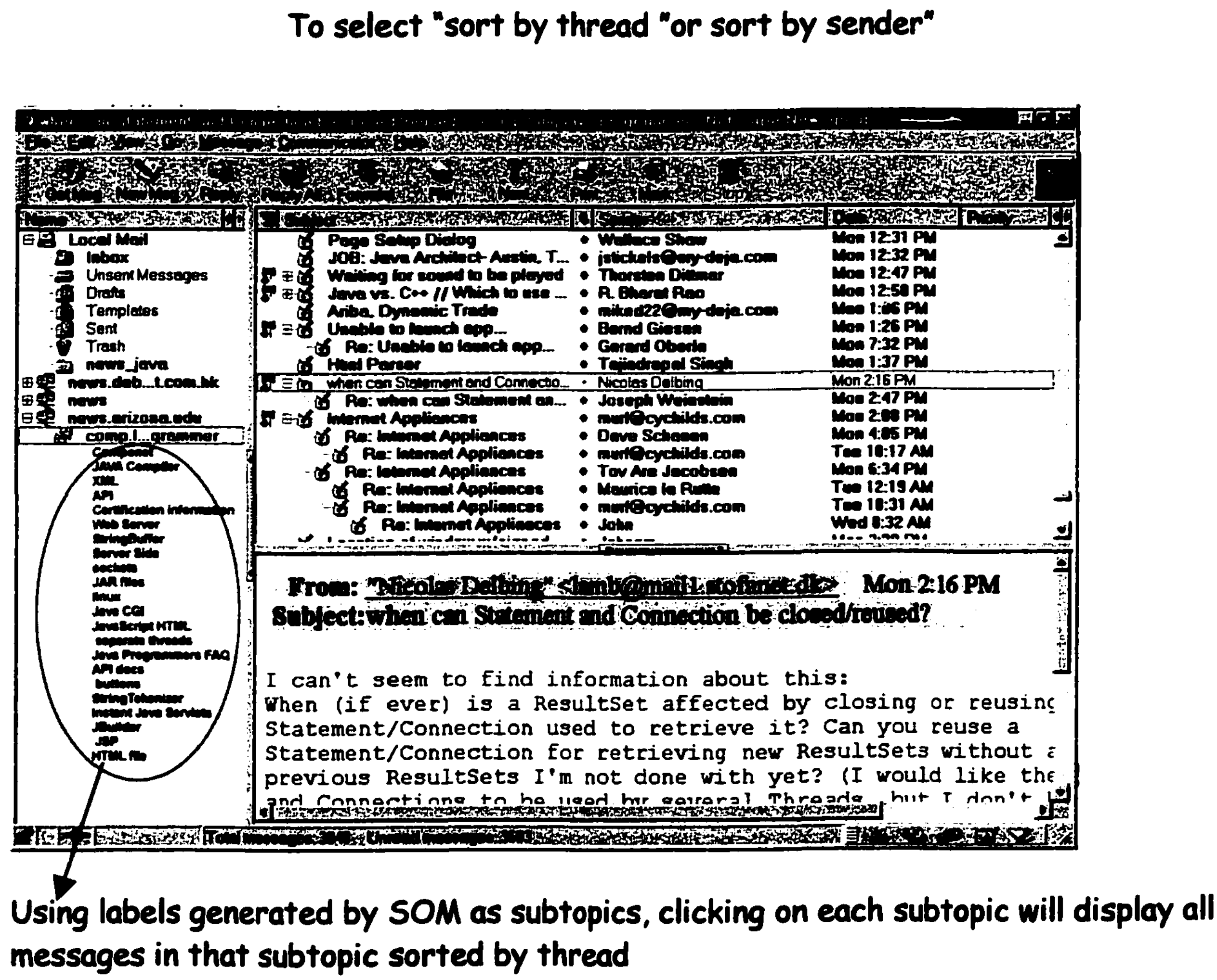


Figure 6.9 Interface of Netscape Messenger

comparable. However, Netscape Messenger does not categorize the messages or identify sub-topics. The experiment used the output of the *Categorizer* as input to Netscape Messenger, so its interface could display information about each sub-topic. Figure 6.9 presents the interface of Netscape Messenger displaying the categorized messages from an electronic discussion forum.

6.4.1 De-featuring Approach

Previous human computer interaction studies have provided a low-level, domain-independent taxonomy of information acquisition and evaluation tasks that users may perform when confronted with an interface (Wehrend & Lewis, 1990; Zhou & Feiner, 1998). The "de-featuring" approach denotes mapping of the domain-independent taxonomy of tasks into a specific domain. Such an approach eliminates the other features of a system and only evaluates the visualization component. This approach has been proven valuable in evaluating a graphical interface (Morse & Lewis, 2000), so it was adopted to evaluate how the graphical interfaces created affect users' information acquisition and evaluation process. Based on the information and the functionality provided by the graphical interface, five types of information acquisition and evaluation tasks (Table 6.1) were selected. Table 6.2 provides some sample tasks after the mapping. To validate the correctness of the mapping, this research had two individuals evaluate the mapping of tasks. The design of tasks was adjusted until the two evaluators agreed with each other.

Table 6.1 Task Types Selected

Task Types	Definition
Identify	Find a visual object with certain feature
Cluster	Find the similarity among visual objects
Compare	Compare based on certain attribute
Rank	Find the extremes (the best and the worst case)
Correlate	When there are multiple attributes, identify certain objects that are similar in one attribute

Table 6.2 Task Examples

Interface Type	Task Type	Tasks
Content Summary	Task1 (identify)	Find the sub-topic or sub-topics that start on 06/26.
	Task 2 (Cluster)	Which of the following sub-topics was discussed for a length of time similar to "XML", "Linux" or "API"?
	Task 3 (Compare)	Which sub-topic, "XML" or "API", has more messages posted on 07/08?
	Task 4 (Rank)	Which sub-topic generated the most discussions on 06/28?
	Task 5 (Correlate)	Which of the following sub-topics start on the same day, "Components", "StringBuffer", or "XML"?
Interaction Summary	Task 6 (identify)	Find the sub-topic or sub-topics whose first thread has two messages
	Task 7 (Cluster)	Which of the following sub-topics is more similar to "Web Server" in its interaction pattern on 06/29, "StringBuffer", or "Linux"?
	Task 8 (Compare)	On which sub-topics "XML" or "Socket", are there more thread?
	Task 9 (Rank)	Please find the sub-topic that has the fewest number of threads.
	Task 10 (Correlate)	Which of the following sub-topic has the same number of threads as "API docs" on 07/03, "buttons" or "HTML files"?
Expert Indicator	Task 11 (identify)	Find the sub-topic or sub-topics whose first participant posted three messages.
	Task 12 (Cluster)	On 07/09, which of the following sub-topic is more similar to "JAR files" in participation pattern, "Web Server", or "buttons"?
	Task 13 (Compare)	On which sub-topic "API" or "JSP", are there more participants?
	Task 14 (Rank)	Please list the three people who posted the greatest number of messages on the sub-topic "socket"?
	Task 15 (Correlate)	On 07/09, which of the following sub-topics have the same number of participants as "XML", "API" or "Web Server"?

6.4.2 Experiment Process and Results

Thirty-one undergraduate and graduate students participated in this study. A subject went through three sessions: *Content Summary* vs. text-based Interface (group by date), *Interaction Summary* vs. text-based Interface (group by thread), and *Expert Indicator* vs. text-based Interface (group by date or by sender). Two task sets were designed for each session and each task set contained five tasks. In each session, a subject used a graphical interface on one set and used the text-based interface on the other set. Tasks were designed to test all attributes of the interface and all task types. A task set was assigned randomly to an interface type. In addition, the order of interface types used and the session order were also randomly assigned to a subject. At the end of each session, a questionnaire designed to collect subjective measures was given to each subject.

Since each task had a correct answer, *task completion* was used as the measure of *effectiveness*. To measure *efficiency*, the experiment employed *time on task* as the measure. In addition, subjective measures including *perceived ease of use* (Smith, 1997), *perceived usefulness* (Doll & Torkzadeh, 1988; Davis, 1989) and *user preference* were also collected through a questionnaire.

A one-way ANOVA test was run to compare the difference between the Communication-Garden (graphical) interface and the Netscape Messenger (text-based) interface. The experiment results were analyzed based on task types.

- ***Cluster*** tasks required a subject to evaluate multiple attributes of visual objects to identify patterns. Most subjects found graphical representations to be very helpful in pattern identification. On the other hand, because the text-based interface of the Netscape Messenger displays messages line by line, subjects felt overloaded when they used this interface to locate patterns. However, although the Overview of the graphical interface provides a big picture without details, some subjects forgot to use it and got lost in scrolling the Display-panel as the volume of information displayed increased. As a result, there was no significant difference in effectiveness between the *Expert Indicator* with many person flowers and the Netscape Messenger. *Overall we found the Communication-Garden system to be more effective and efficient than the Netscape Messenger in **cluster** tasks.*

- ***Rank*** tasks required subjects to browse all visual objects in order to find the extreme value. The ability to pack more information on the screen made the *Communication-Garden system more effective and efficient than the Netscape Messenger in **rank** tasks.* Netscape Messenger users felt overloaded when performing this type of task because they had to make records for every object. Again, we found that some graphical interface users forgot to use the Overview and got lost during the scrolling. In addition, a 6-petal flower was so similar to a seven-petal flower that some subjects made the mistake of selecting the second or the third maximum value as the maximum value.

- ***Identify*, *compare*** or ***correlate*** tasks involved only one attribute. ***Identify*** tasks require browsing all objects to locate objects with a certain attribute value, while ***compare*** and ***correlate*** tasks involve small numbers of objects. One interesting finding in these task types was that the difference of effectiveness between the graphical and the text-based interfaces varied with the attributes tested. When attributes (i.e. start date, number of message) were explicitly presented on the text-based interface, no significant effectiveness difference was found between the graphical and the text-based interfaces. However, when the attributes (i.e., number of participants of a thread) were only implicit on the text-based interface, the graphical interface was significantly more effective than the text-based one. For instance, most Netscape Messenger users thought the thread displayed on Figure 6.2 had four participants (the correct answer is two), while Communication-Garden users had no problem finding the correct answer by simply counting the leaves on a flower. Besides the problem of getting lost during scrolling, some graphical interface users also experienced difficulty remembering the meaning of flower. They also made mistakes when they used only the Overview to accomplish tasks, since the Overview did not provide adequate detailed information. Overall results are described as follows.

- *The Communication-Garden system was more effective and efficient for* ***identify*** *tasks.*

* *The Communication-Garden system was as effective as and more efficient than the Netscape Messenger for **compare** tasks.*

* *The Communication-Garden system was as effective and efficient as the Netscape Messenger forn **correlate** tasks.*

The subjective measures collected indicated that the Communication-Garden system was significantly better than the Netscape Messenger on *perceived ease of use (p =0.000), perceived usefulness (p =0.000)*, and *user preference (p = 0.000)*. This may stem from one text-based system user's frustration when trying to accomplish ***cluster*** and ***rank*** tasks.

6.5 Conclusions

The Communication-Garden system provides an example of integrating social visualization and information analysis technologies to enhance access to knowledge stored in the archive of a CMC process. The approach employed not only provided explicit information about the discussion content, but also enabled users to obtain implicit information about how participants behaved during discussion. Those two types of information are both important in facilitating knowledge sharing and creation.

The empirical study found that the application of visualization techniques was a valuable approach to presenting behaviors of CMC participants. Its graphical representations made attributes that were only implicit on the text-based interface obvious to users. At the same time, the graphical interfaces provided behavior patterns of CMC participants through its multiattribute representation. However, we also found that in addition to an intuitive visual representation, providing meaningful navigation help is also crucial to developing an intuitive interface. Although the graphical representation increased the information density on a computer screen, it remained impossible to present the overview and all details at the same time. How to design a meaningful navigation approach to facilitating different types of tasks is a real challenge. Moreover, the conclusions of this study apply only within a context where specific interface type, task type and information are used and many student subjects may have identical computer skills. The issue of external validity will always be raised.

7. SUMMARY AND CONCLUSION

As a knowledge management strategy, the codification strategy captures and stores knowledge into various knowledge repositories so that users can retrieve knowledge from them (Hansen et al., 1999). Research issues related to knowledge capturing include providing incentives for knowledge sharing, selecting appropriate knowledge to store, and validating the content of knowledge. However, as codification strategy leads to more and more knowledge repositories, its usage may cause information overload, which inevitably will affect the usefulness of knowledge repositories. Integrated with information analysis technologies, information visualization technologies can help to relieve such overload. Visualization technology can facilitate knowledge retrieval in two ways (Shneiderman, 1996). It helps users to specify their information needs, while at the same time it also presents information graphically on a computer screen to support information browsing. However, how information is represented and requested on a computer screen varies with the type of knowledge repository. This dissertation identifies four types of knowledge repositories to apply information visualization and analysis technologies. These include collection of textual document, image repository, multimedia repository, and archive of a communication process. These four types, of course do not cover all the knowledge repository types and it is not the intention of this dissertation to provide a thorough taxonomy of knowledge repository types. The four types have been selected because each of them poses a unique requirement regarding how information should be presented and requested on its interfaces.

The dissertation research demonstrates that applying information visualization and analysis technologies does improve access to knowledge stored in a knowledge repository. While the requirements of interfaces vary with the type of knowledge repository, such requirements can be fulfilled by carefully selecting appropriate visualization and analysis technology. The application of technology facilitates browsing behavior by presenting information in an intuitive way. At the same time, it helps query specification to support searching behavior.

Future research may include applying existing visualization and analysis technology to other types of knowledge repository. Another direction might be to develop a framework for selecting appropriate visualization and analysis technology for various types of knowledge repositories. In addition, while the experiment in Chapter 6 demonstrates the strength of glyph representation, developing powerful and effective glyph representation for information in different domains remains open to exploration.

7.1 The Application of SOM

One common technology that has been utilized for all the four types selected is the SOM algorithm. It has been used as both an analysis and a visualization technique in this dissertation. The rest of this section summarizes the application of SOM to different types of knowledge repository and lessons describes learned from such application.

- *Large Collection of Textual Documents*

Textual documents have been the classical medium type in which to store knowledge. Browsing is an important approach to knowledge retrieval from such repository and can be facilitated by providing a hierarchical subject category. Chapter 3 describes how SOM can be used for the automatic generation of hierarchical subject categories. However, because of the inconsistency between the conceptual model suggested by the SOM and the expectations of users, it is necessary to integrate the domain knowledge of an expert into the process of the hierarchy generation. The empirical study described in Chapter 3 proved the effectiveness of such approach. However, this approach turns an automatic process into a semi-manual approach. The expert is needed to go through the labels of categories generated and remove those that appear unreasonable. Although easier than generating categories manually, such a process still can be tedious as the amount of information proliferates. Improving this process continuous to need further exploration. On the other hand, the level confusion appears to be the main problem when using SOM for the generation of hierarchical subject categories. More work is needed on understanding the relationships among concepts and integrating them into the categorization process.

- *Collection of Images*

After representing images with their texture features, Chapter 4 depicts the use of SOM to categorize images and to present categories generated. By using an image tile as the label of each category, the SOM map generated not only allows users to browse the entire collection but also helps users to query by example. Chapter 4 reports that combination of texture extraction and SOM can categorize images in a way consistent with users' mental model to certain extent, but the SOM usually produces too many categories and some of them are similar to each other. In addition, the texture feature alone is not sufficient to represent an image. Therefore the SOM needs to be integrated with multiple low-level image features in order to achieve more effective categorization. Nevertheless, Chapter 4 demonstrates that using SOM to display categories and to help in the specification of information needs appears to be an appropriate approach to image retrieval.

- *Multimedia Knowledge Repository*

The SOM is also used to categorize textual documents for a multimedia knowledge repository. Integrated with 3D visualization technique, the third dimension of the SOM map indicates the number of documents in each node. Compared with its 2D counterpart, the 3D SOM appears to be more effective and efficient in delivering spatial knowledge. In addition, the 3D interface has also been used to incorporate information in numerical and imagery types. Such incorporation decreases the number of windows required on the screen to display information in multiple media types. However, all information displayed is geo-referenced, which makes it possible to put information together based on coordinates. Therefore in order to apply the same approach to other domains, it will require creating knowledge structure and meta-data that will allow mapping among information in different media types. In addition, although the empirical study demonstrates the role of interactive animation that converts the cognitive process into a perceptual process, it does not completely remove the "hidden subject" effect. How to provide a more intuitive interaction that enables users to rotate 3D objects more effectively still needs more work.

- *Archive of a Computer Mediated Process*

SOM was utilized only as a categorization tool to identify sub-topics of a discussion group, but social visualization techniques were integrated with the SOM algorithm to provide summaries of both discussion content and behaviors of participants. Such combination not only describes how active the participants are in each sub-topic, but also identifies experts or the most active person in each sub-area. These two types of information are valuable for sharing knowledge and have not yet been considered before. The empirical study demonstrates the effectiveness of such floral representation, but it also indicates the necessity to provide more intuitive interaction to facilitate user navigation through the information presented on the interface. In addition, floral representation faces the problem of scalability. As indicated in the empirical study, as the number of pedals increased, the flowers became so similar that users could not distinguish one from another.

7.2 Information Representation and Visualization

Several thoughts have emerged from the dissertation project. When working with multimedia information, it is common is to represent information by applying various media processing technologies. For instance, the dissertation has used AZNP to represent textual information and Gabor filters to represent image. Under certain circumstances, the Gabor filters have been found to be insufficient in image representation. More effective image representation is needed to facilitate image retrieval. In addition, the integration of the representation of information in other media types such as sound or video into knowledge retrieval also needs further exploration. Issues such as query specification and similarity measure still complicate the representation of information in other media types.

In regard to glyph representation, Chapter 6 demonstrates again the power of glyph in representing multiple attributes. However, the metaphor developed needs to be consistent with its users' mental model. For instance, using a face to represent multiple attributes has a long history (Chernoff, 1973). In such representation, shape of face, size of nose, position of ears, shape of eyes, or orientation of eyebrow can represent one attribute, resulting in different facial expressions corresponding to different patterns. However, it is possible that a desirable pattern can end up with a sad face. The flower or garden metaphor developed in this dissertation is a positive example, in which the healthy garden indicates a popular community, an obviously meaningful representation. Therefore, the effectiveness of a glyph representation may largely depend on consistency between the representation and user expectations.

7.3 Managerial Implication

Applying information visualization and analysis technologies helps relieve information overload caused by the use of a knowledge repository. Evaluation studies here demonstrated that the technologies described here are appropriate for supporting query specification and information browsing, indicating that they can be applied to other types of knowledge repositories. For instance, AZNP and SOM can be applied to text-based knowledge repositories such as archive of e-mail, collection of operational manuals, or record of electronic meeting systems. In addition, when combined with appropriate image representation technology, SOM can help users specify their information needs to retrieve imagery information. An organization may want to ensure selecting the most appropriate visualization and analysis technologies to facilitate effective knowledge retrieval.

On the other hand, visualization tools can also facilitate knowledge creation. For instance, 3D visualization can combine information in various media types on the same interface. Such combination enables users to explore the knowledge repository visually, which in turn helps creation of knowledge in the mind of users. The users of the system developed in Chapter 5 may find the surface of an ocean to have the least elevation change, compared with other land surface types. Because human eyes process visual cues in a parallel manner, various visualization tools can help users to visually identify patters that may be difficult to identify by using statistic or data mining algorithms. Such visual exploration might be helpful in financial data analysis, web usage interpretation, and online transaction description. Providing appropriate visualization tools might be effective for knowledge creation within an organization.

Besides overload relief and visual exploration, visualization tools can also solve the problem of information underload, which denotes an insufficiency of easily accessed information for decision making (O'Leary, 1997). For instance, applying SOM to a knowledge repository can not only facilitate information browsing, but also can provide a concept catalog that summarizes the content of the knowledge repository. While knowledge management is about providing the right information to the right people at the right time (Petrash, 1996), such application can help managers to identify the most appropriate repository assigned certain tasks for his/her employees. In another context, the social visualization developed in Chapter 6 depicts the behavior of participants. It not only reveals the liveliness of a subtopic or a computer mediated community, but also identifies experts in certain area. One application of the Communication-Garden system is in software development. While users are encouraged to discuss a new product online, the application of SOM may reveal different aspects of the product that users care about. At the same time, social visualization discloses the aspects of the product that are import to users by depicting where the traffic is. Therefore, a decision maker can decide how to improve the product based on the information provided by the graphical interface.

In summary, applying visualization and analysis technology to facilitate information browsing and query specification is a crucial part of knowledge management. Such application facilitates knowledge retrieval, knowledge creation, and decision making. Visualization tools can relieve information overload, support visual information exploration, and solve the problem of information underload. Therefore, an organization may need to select appropriate visualization and analysis tools to facilitate its knowledge management.

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