Submit to Workshop on Databases and Software Engineering

Semantic Image Retrieval Using Analytical Hierarchy Process

Shyi-Chyi Cheng*, Ching-Fu Chang and Tzu-Chuan Chou#

*Department of Computer and Communication Engineering, #Department of Information Management, National Kaohsiung First University of Science and Technology, 1 University Road, Yenchao, Kaohsiung 824, Taiwan, R.O.C., Tel: +886-7-6011000 Ext. 2025, Fax: +886-7-6011012, e-mail: csc@ccms.nkfust.edu.tw

Abstract

In this paper, a new semantic image retrieval method using the analytic hierarchical process (AHP) is proposed. AHP proposed by Satty used a systematically way to solve multi-criteria preference problem involving qualitative data and was widely applied to great diversity areas. The meanings of an image are multiple and heavily depend on the features used to interpret it. The AHP provides a good way to evaluate the fitness of a semantic description used to represent an image.

A multi-dimensional vector, consists of the values of fitness of semantic descriptions about a given image, is used to represent the content of the image. Based on the vector representation, a similarity measurement between two semantic vectors in which one is from a query image and the other is from a database image is proposed in this study. Given a query image, the retrieved images are ranked according to their values of similarity. Comparing with the traditional text-based semantic retrieval techniques, the proposed method can display the retrievals according to the values of similarity. That is more similar images for a query image will be displayed first and users are easy to decide when they should stop the browsing. Furthermore, a relevance feedback mechanism is added to the system in order to further

* To whom all correspondences would be addressed.

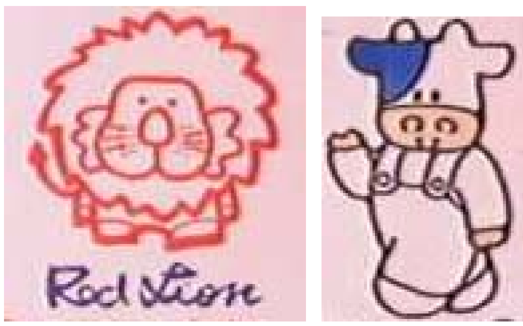
involve users in the retrieval loops. Experimental results show that the performance of the proposed method is excellent as compared to traditional text-based semantic retrieval techniques.
Keywords: Decision making, AHP, Semantic access, Image retrieval, Relevance feedback.

1. Introduction

With the rapidly increasing use of the Internet, the demands for storing multimedia information (such as text, image, audio, and video) have increased. Along with such databases comes the need for a richer set of search facilities that include keywords, sounds, examples, shape, color, texture, spatial structure and motion. Traditionally, textual features such as filenames, captions, and keywords have been used to annotate and retrieve images. As they are applied to a large database, the use of keywords becomes not only cumbersome but also inadequate to represent the image content. Many content-based image retrieval systems have been proposed in the literature [1-4]. To access images based on their content, low-level features such as colors [5-8], textures [9,10], and shapes of objects [11,12] are widely used as indexing features for image retrieval. Although content-based image retrieval is extremely desirable in many applications, it must overcome several challenges including image segmentation, extracting features from the images that capture the perceptual and semantic meanings, and matching the images in a database with a query image based on the extracted features. Due to these difficulties, an isolated image content-based retrieval method can neither achieve very good results, nor will it replace the traditional text-based retrievals in the near future.

Applying similar techniques used in the area of information retrieval [13, 14], text-based image retrieval systems retrieve images by matching two images in which one is from a database and the other is the query image according to the annotation of each image. The text annotation of an image could be captured from the caption of the image by automatically parsing the corresponding document or given by human assessment. One can further extract keywords from the annotation and represent the content of the associated image as a keyword vector which dimension is innately high.

One basic assumption common to all text-based retrieval models is: retrieval is based only upon representations of queries and documents, not upon the queries and documents themselves [15]. And hence, the key to success for developing an effective text-based retrieval system is the accurate content representation. However, the representation of images on the basis of keywords is “uncertain.” For example, most of the people would agree that the object in Fig. (a) is a “lion” according to its shape and the caption of the image. In contrast to Fig. (a), the interpretations to the object in Fig. (b) will be diverse: one may describe it as a “child dressed in a suite of cow-like clothes”; the other may treat it as a “personified cow”. The extraction of semantic descriptions from an image given by human assessment is a highly uncertain process. As a consequence, the retrieval process becomes uncertain.



(a) (b)

Fig. 1. Two images contain different levels of semantic uncertainty. (a) a lion image, (b) an image with a personified cow.

In contrast to the traditional content-based image retrieval, semantic retrieval in general prefers to use some sort of semantic description rather than specify low-level visual features. A good way to allow semantic access to the databases is by means of object-based queries [17]. In this case, objects are used to search the images in the database. The key issue of semantic retrieval is computers must index images at a semantic level as well as human beings do, otherwise, their outputs would be meaningless to us. There are two difficult problems for semantic retrieval by computers: (1) it is not a trivial job to segment meaningful objects from images due to the lack of complete image-understanding models; (2) the problem to assign an object to its class using any existing object recognition technique cannot be totally solved. The use of a human-in-the-loop to resolve the problems that the system cannot solve autonomously is therefore essential for semantic retrieval.

In this paper, a new semantic image retrieval method using the analytic hierarchical process (AHP) [16] is proposed. AHP proposed by Satty [16] used a systematically way to solve multi-criteria preference problem involving qualitative data and was widely applied to great diversity areas [18-20]. Pair comparison is used in this decision-making process to form a reciprocal matrix, so transforming qualitative data to crisp ratios and making the process simple and easy to handle. The reciprocal matrix is then solved by an eigenvector method for determining the criteria importance and alternative performance. The rationale of choosing AHP, despite its controversy of rigidity, is that the problem to assign the semantic description to the objects of an image can be formulated as a multi-criteria preference problem. As shown in Fig.1, the meanings of an image object are multiple and heavily depend on the features used to interpret it. The AHP provides a good way to evaluate the fitness of a semantic description used to represent an image object.

A multi-dimensional vector consists of the values of fitness of semantics about a given image is used to represent the content of the image. Based on the vector representation, a similarity measurement between two semantic vectors in which one is from a query image and the other is from a database image is proposed in this study. Given a query image, the retrieved images are ranked according to the values of similarity. Comparing with the traditional text-based semantic retrieval systems, the proposed method can display the retrievals according to the values of similarity. That is more similar images for a query image will be displayed first and users are easy to decide when they should stop the browsing. Furthermore, A relevance feedback mechanism is added to the system in order to further involve users in the retrieval loops. Experimental results show that the performance of the proposed method is excellent as compared to traditional text-based semantic retrieval systems.

The remainder of this paper is organized as follows. Section 2 presents the use of the analytical hierarchy process for semantic access to an image database. Section 3 presents the proposed relevance feedback. Followed by some experimental tests to illustrate the effectiveness of the proposed image retrieval method in Section 4. Finally, a conclusion is drawn in Section 5.

2. Proposed semantic image retrieval using AHP

A. A brief review of AHP

The AHP usually consists of three stages of problem solving: decomposition, comparative judgments, and synthesis of priority. The decomposition stage aims at the construction of a hierarchical network to represent a decision problem, with top representing overall objectives and the lower levels representing criteria, subcriteria, and alternatives. With the comparative judgments, users are requested to set up a comparison matrix at each hierarchy by comparing pairs of criteria or subcriteria. A scale of values ranging from 1 (indifference) to 9(extreme preference) is used to express the users preference. Finally, in the synthesis of priority stage, each comparison matrix is then solved by an eigenvector method for determining the criteria importance and alternative performance.

The following list provides a brief summary of all processes involved in AHP applications:

1. Specify a concept hierarchy of interrelated decision criteria to form the decision hierarchy.
2. For each hierarchy, collect input data by performing a pairwise comparison of the decision criteria.
3. Estimate the relative weightings of decision criteria by using an eigenvector method.
4. Aggregate the relative weights up the hierarchy to obtain a composite weight which

represents the relative importance of each alternative according to the decision maker's assessment.

One major advantage of AHP is it is applicable to the problem of group decision making. In group decision setting, each participant is required to set up the preference of each alternative by following the AHP method and all the views of participants are used to obtain an average weighting of each alternative.

B. Semantic image classification using AHP

We view an image as a compound object containing multiple component objects which are then described by several semantic descriptions according to a semantic hierarchy. The task to construct a concept hierarchy for assigning the semantics to an image object is not a trivial work because the domain-specific knowledge should be included in the hierarchy. Fig. 2 shows the image classification hierarchy [22] defined by Intellectual Property Office, Taiwan for censoring trademark registration applications. Based on the hierarchy, the method to involve the semantic access to an image database in the AHP applications is proposed in this study. To convenience the illustration, the classification hierarchy is abbreviated as IPO hierarchy.

There are twelve subjects in the top level of IPO hierarchy and a two-digit code ranging from '01' to '12' is used to specify the subject an image object belongs. Each top-level subject is then divided into several sub-subjects and each sub-subject is again decomposed into several third-level subjects. The codes to locate the second-level subjects and the third-level subjects where an image object assigned are 'A' to 'Z' and '01' to '99', respectively. A composite path code is formed by aggregating the code of each level for specifying a particular meaning to an object. For example, if a path code '01A01' is given to semantically describe an image object, the content of the object would include a man and an aircraft. Note that there may exist multiple path codes to interpret an image objects according to different aspects of features.

The simplest way to retrieve images from a database on the basis of path codes is to combine the path codes of a query image into a Boolean query expression. Unfortunately, we can’t distinguish the differences of the database images relative to the query image if they all share common path codes with the query image. To judge whether a retrieved database image

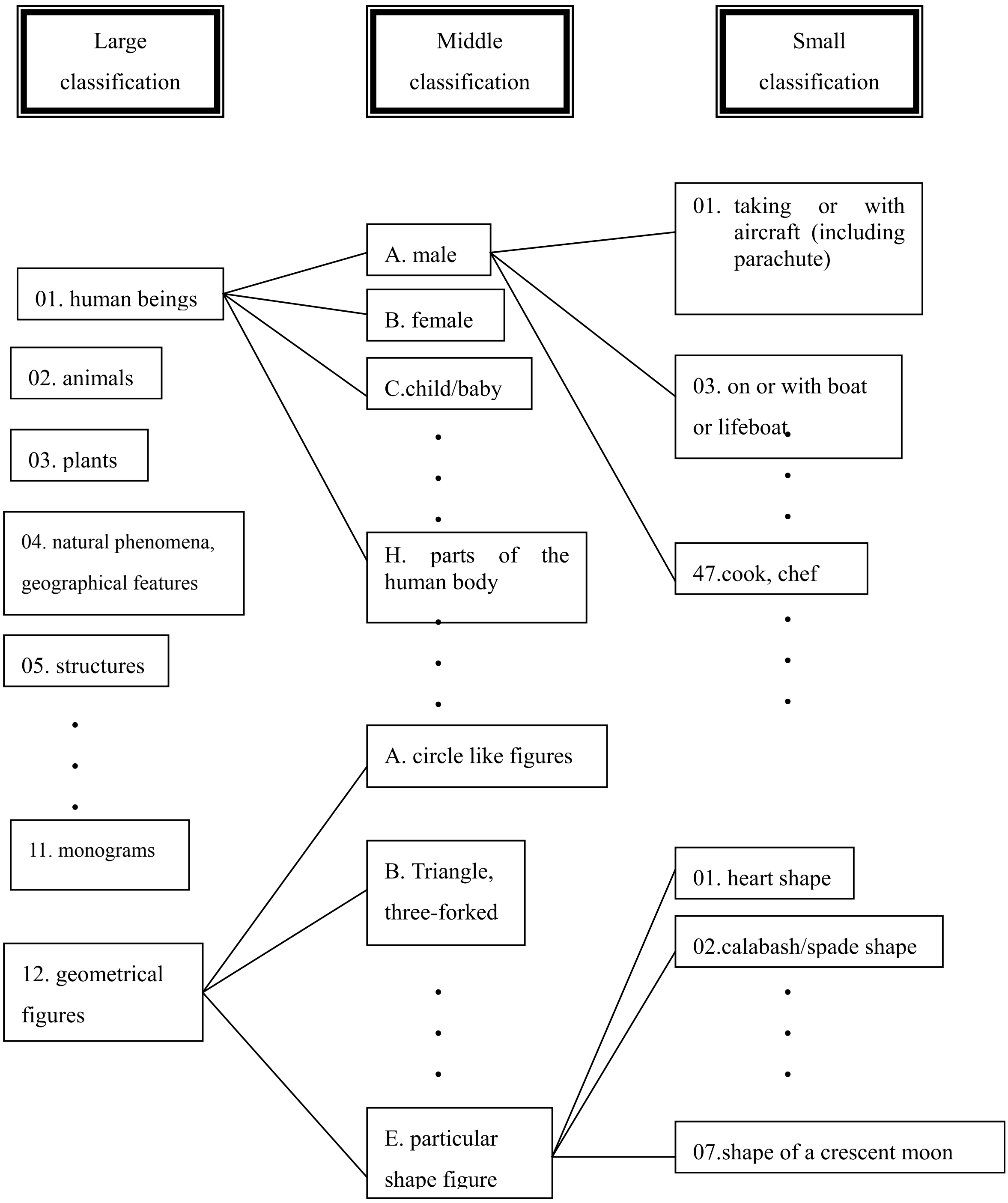


Fig. 2. The image classification hierarchy defined by Intellectual Property Office, Taiwan for censoring trademark registration applications.

is relevant to a query image is the duty of users in such kind of systems. In the worst case, users would browse all the retrievals to make sure that a database image is relevant to a query image and this becomes too cumbersome to use the system, especially when the size of database is large.

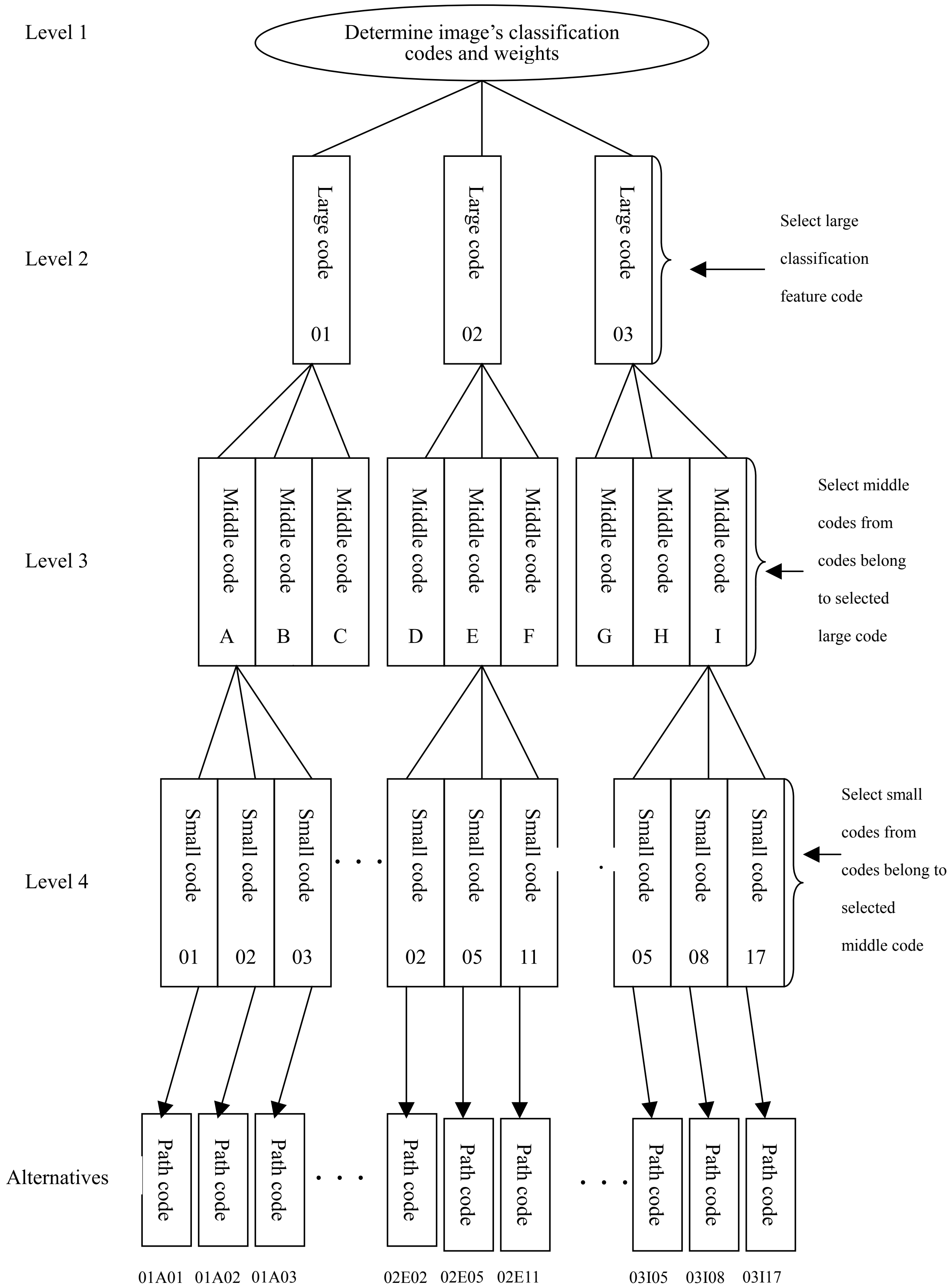


Fig. 3. Image classification selection model using AHP

A question arises naturally: is the weight of each path code of an image object equivalent? The answer to the problem is of course no. Some path codes are obviously important than others for a specific image object. For example, the semantic description “personified cow” is more important than the code with the semantic description “child dressed in a suite of cow-like clothes” for the image object in Fig. 1(b) according to the authors’ opinion.

Fig. 3 shows the path code selection model using AHP. At the highest level (level 1) of the hierarchy is the objective that is to be fulfilled when classifying an image. The objective can be classified into twelve large classification codes which reveal the categories that the image belongs. Each large classification code is further classified into multiple second-level classification codes which measure the shape and texture differences among the images classified into the same large classification. Note that each image might consist of several sub-objects. For example, a human being image object can be further torn into several segments, such as the head, the body, and the limb. The small classification codes, the level 4 codes, focus the semantics of each part of an image. Another purpose of small classification codes is to specify the semantics about the spatial composition of individual parts of an image.

C. Object representation

Assume the path codes of the semantic classification hierarchy is numbered from 1 to *n*. Given an image I, the content of the image is represented by a semantic vector which is defined as

$$I = (w_i, w_2, \ldots, w_n), \ \sum_{i=1}^{n} w_i = 1$$

where w_i denotes the weighting of the *i*th path code. Although the value of *n* is large, in any vector representing an image, the vast majority of the components will be zero. The reason is the number of objects perceived in an image is generally small. In practice a more compact representation is used, consisting only the weights for path codes actually present in the image. The key to success in using this model is to maintain dimensional compatibility. That is, the system must be designed to ensure that the comparison of two images (or a database image and a query image) is always based on comparing the same path codes in each image.

Assigning weights to image path codes in a vector is a complex process. Weights can be assigned automatically in an image, based on the object recognition techniques. However, this problem is far away from being totally solved. Instead of that, in this paper, weights are assigned using the analytical hierarchy process. Note that the numerical characteristic of a weight limits the possibility of assigning it directly through human assessment. One major advantage of using AHP in assigning weights to image path codes in a vector is that users are only required to set the relative importance of two semantic descriptions. The values of weights are calculated automatically.

Before the performance of pairwise comparisons, users of the system are given an instruction on how to conduct comparison among the semantic descriptions (path codes) with respective to the immediately proceeding semantic description in the hierarchy. Their judgment of the importance of one semantic description over another can be made subjectively and converted into a numerical value using a scale of 1 to 9 where 1 denotes equal importance and 9 denotes the highest degree of favoritism [16-21]. Table 1 lists the possible judgments and their representative numerical values.

The numerical values representing the judgments of the comparisons are arranged in a reciprocal matrix for further calculations. The main diagonal of the matrix is always 1. Users are required to adopt a top-down approach in their pairwise comparisons. In other words, the importance of the large classification codes is first evaluated with respect to a given image.

Given an image, the first step of the classification process using AHP is to choose the large classification codes and evaluate their relative importance by performing pairwise comparisons. For example, Fig.4(a) containing a man that is pulling a carriage is the target of classification. Three image objects, which can be classified into the three level 2 image categories -- “human beings”, “animals”, and “means of conveyance”, exist in Fig. 4(a). Fig. 4(b) is the corresponding level 2 reciprocal matrix for judging the relative importance of the three semantic descriptions. An eigenvector method can be used to calculate the weightings of the three subjects in representing the image.

Table 1 Pairwise comparison judgments between semantic description A and semantic description B.

Judgment	Values
A is equally preferred to B	1
A is equally to moderately preferred over B	2
A is moderately preferred over B	3
A is moderately to strongly preferred over B	4
A is strongly preferred to B	5
A is strongly to very strongly preferred over B	6
A is very strongly preferred over B	7
A is very strongly to extremely preferred over B	8
A is extremely preferred to B	9

Follow the same procedure, the weightings of the middle and small classification codes with respective to the given image can be calculated. Note that there are three reciprocal matrix need constructed if three large classification codes are selected to describe an image. Also, the number of reciprocal matrix for evaluating the weights of small classification codes will depend on the number of middle classification codes used to describe an image. Let x , y and z be the numbers of large, middle and small classification codes, respectively, used to code an image. The number of reciprocal matrix for the image is $x \times y \times z$ and it is actually equal to the number of path codes used to describe an image. It would be too cumbersome to classify a complex image using AHP. Fortunately, this problem would not occur because most of the images do not need a large amount of path codes to describe them. Most of them have at most 4-5 path codes according to our experience.

As mentioned above, a path code consists of three parts, the large classification code, the middle classification code and the small classification code. The weighting of the path code in representing an image is easily to compute as the product of the local weights of the three classification codes. Note that the local weight of a un-selected classification code is zero and it is easy to show that the value of the weight of a path code is within the interval [0,1].

(a)

Image Classification	human beings	animals	means of conveyance
Human beings	1	1/7	1/5
animals	7	1	2
means of conveyance	5	1/2	1

(b)

Fig. 4. An example image to be classified: (a) the image; (b) the corresponding reciprocal matrix with respect to (a) for calculating the local weightings of the level 2 semantic descriptions in representing the image.

D. Image Similarity

When the vector model of retrieval is used, similarity measurements can be associated either with the idea of distance, following the philosophy that images close together in the vector space are likely to be highly similar, or with an angular measure, based on the idea that images "in the same direction: are closely related [23].

In this study, we use the widely used cosine measure for vector-based matching. The cosine measure is not a distance measure, but rather is developed from the cosine of the angle between the vectors representing two images (or a database image and a query image). Its definition is

$$\delta(D,Q)=\frac{\sum_i (w_i^D \times w_i^Q)}{\sqrt{\sum_i (w^D_i)^2}\times\sqrt{\sum_i (w^Q_i)^2}} \tag{1}$$

where w_i^D and w_i^Q are the weightings of the *i*th path code of a database image *D* and a query image *Q*, respectively. Using the cosine transforms the angular measure into a measure ranging from 1 for the highest similarity to 0 for the lowest.

The cosine measure does not consider the distance of each image from the origin, but only the direction. Hence two images that lie along the same vector from the origin will be judged identically, despite the fact that they may be far apart in the image space. Among the metrics that consider the distance of each image from the origin and are widely used are the L_p metrics. They are defined by the equation

$$L_p(D,Q)=\left[\sum_i | w_i^D - w_i^Q |^p\right]^{1/p}. \tag{2}$$

Commonly used values for p include p=1 (city block distance), p=2 (Euclidean distance), and $p=\infty$ (maximal direction distance). Euclidean distance is the best known of these, corresponding to ordinary straight-line distance. Based on Euclidean distance, the similarity measurement can be defined as

$$\delta(D,Q)=1-\frac{L_2(D,Q)}{Max_k[L_2(D_k,Q)]}. \tag{3}$$

These two similarity measurements are implemented in our system and results in almost the same retrievals.

E. Image retrieval strategy

Each database image is indexed in the database as a three-tuple *t* which is an ordered list of 3 values $t=<id, pc, w>$,where *id* denotes the identification of an image, *pc* is a path code to represent the image, and *w* is the weighting of *pc*. The algorithm to semantically retrieve images from an image is briefly summarized as follows.

Algorithm. Semantic image retrieval using AHP.

Input: A query image Q.

Output: Retrieved image set.

Method:

Step 1. Assign the path codes to represent the content of image Q.

Step 2. Calculate the weightings of the path codes of Q using AHP.

Step 3. Retrieve all the images which share at least one path code with Q from the database.

Step 4. For each image *I* retrieved in Step 3, calculate the value of similarity between the two images *I* and *Q* using the cosine measurement.

Step 5. Rank and display the images in the previous step to the user according to their values of similarity.

3. Proposed relevance feedback mechanism

Relevance feedback consists of users feeding back into the system decisions on the relevance of retrieved images. Basically, the system retrieve a set of images in response to a query and present these to the user. The user then examples the images and make decisions on the potential relevance of each image. Normally, there are cases about this decision: (1) an image is relevant (a positive example); (2) an image is not relevant (a negative example); (3) no judgment is being make on a given image. The system uses these judgments to alter its retrieval behavior and a new set of images is then presented to the user. The cycle can be repeated for several times achieve the real information need of the user.

One problem of semantic access to an image database is the interpretation of an image heavily depends on the features that the user used to describe it. And hence, users will have different interpretations for an image according to their different experiments. Relevance feedback is a good way to smooth these variations.

In this implementation, a simple linear transformation is used to modify the initial semantic vector of a query image by relevance feedback. Suppose the query, the positive example, and the negative example are represented by the semantic vectors $< q_i, q_2, ..., q_n >$, $< p_i, p_2, ..., p_n >$, and $< n_i, n_2, ..., n_n >$, respectively. Choose two values $\alpha, 0 \le \alpha \le 1$ and $\beta, 0 \le \beta \le 1$, and replace each q_i by

$$q_i' = q_i + \alpha \times (p_i - q_i) - \beta \times n_i . \qquad (4)$$

Note that each q_i should be within the interval [0,1] and hence we have $q_i' = 0$ if $q_i' < 0$. In this implementation, the values of α and β are both set to be 0.1. Each positive example and each negative example should be applied to modify the query if the user specifies multiple positive examples and multiple negative examples.

Individual weights of path codes are modified in different ways using Equation 4, depending on how they occur in the query and the positive example. There are four cases:

1. A path code is used in both the query and the positive example. In this case, the type of modification using the simple linear transformation seems most appropriate.
2. A path code is used in the query but not used in the positive example. In this case, the path code is slightly reduced ($(p_i - q_i) < 0$), on the grounds that the user normally is not interested in this path code.
3. A path code is not used in the query but used in the positive example. In this case, the path code is slightly increased ($(p_i - q_i) > 0$), on the grounds that the user normally is interested in this path code.
4. A path code is neither used in the query nor the positive example. In this case, the path code has weight value 0 in both the query and the positive example, and hence the weight of the path code remains 0 after applying Equation 4.

Similarly, there are also four cases in modifying the weight of a path code of a query by the negative example using Equation 4:

1. A path code is used in both the query and the negative example. In this case, the path code is slightly reduced, on the grounds that the user normally is not interested in this path code.
2. A path code is used in the query but not used in the negative example. In this case, the weight of the path code is not changed because n_i =0.
3. A path code is not used in the query but used in the negative example. In this case, the weight of the path code remains 0 because $q_i' < 0$.
4. A path code is neither used in the query nor the negative example. In this case, the path code has weight value 0 in both the query and the positive example, and hence the weight of the path code remains 0 after applying Equation 4.

To sum up the weights of the semantic vector of the query after the process of relevance feedback might not be 1, and hence each weight should be normalized by:

$$\tilde{q}_i = \frac{q_i'}{\sum_{k=1}^{n} q_i'} .$$

4. Experimental results

In order to evaluate the proposed approach, a series of experiments was conducted on an Intel PENTIUM-IV 1.5GMhz PC and a trademark image database consisted of 657 trademark images was used. Each image in the database is first analyzed by the AHP for testing the retrieval approach. Query images are randomly extracted from these images.

The retrieval technique based on Boolean queries proposed by Intellectual Property Office, Taiwan was also used for performance comparison. Before the evaluation, human assessment was done to determine the relevant matches in the database to the query images. The top 100 retrievals from both the system of Intellectual Property Office (IPO), Taiwan and the proposed approachs were marked to decide whether they were indeed visually similar in color and shape. The retrieval accuracy was measured by precision and recall

$$\text{Precision}(K) = C_K/K \text{ and } \text{Recall}(K) = C_K/M \qquad (24)$$

where K is the number of retrievals, CK is the number of relevant matches among all the K retrievals, and M is the total number of relevant matches in the database obtained through human assessment. The average precision and recall curves are plotted in Figs. 5 and 6. It can be seen that the proposed method achieves good results in terms of retrieval accuracy compared to IPO's method. This shows the effectiveness of the proposed method that successfully puts the related images in response to a query at the front of the retrieval list.

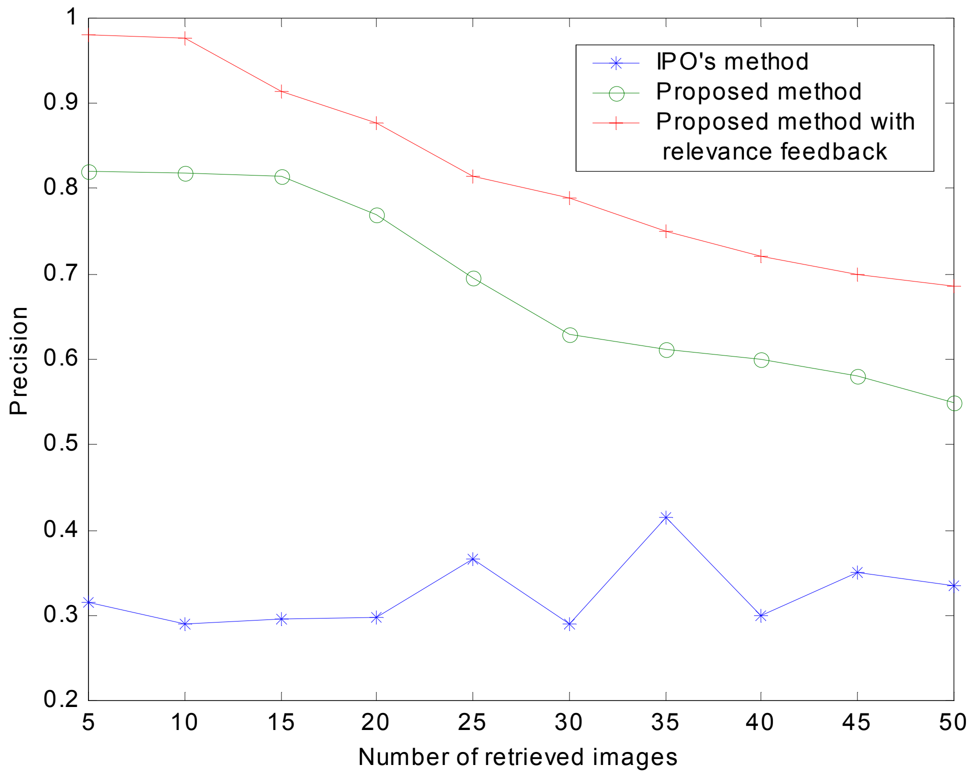


Fig. 4. Average precision versus number of retrieved images.

Fig. 6 shows a retrieval example of a "lion" query image. The retrievals are presented to the user in the page-by-page style and it is easily to find that most of the related images locate at the previous pages. One can also begin the relevance feedback cycles through the user interface of the system to refine the retrieval results.

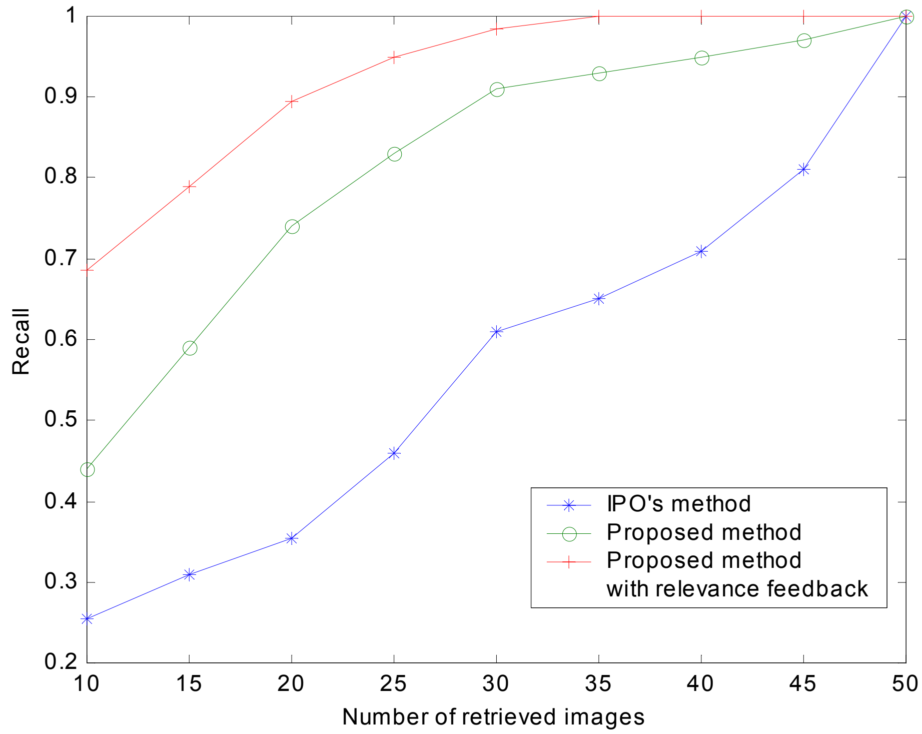


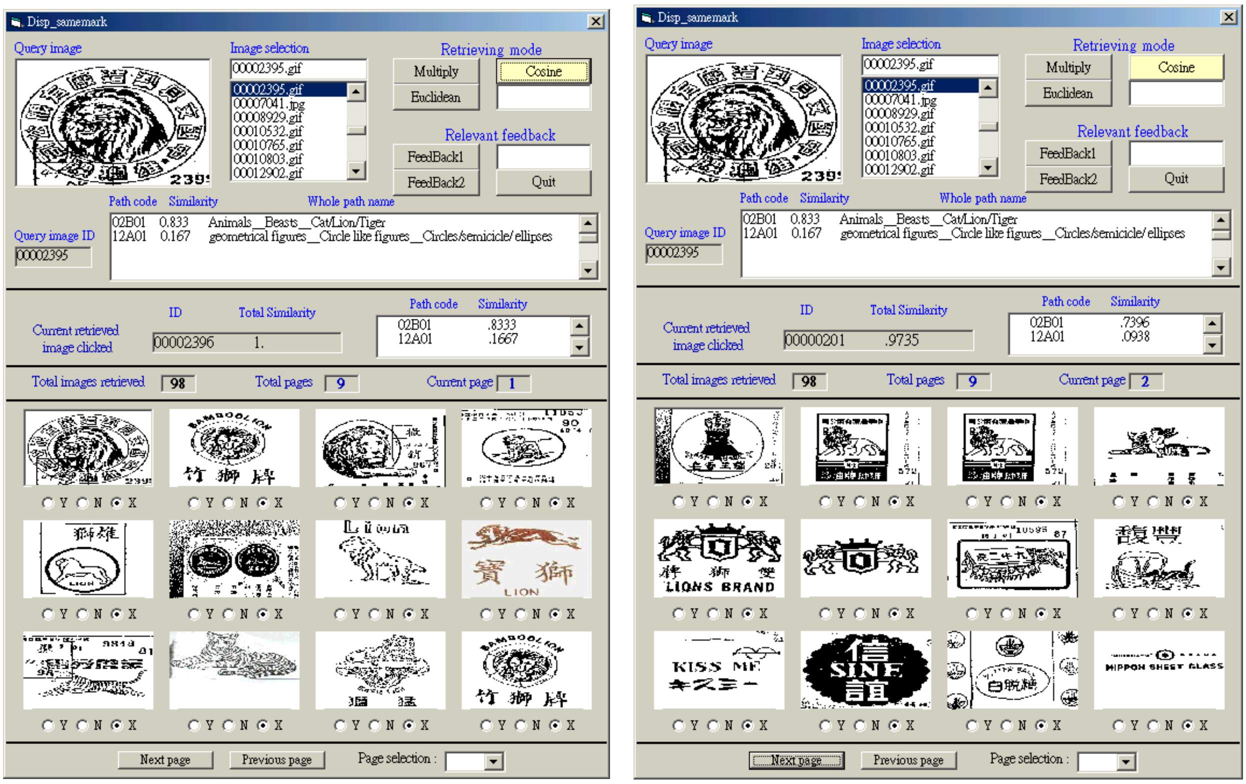
Fig. 5. Average recall versus number of retrieved images.

5. Conclusions and future works

Although content-based image retrieval is extremely desirable in many applications, it must overcome several challenges including image segmentation, extracting features from the images that capture the perceptual and semantic meanings, and matching the images in a database with a query image based on the extracted features. Due to these difficulties, an isolated image content-based retrieval method can neither achieve very good results, nor will it replace the traditional text-based retrievals in the near future.

The contributions of this paper include the following. Firstly, a new semantic image retrieval method using the analytic hierarchical process (AHP) has been proposed in this paper. The AHP proposed by Satty has been successfully used to improve the problem of multi-interpretation characteristics of an image when we focus on different types of features. Secondly, the method to rank retrieved images according to their similarity measurements is proposed using a semantic vector model. Finally, a relevance feedback mechanism for semantic image retrieval is proposed in this study. Experimental results show that the performance of the proposed method is excellent as compared to traditional text-based semantic retrieval techniques.

To classify an image by human assessment is too cumbersome to use the system. Future work will deal with shortening the gap between the traditional content-based image retrieval techniques and the high-level semantic access methods. The method to apply AHP to the content-based image retrieval systems is an on-going study of the authors.



(a) (b)

Fig. 6. A retrieval example of a "lion" query image: (a) page 1 of the retrievals; (b) page 2 of the retrievals.

REFERENCES

[1] C. Faloutsos et. al., Efficient and effective querying by image content, *Journal of Intelligent Systems*, 1, 95-108 (1994).

[2] M. Flickner et. al., Query by image and video content: the QBIC system, *IEEE Computer*, 28(9), 23-32 (1995).

[3] A. Pentland, R. Picard, and S. Scalroff, Photobooks: Tools for Content-based manipulation of image databases, *SPIE Conf. On Storage and Retrieval of Image and Video Databases II*, 33-47 (1994).

[4] B. M. Mether, M. S. Kankanhall, and W. F. Lee, Content-based image retrieval using a composite color-shape Approach, *Information Processing and Management,* 34(1) 109-120 (1998).

[5] M. Swain and D. Ballard, Color indexing, *Int. J. Comput. Vision,* 7(1), 11-32 (1991).

[6] J. Huang, S. Kumar, M. Mitra, W.-J. Zhu, and R. Zabih, Image indexing using color correlograms, in *IEEE Comput. Soc. Conf. Comput. Vision Pattern Recognition*, Puerto Rico, June, 744-749 (1997).

[7] X. Wan and C.-C. Jay Kuo, A new approach to image retrieval with hierarchical color clustering, *IEEE Trans. On Circuits and Systems for Video Technology,* 8(5), 628-643 (1998).

[8] S.C. Pei and C.M. Cheng, Extracting color features and dynamic matching for image data-base retrieval, *IEEE Trans. On Circuits and Systems for Video Technology,* 9(3), 501-512 (1999).

[9] B. Manjunath and W. Ma, Texture features for browsing and retrieval of image data, *IEEE Trans. Pattern Anal. Machine Intell.*, 18, 837-842 (1996).

[10] Z. Wang, Z. Chi and D. Feng, Content-based image retrieval using block-constrained fractal coding and nona-tree decomposition, *IEE Proc.-Vis. Image Signal Process*, 147(1), 9-15 (2000).

[11] R. Methrotra and J. Gary, Similar-shape retrieval in shape data management, *IEEE Computer*, 28, 57-62 (1995).

[12] A. K. Jain and A. Vailaya, Image retrieval using color and shape, *Pattern Recognition*, 29, 1233-1244 (1996).

[13] C. Faloutsos, Access Methods for Text, ACM Computing Surveys, Vol. 17, No. 1, 1985.

[14] V. N. Gudivada et al., Information Retrieval on the World Wide web, IEEE Internet Computing, Vol. 1, No. 5, 1997.F. Crestain, M. Lalmas, C. J. V. Rijsbergen, and I. Campbell, "Is This Document Relevant? … Probably": A Survey of Probabilistic Models in Information Retrieval, ACM Computing Surveys, 30(4), 527-552(1998).

[16] Saaty, T.L., 1980. The Analytic Hierarchy Process. McGraw-Hill, New York.

[17] R. Jain, Content-Centric Computing in Visual Systems. In Proc of 9th International Conference on Image Analysis and Processing, 1-13 (1997).

[18] T. L. Satty, Analytical Planning – The Organization of Systems, Pergamon Press Inc., 1985.

[19] Mmaggie C. Y. Tam and V. M. Rao Tummala, An Application of The AHP in Vendor Selection of a Telecommunication System, The International Journal of Management Science, 29 (2001) 171-182.

[20] Hokey Min, Location Analysis Of International Consolidation Terminals Using The Analytical Hierarchy Process, Journal of Business Logistics, 15(2), 25-44 (1994).

[21] V. S. Lai, R. P. Trueblood, B. K. Wong, Software Selection: A Case Study Of The Application of The Analytical Hierarchy Process To The Selection Of Multimedia Authoring System, Information & Management, 36(1999), 221-232.

[22] Pictorial Trademark Retrieval System, Intellectual Property Office, Taiwan, http://www.moeaipo.gov.tw/trademark/search_trademark/search_trademark_simpicF.asp

[23] R. R. Korfhang, Information Storage and Retrieval, John Wiley & Sons, Inc.