A Multi-agent System for Multimedia Information Retrieval

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Abstract

The purpose of this paper is to describe a multi-agent system for collaborative multimedia information retrieval in an electronic retailing application. We use content-based information (CBIR) retrieval for multimedia data including full-texts and images. Content-based image retrieval deals with retrieving data based on automatic content analysis as opposed to manual annotations, such as metadata specifications. While both collaborative agent technology and content-based information retrieval have been developed in previous research, few papers have attempted to combine both technologies in the same problem area. In this paper we describe a collaborative multi-agent system for multimedia information retrieval in an electronic commerce application.

Keywords: Software agents, content-based image retrieval, electronic retailing, electronic commerce, image analysis, computer-assisted sales

Introduction

Electronic retailing (e-tailing) is one of the key applications of electronic commerce (e-commerce). It entails providing an electronic storefront to allow customers to search for products, submit orders online, and have orders shipped directly to their receiving address. E-tailing has become popular in both business-to-business (B2B) as well as business-to-consumer (B2C) e-commerce. An example of e-tailing in B2B e-commerce is Grainger (www.grainger.com), a major player in the maintenance, repair, and operations (MRO) market with a $200 billion annual sales of hard-good supplies ranging from zip screws to industrial pumps (Neumann, 2000). An example of a B2C e-tailer is Amazon.com, which has been dubbed the "e-tailing king", because of its fast-paced growth in on-line revenues.

The process of e-tailing consists of several steps: attracting customers to the electronic market place (attract), informing customers about the relevant content at the Website (inform), customizing product/service offerings to suit customer needs (customize), market making through transactional support using catalogs, auctions, exchanges, and barter models (transact), providing payment and financing functions for online transactions (pay), providing post-sales support such as customer service and order tracking through customer interaction platforms (interact), shipping of orders (deliver), and personalization of e-commerce Websites to analyze patterns of behavior to ensure better interaction in the future (personalize) (Sawhney et al. 2000). Many of these activities, including inform, customize, interact, and personalize require efficient content management, which deals with combining, cleansing, normalizing, aggregating, integrating, and updating product and service information available through an e-commerce Website.

Agent technology has been identified to have the potential to significantly enhance on-line shopping (for example Collis et al 1999). Agent-based commerce can help customers in locating the "best buys" with minimal effort, which in turn can benefit vendors by lowering their costs and increasing their customer base. Typically such systems consist of two types of agents: user agents

and vendor agents. User agents typically need to identify a customer's preferences by asking pertinent questions and/or using covert techniques such as *adaptive profiling* (Soltysiak et al 1998). Such user profiles play an important role in the effectiveness with which a sales agent can select and rank equivalent products without user arbitration. Once user preferences are identified, the user agent contacts vendor agents, communicates the user requirements, negotiates on product quality, suitability, and price, and filters the responses back to its owner.

The methodology presented in this paper can be applied to a number of different aspects of content management for an e-commerce application. These include providing an efficient search mechanism through product catalogs, enabling an electronic sales agent to identify alternative product choices, and receive expert advice to make the "best" selections. Traditionally human sales agents have performed these functions in brick-and-mortar stores. There are several advantages of automating such tasks. For example, an electronic sales agent is not restricted to limited hours of operation, is capable of helping multiple customers concurrently, is able to process larger volumes of information in less amount of time, is less obtrusive, is less expensive, is not susceptible to mental setbacks if a sale does not go through, and can perform at a high level of efficiency for an indefinite period of time. On the other hand, an automated sales agent is not as flexible and may miss non-programmable cues that a human sales agent can pick up in special circumstances. There are further uses of a system such as this. For example, companies can manage visual information in electronic formats instead of relying on printed catalogs. Fashion designers can store and retrieve previous designs electronically, as well as create new designs efficiently. Such a system can also be helpful in *global sourcing*, which is an important issue in the textile and apparel industry (Lau et al 1998). Various members of the supply chain including fabric manufacturers, cut-and-sew plants, and retailers often need to look for different suppliers from large printed catalogs for different resources such as fiber, fabric, and apparel. An automated system for searching can significantly improve supply chain efficiency through streamlining communication and mid-course correction of production and procurement plans.

The methodology we describe in this paper utilizes visual information, which is an important characteristic for many products such as apparel, designer costumes, interior designs of homes and automobiles, and landscaping. It is difficult to express visual information in non-visual terms such as textual descriptions. Hence there is a need for the ability to store, index, search, and retrieve visually rich product information using their visual features such as color, texture, and shape, instead of having to rely on textual annotations. In order to accomplish this objective, we draw upon the research and development in the area of content-based image retrieval (e.g., Barber et al 1995, Chang et al, 1991, 1996, Hafner et al 1995, Holmes et al 1992). While CBIR methodologies have been applied in a wide range of domains such as environmental modeling, medical applications, and satellite image analysis, this is one of the first applications of CBIR in the domain of electronic commerce in general and electronic retailing in particular.

Previous work on CBIR

In recent years, research and development in the content-based image retrieval has mainly focused n image features, such as color, shape, texture and spatial relationships. In addition, many content-based image retrieval systems and methods have been developed for various applications, such as geographic information systems and medical image databases.

To analyze image features, (Swain and Ballard 1991) use color histograms to identify objects and propose a histogram intersection method for the color indexing of multicolored objects.

In addition, (Smith and Chang 1995, 1996) use the binary set representations method for the automated extraction of color and texture of the image. This method is for the automated extraction of regions and representation of their color contents. Since the color histogram lacks spatial information, (Pass et al. 1996) provide a color-based method for images that integrates color histograms and spatial relationships among features of the image.

Texture is also an important element to human vision and homogeneous patterns or spatial arrangement of pixels (Faloutsos at al 1993). Texture is enhanced by the features of directionality, coarseness, granularity, and contrast (Equitz 1993). The most widely used collection of features is Brodatz's image texture (Brodatz 1993), which is used in techniques for texture analysis. (Smith and Chang 1995) describe a texture set approach for indexing in order to extract spatially localized texture information.

The retrieval of shape is one of the most challenging aspects to content-based image retrieval. Jagadish provides image indexing methods based on shape and uses a few BRs(Minimum Bounding Rectangle) to extract features from shapes (Jagadish 1991). Faloutsos et al. 1993 uses as features the area, circularity, major axis orientation and a set of algebraic moment invariants for features. In addition, the shape-based technique allows users to ask for objects similar in shape to a query.

For indexing of spatial data objects, Guttman proposes the R-tree method (Gutman 1984) that is a successful variant. Beckmann et al. provide the R*-tree (Beckmann et al 1990), which proposes an access method that efficiently supports multidimensional points and spatial data. Both R-tree and R*-tree have been used most often for the spatial data objects search in multi-dimensional space even if they suffer from an overlap problem. In addition, the 2-D strings method used for identifying spatial relationships among the objects and its variants has been used (Chang 1987).

As we discussed above, current image retrieval systems typically support image features, such as color, shape, texture, and spatial relationships. However, current content-based image retrieval systems ignore many important features, such as scale independence, orientation, topological relationships, and measurement of similarity, since these features have more complex structures. Only a few content-based image retrieval systems are partially used by these aspects for their image retrieval system, such as Photobook, VisualSEEk, and COIR. These systems support these aspects as a small part of their image retrieval systems.

Prominent examples for content-based image retrieval systems include QBIC, Virage, Photobook, Chabot, VisalSEEk, WebSEEk, SaFe, and COIR. QBIC (Niblack 1993) and Virage (Bach et al 1996), developed at IBM and Virage Inc. respectively, are systems for an image retrieval based on image features, such as color, shape and texture. The QBIC system uses image analysis to process queries for an image database. These two systems support image matching and keyword-based retrieval functionality on the whole image. Photobook (Pentland et al 1994), developed at MIT, proposes a compact representation method, which is called semantic-preserving image compression, to preserve essential image similarities and to quick search in a large number of images. Chabot (Ogle et al 1995), developed at UC Berkeley, describes a method for metadata, keywords, concepts, and color distributions to retrieve image. Chabot supports concept definition functionality for content-based image analysis and proposes the integration of relational database system with content-based techniques. In these systems, features of the whole image is used, spatial relationships are not supported. That is, these systems provide querying of whole images and extracted regions by color, shape and texture.
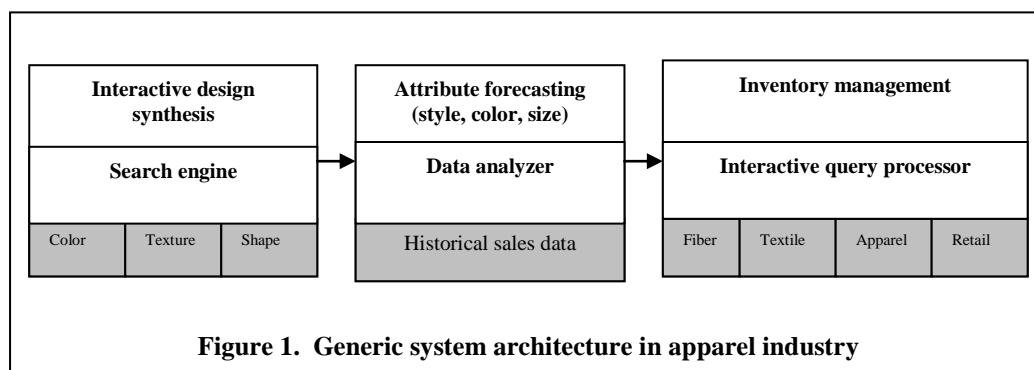
VisualSEEk (Smith et al 1996), developed at Columbia University, provides an image retrieval method using color, shape, texture and spatial relationships for individual regions. For browsing and searching of visual information on the Web, they also developed WebSEEk (Smith et al 1997) image search engine, which provides an essential function of cataloging the visual information on the web. In order to search for images by arrangements and visual features of regions, they developed (Smith at al 1997a), which is a system for image searching; it integrates spatial and feature querying. SaFe proposes a method of fully automated region and feature extracting and indexing. The system assumes users can specify region sizes and locations accurately, since they are using the quadtree structure, which is based on the exact location of centroid.

COIR (Hirata et al 1996) developed at NEC, provides an object-based similarity matching method. In this system, color, shape, and spatial relationships of objects are used for image retrieval. However, this system is limited to supporting a positional type of spatial relationships: left, right, above, and below and possible combinations of any of the four.

Methodology

In this section we first describe the system architecture. Next we present how shapes, colors, and textures are used in characterizing the visual features of products. Next, we discuss how these features are used to define *similarities* among products. Lastly we illustrate how the methodology can be applied in electronic retailing. The methodology is presented in the context of an apparel retailer selling men's wear such as dress shirts, trousers, sports jackets, sweaters, and shoes.

The methodology can be used in a number of ways. It can be applied to activities relevant to downstream members in a supply chain, including fashion designers, market forecasters and retailers, and as well as upstream members such as apparel, textile, and fiber manufacturers. Figure 1 shows an integrated architecture of the proposed system that can be applied across channel partners in an apparel industry. The system would allow fashion designers to interactively develop new designs by retrieving the appropriate combinations of color, texture, and shapes through mix and match. Designers can specify the percentage of color in designing a print pattern. Color images are converted into gray scales before computing the texture features.

Interactive design synthesis			Attribute forecasting (style, color, size)	Inventory management			
Search engine			Data analyzer	Interactive query processor			
Color	Texture	Shape	Historical sales data	Fiber	Textile	Apparel	Retail

Figure 1. Generic system architecture in apparel industry

End users (potential customers) can use an electronic catalog to browse through the apparels, search for a particular combination of color, and texture, and can interactively retrieve

clothing that are *similar* to the ones that have already been retrieved. We describe the interactions of end-users in terms of *browsing* and *searching*, where browsing refers to the activity of scanning through various items on display and searching implies that the user is looking for one or more items with a specific set of criteria in mind. The system is designed on the premise that good search mechanism would maximize *recall* and *precision,* while a good browsing mechanism would expose the largest range of items in stock with the minimum amount of effort.

System Architecture

The system consists of two agents: shopping agent and vendor agent. The shopping agent collects user requirements and passes them to the vendor agent. The shopping agent has been implemented in Oracle Developer and is being ported to the Web using Oracle Developer server. The vendor agent retrieves one or more products based on their similarities with that of the user requirements supplied by the user agent. An image-processing module is used to analyze an image and obtain geometric features such as perimeter, area, minimum diameter, and maximum diameter, color histogram, and pixel intensities. The geometric features are used to compute shape parameters, which are subsequently loaded in a database. The image processing module also generates color histograms and pixel intensities and stores them as ASCII text files, which are then loaded into an Oracle database (version 8i) using the SQL*LDR utility. Subsequent processing of data is done using PL/SQL procedures and functions stored at the database server. The overall system architecture is shown in Figure 2.
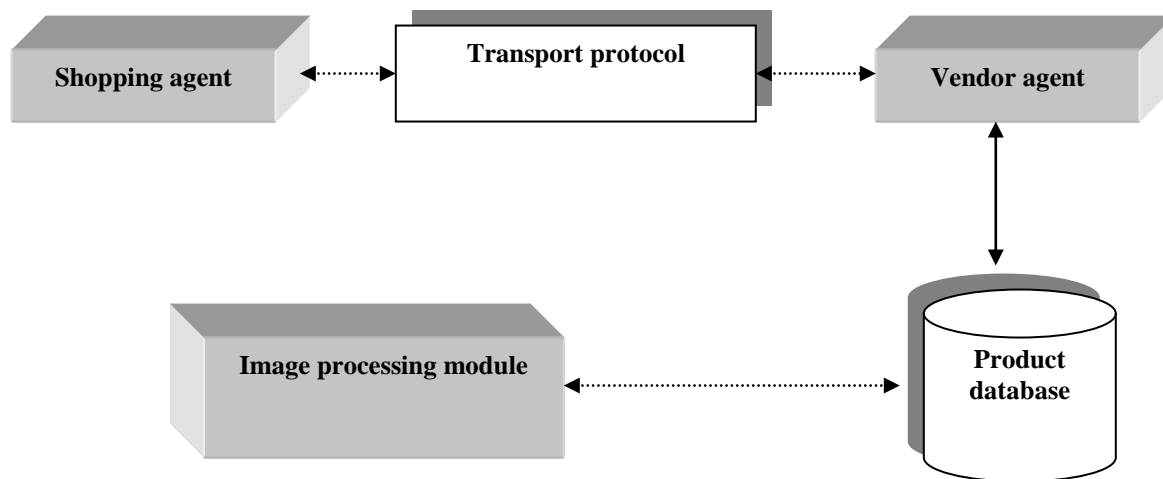
Figure 2. System Architecture

Image processing

Image processing is done using the WiT visual programming software (Logic Vision 1999). To generate the shape of an image, its bitmapped image is read from the file system and it is fed as an input to an operator called *getData*, which outputs a vector containing the graphical object specified in an interactive manner. The graphical object is specified using a rectangular window within the image indicating the region of interest. The output of *getData* is fed into another operator called *getBlobsRoi*, which performs a connectivity analysis on run lengths within the rectangular area of interest. The algorithm for *getBlobsRoi* scans from top to bottom and left to right of the selected region, and collects run lengths represented as non-zero pixels within the region. Next another operator called *getFeatures* computes feature vectors from the blob vector obtained from the *getBlobsRoi* operator. Lastly, the *getPerimeter* operator determines the perimeter length, area, maximum and minimum radii, from which the shape parameters are computed. The histogram is obtained in a similar manner with an operator called *histogram*, which computes the frequency distribution of values in an input image. Texture data is obtained using the *getArray* operator that extracts a two-dimensional array of pixel values from an input image. A session through the image analysis phase is shown in Figure 3, where the top left corner shows the results of each operator, the window at the center shows the script, and on the right side is the result of the *getPerimeter* operator.

Characterizing visual features:

The visual features of an object can be characterized by *shape*, distribution of *color*, and *texture*. In the context of apparel, shapes can be used to characterize printed patterns. We use two parameters to characterize shape: *surface regularity* and *roundness*. In addition, it is also possible to specify relative locations and topologies of smaller component shapes to create composite shapes. We use *color histogram* to characterize the color distribution of a print. For texture analysis, we use *contrast*, *coarseness*, and *directionality*. Besides shape, color, and texture, it is also possible to specify the sizes of printed patterns using *area* and *perimeter*. We describe the details of the computation of shape, color, and texture parameters in the following subsections.

Characterization by shape

Most real-life objects are irregular in shape, and hence there is no universal approach to quantify the shape of an arbitrarily shaped object. However, the shape of an object can be parameterized with the help of some measurable properties. A good choice of a parameter should yield a known value in the ideal case (Unwin 1981). We have selected four shape parameters that describe two orthogonal shape characteristics of an object: surface regularity (irregularity) and roundness (elongation). These shape parameters are adopted from Ireton 1991, Russ 1995,Unwin 1981. If the object is a perfect circle, all of the shape parameters would equal to 1, which satisfies the requirement in Unwin 1981. The shape parameters are described in more detail below:
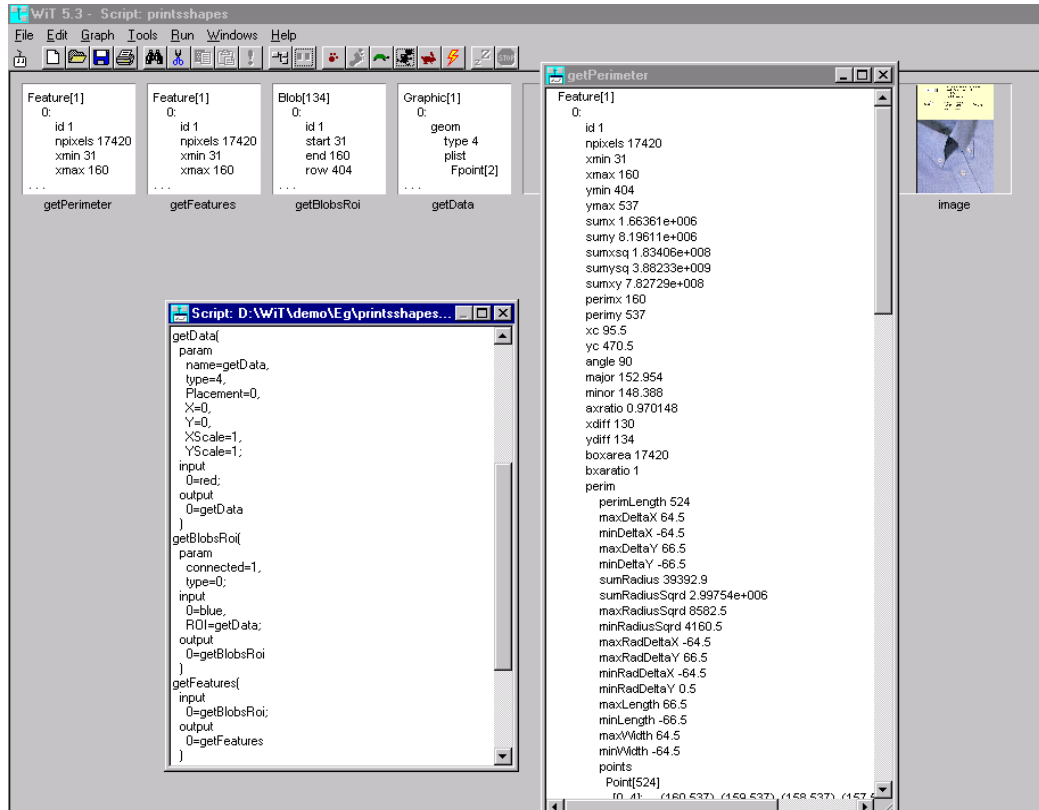
Figure 3. Image analysis

Surface regularity: Surface regularity refers to the smoothness of the surface of an object. Surface regularity is described by two shape parameters: *surface regularity* (σ) and *form factor* (ϕ), defined in Equations 1 and 2 respectively.

$$\sigma = \sqrt{(a/a_c)} \tag{1}$$

$$\phi = 4*\pi*\text{Area}/\text{perimeter}^2 \tag{2}$$

Surface regularity in Equation (1) is measured in terms of the amount of area covered as compared to a circle of equal perimeter: *a* and a_c are the areas of the image object and a circle with equal perimeter respectively. The form factor in Equation (2) is high for objects that have a high area to perimeter ratio. Form factor and surface regularity are positively correlated.

Roundness (elongation): Roundness (ρ) is inversely proportional to elongation and is described by Equation (3)

$$\rho = (4*\text{Area})/\pi* (\text{diameter}_{max})^2 \tag{3}$$

7

Roundness is high for objects that are well-rounded in every direction. Thus objects with long extremeties will have relatively low roundness. Elongation α is measured by *aspect ratio* (defined by Equation (4) which is high for objects that are elongated in one or more directions.

$$\alpha = \text{diameter}_{max}/\text{ diameter}_{min} \tag{4}$$

The diameter$_{max}$ in Equation (4) is computed as the distance between two extreme boundary points, while diameter$_{min}$ in Equation (4) is obtained by computing the minor axis of an ellipse whose area is equal to that of the object and whose major axis is equal to the maximum diameter.

All shape parameters are ratios, a consequence of which is that if the shape of an object remains constant but its size changes, then the values of the parameters would vary relatively slowly as compared to when the shape varies but the size remains constant. Thus, two objects with the same shape but different sizes will be detected to be more similar than two objects with different shapes but the same size. The shape computations are done from run-length coding og images as described in (Gangopadhyay 1999), using the WiT 5.3 image processing software.

Characterization by color

For each image we create a color histogram, which is a count of the number of pixels for each of the 256 color bins. Color-based search requires comparing the histograms of a sample image with that of a target image. We compare the histograms of the image selected by the user (we refer to it as the example image) and the target image by using the methodology described in [Barber 1995]. Let H_e and H_t be the histograms of the example and target images respectively. The element by element difference between H_e and H_t is the difference histogram H_d. The similarity $|S|$ between the example image and the target image is computed by the following formula:

$$|S| = H_d{}^T M H_d \tag{5}$$

where $H_d{}^T$ is the transpose of H_d, and M is the symmetric color similarity matrix $m_{i,j}$ represents the similarity between colors i and j in the color spectrum. This method accounts for the perceptual difference between any two pairs of colors as well as the difference between the different shades of a given color.

In order to reduce the amount of on-line processing, we preprocess the color similarity of all images and generate a similarity matrix based on color, which is stored as a 3-tuple *<image$_i$, image$_j$, sim>*, where *1<i< N -1, i+1< j < N,* and *i$\neq$ j,* and *N* represents the number images in the database.

Characterization by texture
The texture of an image is characterized by its *contrast, coarseness,* and *directionality* properties, which are derived from the first-order statistics of the edge distribution (Tomita 1990). Contrast is a measure of local variations of intensity, with higher variation of intensity representing higher contrast. Coarseness is measured with the number of texture elements in a fixed-size window, with a smaller number of texture elements representing higher coarseness.

$$|s(x,y)| = \sqrt{(f_x(x,y)^2 + f_y(x,y)^2)} \tag{6}$$

$$\Theta(x,y)=tan^{-1}(f_y(x,y)/f_x(x,y))+\pi/2 \tag{7}$$
$$f_x(x,y)=f_x(x+1,y)-f_x(x-1,y) \tag{8}$$
$$f_y(x,y)=f_y(x,y+1)-f_y(x,y-1) \tag{9}$$

In equation (6), $s(x,y)$ represents strength, which is a relative difference in pixel intensity along the x and y axes respectively. $f_x(x,y)$ is the difference in pixel intensity along the x axis and $f_y(x,y)$ is the difference in pixel intensity along the y axis. Coarseness and contrast represent the density of edge and mean of edge strengths respectively. $\Theta(x,y)$ represents directionality which is computed by developing a histogram of edge directions and detecting the number of clusters. If the histogram yields no distribution it would mean that there is no directionality in the pattern.

Shopping Agent

The shopping agent uses a Web-based system for interacting with end-users, who can browse through product offerings, search for products based on color and texture similarity, as well as shapes and sizes of prints. The system uses color as the default feature to be used in the absence of a user-defined feature. There are three ways that the system interacts with a user: assist the user to identify apparels based on visual characteristics and provide technical guidance by suggesting pieces of apparel that the user may want to consider along with an item selected by them. As an example of the technical guidance in purchasing decision, if a user is purchasing a dress shirt, the system suggests matching ties, trousers, jackets, and sweaters that could also be purchased as a bundle. It should be noted that the *matching* pieces of apparels are based on contrast as well as similarities. A sample session through the system is shown in Figure 6.
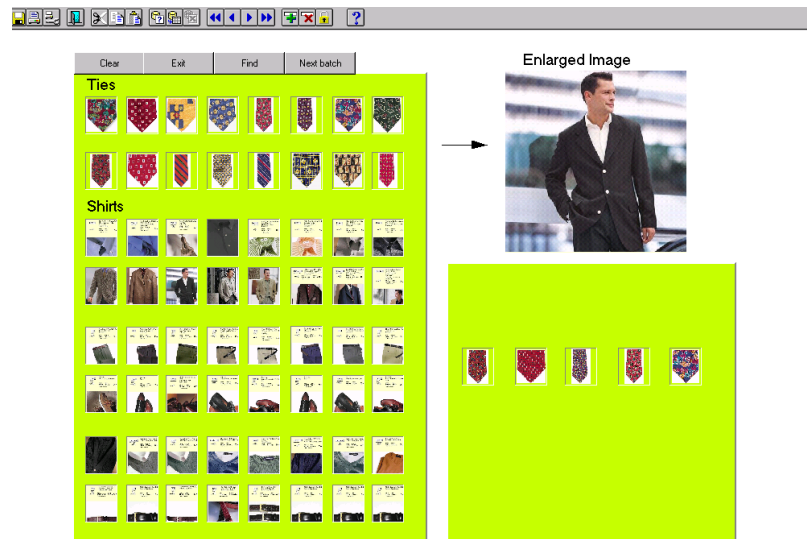

Figure 6. Sample session through the system

The left hand side of Figure 6 shows a sample of products available in the page. These products are shown as thumbnail images and categorized into groups such as *ties*, *shirts*, *jackets*, *trousers*, etc.

For each category sixteen products are shown in order to fit the as many items as possible in one page. If the user wants to browse through additional items, they can retrieve the next batch of sixteen by pressing on the button *Next Batch.* Since only images are shown, the user can browse through a larger number of products at once than is found in most Web pages. Once the user has selected a certain item, and intends to examine it more detail, an enlarged image is displayed on the right side of the screen. Additional information such as product price and textual descriptions of the material etc. can also be obtained at this point. The user can then request for other pieces of apparels that will *match* with the one selected, or other pieces of apparel that are *similar* to the one selected, based on shape, color, and texture features.

Conclusion

In this paper we have described an multi-agent system for electronic retailing in the fashion, textile, and clothing industry. The system supports color, texture, and shape-based search for apparels, and enables "cross-selling" of products. The system has been implemented for electronic retailing, but can also be used in other parts of supply chain management such as design synthesis, forecasting of consumer demands, and inventory management by supply chain members. Such a system is also potentially useful for customer relationship management and personalization. In addition to business-to-consumer e-commerce, an electronic catalog can also use this methodology for business-to-business e-commerce by providing a visual communication medium for products with visually rich attributes that are difficult to express in textual descriptions.

The future plans for the system is to extend it with an interactive virtual apparel platform that would store physical characteristics of potential virtual shoppers and provide an interactive "virtual fitting room" with different backgrounds. Such a system can also be useful for other supply chain members to plan production schedules based on demand forecasts that can minimize inventory cost and maximize profit.

References

R. Aylett, F. Brazier, N. Jennnings, M. Kuck, H. Nwana, and C. Preist. "Agent Systems and Applications," *The Knowledge Engineering Review,* 13(3), 303-308, 1999.

R. Barber, W. Equitz, C. Faloutsos, M. Flickner, W. Niblack, D. Petkovic, and P.Yanker. "Query by Content for Large On-Line Image Collections," in A Guided Tour of Multimedia Systems and Applications (B. Furht and M.Milenkovic Eds.) IEEE Computer Society Press, 1995.

J. R. Bach, C. Fuller, A. Gupta, A. Hampapur, B. Horowitz, R. Humphrey, R. Jain, and C.-F. Shu. "The Virage image search engine: An open framework for image management", Storage and Retrieval for Still Image and Video Databases, 1996.

N. Beckmann, H.-P. Kriegel, R. Schneider and B. Seeger, "The R*-tree: An Efficient and Robust Access Method for Point and Rectangles" ACM SIGMOD'90, 1990.

P. Brodatz. Textures; a photographic album for artists and designers, Dover Publications, 1966.

S. K. Chang and E. Jungert. *Symbolic Projection for Image Information Retrieval and Spatial Reasoning*, Academic Press, 1996.

S. K. Chang, Q. Y. Shi, and C. W. Yan. "Iconic Indexing by 2D Strings," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 9:413-428, 1991.

J. C. Collis and L. C. Lee. "Building Electronic Marketplaces with the Zeus Agent Tool-Kit," in *Agent Mediated Electronic Commerce* (P. Noriega and C. Sierra Eds.) Springer 1999.

W. Equitz. "Retrieving images from a database using texture - algorithms from the QBIC system". *IBM Technical Report* 1993.

C. Faloutsos and W. Equitz and M. Flickner and W. Niblack and D. Pekovic and R. Barber. "Efficient and Effective Querying by Image Content", *IBM Technical Report*, 1993.

Gangopadhyay, A. "Efficient Retrieval of Images Based on Content", in proceedings of the *1999 Annual Meeting of the Decision Sciences Institute*, 516-518, November 1999.

Guttman, A. "R-trees: a Dynamic Index Structure for Spatial Searching", *Proceedings of the 13th Asociation for Computing Machinery SIGMOD Conference*, 1984, 47-57.
J. Hafner, H. S. Sawhney, W. Equitz, M. Flickner, and W. Niblack. "Efficient Color Histogram Indexing for Quadratic form Distance Functions," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(7):729-736, 1995.

K. Hirata, Y. Hara, H. Takano, and S. Kawasaki. "Content-Oriented Integration in Hypermedia Systems", Proceedings of 1996 ACM Conference on Hypertext, 1996.

R. D. Holmes and E. Jungert. "Symbolic and Geometric Connectivity in Graph Methods for Route Planning in Digitized Maps," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 14(5):549-565, 1992.

M. A. Ireton and C. S. Xyedeas. "Classification of Shape for Content Retrieval of Images in a Multimedia Database", in *Proceedings of the Sixth International Conference on Digital Processing of Signals in Communication*, 1991.

H. V. Jagadish. "A Retrieval Technique for Similar Shapes", *ACM SIGMOD'91*, 1991.

T.K. Lau and I. King. "Montage: An Image Database for the Fashion, Textile, and clothing Industry in Hong Kong," in Computer Vision-ACCV'98, R. Chin and T-C. Pong (eds), Vol. 1, 1998, Springer, 410-417.

Logic Vision. "Wit Visual Programming Software: Operator Reference Manual", Logic Vision, Burnaby, Canada, 1999.

D. Ndumu, H. Nwana, L. Lee, and H. Haynes. "Visualization and Debugging of Distributed Multi-Agent Systems," *Applied Artifical Intelligence Journal,* 13 (1), 1999, 187-208.

A. Neumann. "A Better Mousetrap Catalog," Business 2.0, February 2000, 117-118.

W. Niblack, R. Barber, R., W. Equitz, M. Flickner, E. Glassman, Petkovic, D. P. Yanker, C. Faloutsos, and G. Taubin, G. "The QBIC Project: Querying Images by Content Using Color, Texture, and Shape", Proceedings of the SPIE Conference on Storage and Retrieval for Image and Video Databases, 1993, 173-187.
H. Nwana and D. Ndumu. "A Perspective on Software Agents Research," *The Knowledge Engineering Review,* January 1999.

V. E. Ogle and M. Stonebraker. "Chabot: Retrieval from a Relational Database of Images", *IEEE Computer*, 28(9), 1995, 40-56.

G. Pass, R. Zabih, and J. Miller, "Comparing Images using Color Coherence Vectors," in *Proceedings of the ACM Multimedia Conference*, 1996. M. Sawhney and J. Davis. "How it Works," Business 2.0, February 2000, 112-113.

A. Pentland, R. W. Picard, and S. Sclaroff, "Photobook: Tools for Content-Based Manipulation of Image Databases", Proceedings of the SPIE Storage and Retrieval Image and Video Databases II, 1994.

J. R. Smith and S.-F. Chang. "Automated Image Retrieval Using Color and Texture", Columbia Technical Report, 1995.

J.R. Smith, and S.-F. Chang. "VisualSEEK: a Fuly Automated Content-based Image Query System", Proceedings of the ACM Multimedia Conference 1996.

J. R. Smith and S.-F. Chang. "Tools and Techniques for Color Image Retrieval", International Symposium on Electronic Imaging: Science and Technology - Storage and Retrieval for Image and Video Database, 2670, 1996.
J. R. Smith and S.-F. Chang. "WebSEEk: A Content-based Image and Video Search Engine for the World-Wide Web", *IEEE Multimedia*, 1997.

J. R. Smith and S.-F. Chang. "SaFe: A General Framework for Integrated Spatial and Feature Image Search", IEEE Signal Processing Society 1997 Workshop on Multimedia Signal Processing, 1997.

S. Soltysiak and B. Crabtree. "Automatic Learning of User Profiles: Towards the Personalization of Agent Services," *BT Technology Journal,* 16(3), July 1998.

M. J. Swain and D. H. Ballard. "Color indexing", *International Journal of Computer Vision* 7(1), 1991.

H. Tamura, S. Mori, and T. Yamawaki. "Texture Features Corresponding to Visual Perception," *IEEE Transactions of Systems, Man, and Cybernetics*, SMC-8(6): 420-273, 1978.

F. Tomita and S. Tsuji. Computer Analysis of Visual Textures, Kluwer Academic Publishers, 1990.

D. Unwin. Introductory Spatial Analysis, Methuen, London, 1981.