A New Approach to Image Retrieval by Fast Indexing and Searching

J. You[1] H. Cohen[2]
[1]School of Computing and Information Technology
Griffith University, Brisbane, QLD, Australia 4111
you@cit.gu.edu.au
[2]School of Computer Science and Computer Engineering
La Trobe University, Bundoora, VIC Australia 3083
harvey@latcs1.lat.oz.au

Abstract

This paper presents a new approach to fast image retrieval in a distributed environment. Focusing on content-based image retrieval, we introduce a dynamic indexing and searching scheme to effectively collect image data from distributed image database. In addition, transportable agents are used as the steering tool for parallel implementation of the proposed algorithms to increase speed.

Keyword: content-based image retrieval, image indexing and searching, feature extraction, transportable agent, distributed computing

1 Introduction

The rapid development of multimedia systems spans vast areas in computer science and requires intelligent problem-solving systems to access and retrieve information stored in various formats and media forms with robustness, reliability and efficiency. Very large collection of images (image libraries) are becoming common and networking and wireless communication offer users unprecedented access to these collections distributed over networks. Nowadays, users have a clear preference for accessing images in these collections based on their content. Creating indices for these collections by hand is unlikely to be successful, because these databases can be gigantic [1]. Determining how to index and search an image by its content from large image databases is an active research area across many disciplines. Its applications cover a wide range including defense and civilian satellites, military reconnaissance and surveillance flights, fingerprinting and mug-shot-capturing, scientific experiments, biomedical imaging, and home entertainment systems.

Despite of the wide applications, it is difficult to have a uniformed searching engine for the retrieval task that suits various image contents. At first glance, an image retrieval task appears deceptively simple because humans seem to be so good at classifying information from a large collection of images in terms of its colours, textures, shapes and object positions. Unfortunately, in an unconstrained environment, such a task is beyond the reach of current technology in image understanding. There are three primary issues for content-based image retrieval (CBIR): *image feature extraction and representation, similarity measure,* and *retrieval methods.* Currently a large proportion of research into CBIR has been centred on issues such as which image features are extracted, the level of abstraction manifested in the features, and the degree of desired domain independence [2]. However, little has been reported about the significant connections and combinations between image feature extraction/representation, similarity measure and retrieval methods. Moreover, most of the existing methods are single-machine oriented even though different image collections are distributed located. In order to effectively index and search images with specific features from distributed image collections, it is essential to develop algorithms for dynamic indexing and searching. More specifically, a sort of "agents" is required that can be launched to create index based on specific image feature or to search specific images with given content. In this paper, we use transportable agents as a tool to achieve network-transparent image indexing and searching, which can

- simultaneously extract useful pictorial information from different image collection sources on the network,
- categorise images by an index-on-demand scheme that allows users to set up different index structures for fast searching, and
- support a flexible searching scheme that allows users to choose effective methods to retrieve images.

This paper presents a new approach to image retrieval by using a platform-independent transportable agent as tool to support dynamic image indexing and flexible image searching. Section 2 introduces the concept of platform-independent transportable agent while Section 3 briefly describes a method for image feature extraction and representation. Section 4 highlights a parallel algorithm for fast image indexing and searching. The initial experimental results and conclusion are presented in Section 5 and 6 respectively.

2 Platform-Independent Transportable Agent

Transportable agents are programs, typically written in a safe language, such as, TCL and Telescript, which may be dispatched from a client computer and transported to a remote server computer for execution. As an emerge paradigm for distributed computing, transportable agents can provide all functions supported by traditional client-server model. Depending on the extra features added to the safe language, an agent not only can migrate between computers, it also can fork and join. These extra features make transportable agents more suitable for transactions and information retrievals that require high flexibility [2].

In the work reported in this paper, we extended an available Java-based Agent, such as Java-To-Go from Berkeley [3]. Initially, we added migration, communication, synchronization, control and management functions to the package, which enhanced its functionality. A simple agent launched by a user can be deployed on servers first, and then requests can be sent from the client to the deployed agents as in traditional client-server model. The agent will receive requests from clients, perform required operations before sending back results. In the second stage, a control mechanism (like a Workflow) will be added into the package developed in the first stage. An agent then follows the control strategy to travel between servers and performs its functions on its path. Finally, the agent can be reclaimed from the final destination. In addition, a transportable agent can be launched from a mobile computer to the Internet. In such a case, after the launch of the agent, the mobile computer will be disconnected from the agent. On the completion of the specified computing task by the agent, the user can regain the control on the transportable agent from the final destination. Figure 1 shows the movement of an agent with a specific computing task, where an agent jumps from machine to machine and interacts with resources on each machine.

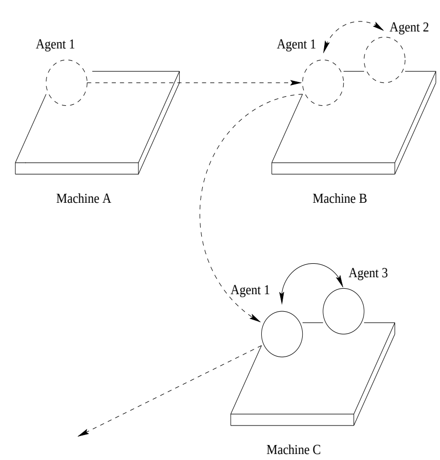

Figure 1: The abstraction of transportable agent

3 Image Feature Extraction and Representation

In the computer vision approach to retrieval, the user wants to find an image with certain attributes. These attributes are computed from pixel values and may correspond to local colour, texture, or matched filter response, the shape or arrangement of regions defined by those attributes. To fulfill a request, the system gives each image a relevance score, and presents them to the user in order of relevance. In the work reported here, we aim to convert gray-scale image to feature image by detecting image feature points. Unlike the existing approaches [6] which mostly rely on different individual operators to detect image feature points, we proposed new types of fractional functions as discrimination functions to perform robust (in the presence of noise), selective (band limited) and contextual feature extraction [7]. The detected feature points for each image are pre-detected off-line and will be used to calculate coarse features for fast image indexing.

The generalised discrimination functions $g(\xi)$ are defined within the bounds of a multi-dimensional coordinate system ξ. In the case of one-dimensional time-domain signals, ξ represents time t; for time-invariant images, ξ refers to the spatial coordinates (x, y); and for time-dependent images, ξ means (x, y, t). Let $f(\xi)$ be a multi-dimensional periodic or aperiodic function defined over $\xi \in [-\infty, \infty]$ in terms of their zero crossings or zero nodes (with at least one zero-crossing). Therefore, the generalised discrimination function $g(\xi)$ is defined as

$$g(\xi) = \begin{cases} f(\xi) & if\ \xi \in [k_m, k_n] \\ 0 & otherwise \end{cases}$$

such that

$$\int_{-\infty}^{\infty} g(\xi) d\xi = \int_{k_m}^{k_n} f(\xi) d\xi = 0$$

where k represents a zero crossing (k_m and k_n refers to m^{th} and n^{th} zero crossing respectively), m, n are any integers and $m < n$.

By introducing such a general form, discriminations for feature extraction can be generalised with any order, size and shape or a combination of the three. All such discrimination functions perform differentiation with inherent aggregation. In addition, these functions are orthogonal to the aggregation weighting functions.

With respect to the dynamic image feature extraction we also focus on the so called 'spatial-statistical' measurement to represent texture feature in image, which involves the computation of statistics of various local image functions. Rather than representing such texture measurement in its true value as reported in the related literatures [7], [8] and our previous studies [9], we extended the fuzzy compactness approach [10] to measure fuzziness in terms of texture energy [11] via fuzzy set [12]. An image I of size $M * N$ and L levels of brightness can be considered as an array of fuzzy singletons, each associate with a value of membership representing its degree of brightness relative to some brightness level l, $l = 0, 1, 2, ..., L-1$. Such an assumption can be expressed in the notation of fuzzy sets as follows:

$$X = \{\mu_X(x_{ij}) = \mu_{ij}/x_{ij}; i = 1, 2, ..., M; j = 1, 2, .., N\},$$

where $\mu_X(x_{ij})$ or $\mu_{ij}/x_{ij}(0 \leq \mu_{ij} \leq 1)$ denotes the grade of featuring some brightness property μ_{ij} by the (i, j)th pixel intensity x_{ij}.

In his previous work, Pal[10] introduced the index of fuzziness to reflect the average amount of ambiguity (fuzziness) presented in an image I by measuring the distance between its fuzzy property μ_x and the nearest two-level property μ_X. A linear index of fuzziness is defined below:

$$\begin{aligned} v_i(X) &= \tfrac{2}{MN} \textstyle\sum_i \sum_j |\mu_X(x_{ij}) - \mu_{\mathbf{X}}(x_{ij})| \\ &= \tfrac{2}{MN} \textstyle\sum_i \sum_j \mu_{X \cap \overline{\mathbf{X}}}(x_{ij}) \\ &= \tfrac{2}{MN} \textstyle\sum_i \sum_j min(\mu_X(x_{ij}), 1 - \mu_X(x_{ij})) \\ & m = 1, 2, ..., M; n = 1, 2, ..., N, \end{aligned}$$

where $\mu_{\underline{\mathbf{X}}}(x_{ij})$ denotes the nearest two-level version of $\mathbf{X}$ such that

$$\mu_{\underline{\mathbf{X}}}(x_{ij}) = 0 \quad \text{if } \mu_{\mathbf{X}}(x_{ij}) \leq 0.5$$
$$= 1 \quad \text{otherwise.}$$

In contrast to the conventional measurement of fuzziness in a gray scale image detailed above, we extended this approach by applying the distance measurement to feature image rather than the original image in gray scale. Accordingly, X refers to the image feature set and x_{ij} represents the certain feature measurement.

Furthermore, visual shape of an object is another important datum in real world. In general, it is difficult to uniquely describe an object's shape in terms of alphanumeric descriptors [13]. We proposed to combine invariant moments computing and B-Spline curve representation to represent shape features.

4 A Parallel Indexing and Searching Scheme

The problem of how to measure image similarity is a challenging issue for image indexing. It is unreasonable to expect that image database retrieval should only involve a single attribute at a time. In the visual domain, many low-level attributes of the picture conspire to generate the rich image content. Thus many attributes need to be considered simultaneously for effective content-based image indexing. Rather than combining different features by fixed weights as reported in some research and industrial systems [9], we propose to combine measures by ranking each image when ordered by relevance score in terms of its fuzziness membership. We further combine the ranks of different features with unequal weights to get a new similarity measure. In addition, we introduce a learning procedure to produce the optimal combination of feature representation for effective similarity measurement. We used a decision tree for such a purpose. In contrast to the set-covering [14] and decision-list [15], our decision-tree learning strategy uses fuzzy set membership to make decisions, not raw feature values. Consequently in an interactive setting the learner is expected to classify all training points correctly. Furthermore, we also propose an automatic bias selection method for continuous learning so as to improve the learning ability. As opposed to multi-strategy learning, which selects among several fixed biases, continuous learning adds the ability to construct new biases on the fly. A straightforward solution is to give each feature grouping a weight which can vary depending on the kind of problem being solved. We will use a lookup table to store all the possible weights during the search for the best weight function over groupings.

It should be pointed out that indexing tabular data for exact matching or range searches in traditional databases is a well-understood problem, and structures like B-trees provide efficient access mechanisms. However, in the context of similarity matching for visual images, traditional indexing methods may not be appropriate. Consequently, data structures for fast access of high-dimensional features for spatial relationships have to be developed. As discussed above, we introduce fuzziness membership with different weights to combine different feature measurements to a single entity for fast image grouping. Corresponding to the image database, a 2D matrix is used to represent the image entities in the database, which is row ordered in terms of the fuzziness membership. The classification task is to identify candidates in the matrix which has the minimum difference with the input sample measurement. Consequently, a fast parallel searching procedure in such a matrix with sorted rows is essential. In the work reported in this paper, we aim to apply parallel search and multisearch algorithms by use of transportable agent in a distributed computing environment to improve efficiency.

5 Experimental Results

For a given texture image shown in Figure 2, Table 1 lists some statistical measurements such as mean, standard deviation SDV, Skewness $SKEW$, Entropy together with the signal to noise ratio SNR for the comparison of the performance at different fractional order.

Figure 2: An example image

Table 1: Statistical measurements at different fractional order

order	Mean	SDV	Skeweness	Entropy	SNR
0.0	129.91	46.65	-2.24	3.58	0.00
0.2	131.75	47.43	-2.21	3.79	22.78
0.3	136.32	50.08	-2.16	3.72	19.57
0.4	138.79	50.55	-2.18	3.90	19.28
0.5	133.48	47.87	-2.21	3.75	23.01
0.6	134.07	48.01	-2.22	3.50	23.91
0.7	134.29	48.08	-2.22	3.70	22.92
0.8	137.47	48.14	-2.22	3.81	22.91
0.9	134.68	48.20	-2.22	3.91	22.86

The advantage of use of fuzzy set for image feature indexing is demonstrated in Figure 3 by comparing histogram distribution of the selected features. For the given image shown in Figure 2, Figure 3(a) is the gray scale distribution and Figure 3(b) is the texture energy distribution. Our test results show that the histograms of feature distribution (*e.g.* textures, and shapes) provide better feature measurements for indexing.

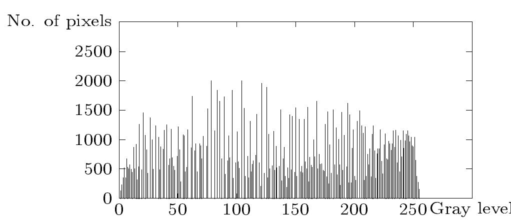

Figure 3(a): Histogram of gray-scale distribution

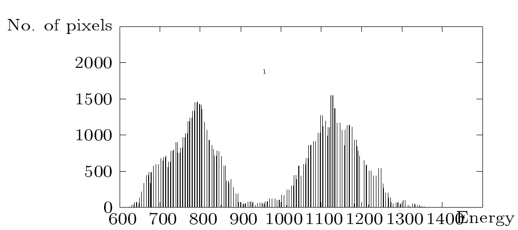

Figure 3(b): Histogram of texture energy distribution

6 Conclusion

We conclude that the selective feature extraction with respect to colours, textures and shapes proves to be powerful for image representation. The combination of multiple similarity measures using *fuzzy set* provides a simple measurement for image indexing. Furthermore, the parallel implementation using transportable agents reduce the execution time. Such an approach will be useful for real-time object recognition and fast image archiving.

References

[1] S. Belongie, C. Carson, H. Greenspan and J. Malik, "Recognition of images in large databases using colour and texture", Technical Report, Computer Science Division, University of California at Berkeley, 1996.

[2] V.N. Gudivada and V.V. Raghavan, "Content-Based Image Retrieval Systems", Guest Editors, *IEEE Computer*, Sept. 1995

[3] C. Harrison, D. Chess and A. Kershenbaum, "Mobile Agents: Are they a good idea", Research Report, IBM Thomas J. Watsoon Research Center, 1995.

[4] W.Li and D.G. Messerschmitt, " Mobile Agent-based Network Signaling for Resource Netotiations" Workshop on Resource Allocation Problem in Multimedia Systems, IEEE Real-time Systems Symposium, 1996, Washington DC..

[5] T.M. Caelli and D. Reye, "On the classification of image regions by colour, texture and shape", Pattern Recognition, Vol.26, No.4, pp. 461-470, 1993.

[6] D. Marr and E. Hildreth, "Theory of edge detection", Proc. R. Soc. Lond. B, Vol.207, pp. 187-217, 1980.

[7] S. Hungenahally, "On Discrimination Functions for Image Feature Extraction", Ph.D thesis, supervised by A. Sattar and J. You, Griffith University, July, 1996.

[8] R. M. Haralick, "Statistical and structural approaches to texture", Proc. IEEE, Vol. 67, pp. 786-804, 1979.

[9] R. Picard, "A society of models for video and image libraries", IBM Systems Journal, April, 1996.

[10] J. You, and H.A. Cohen, "Classification and segmentation of rotated and scaled textured images using texture 'tuned' masks", Pattern Recognition, Vol. 26, No. 2, pp. 245-258, 1993.

[11] S.K. Pal and A. Rosenfeld, "Image enhancement and thresholding by optimization of fuzzy compactness", *Pattern Recognition Letters*, Vol. 7, pp. 77-86, 1988.

[12] K.I. Laws, "Textured Image Segmentation", Ph.D thesis, University of Southern California, January, 1980

[13] L.A. Zadeh, Fuzzy Sets and Their Applications to Cognitive and Decision Processes, Academic Press, London, 1975.

[14] D. Haussler, "Quantifying inductive bias: AI learning algorithms and Valiant's learning framework", *Artificial Intelligence*, Vol. 36, pp. 177-221, 1988.

[15] R. Rivest, "Learning decision lists", *Machine Learning*, Vol. 2, pp. 229-246, 1987.

[16] R. Mehrotra and J.E. Gary, "Similar-shape retrieval in shape data management", IEEE Trans. Computer, Vol. 28, No. 9, pp. 57-62, 1995.

[17] F.S. Cohen, Z. Huang and Z. Yang, "Invariant matching and identification of curves using B-splines curve representation", *IEEE Tran. on Image Processing*, Vol. 4, No. 1, 1995, pp. 1-10.