Dynamic Feature Selection and Coarse-To-Fine Search for Content-Based Image Retrieval

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Abstract. We present a new approach to content-based image retrieval by addressing three primary issues: image indexing, similarity measure, and search methods. The proposed algorithms include: an image data warehousing structure for dynamic image indexing; a statistically based feature selection procedure to form flexible similarity measures in terms of the dominant image features; and a feature component code to facilitate query processing and guide the search for the best matching. The experimental results demonstrate the feasibility and effectiveness of the proposed method.

1 Introduction

The generation of large on-line collections of images has resulted in a need for new methods which can 1) find all images similar to a given image; 2) identify images containing a specified object; 3) determine the derivatives of the original input image; and 4) recognize images represented by specified colors, textures or shapes. In general, image retrieval (IR) approaches fall into two categories: attribute-based methods and content-based methods. Attribute-based methods represent image contents using text and structured fields. Examples of such methods include Kodak Picture Exchange System (KPX) and PressLink library. However, the scope of applications of such methods is limited because it is difficult to describe image details such as irregular shapes and jumbled textures in text.

Content-based image retrieval (CBIR) requires an integration of research in computer vision, image understanding, artificial intelligence and databases to address the problem of information retrieval from large collections of images and video frames. The developments in this area are surveyed in [1], [2], [3], [4]. The CBIR approach is based on the integration of feature-extraction and object-recognition during the management of image databases to overcome the limitation of attribute-based retrieval. Traditionally designing a CBIR technique involves three primary issues: image feature extraction and representation, similarity measures, and image indexing and searching. Currently a large proportion of research into CBIR is centered on issues such as which image features are extracted, the level of abstraction manifested in the features, and the degree of desired domain independence. Examples of CBIR systems include QBIC, Virage, Photobook, CANDID, Garlic, MetaSEEK, WebSeek and C-BIRD. Although the existing

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techniques resolve the design issues in various ways [2], they have the following limitations: 1) the selection of image feature(s) for indexing and matching is pre-defined and lacks flexibility; 2) the multiple features are not integrated for similarity measures; 3) the search for the best matching is computationally expensive and somewhat domain dependent for object recognition by features. It is thus of significant interest to develop a general methodology for effective image feature extraction, indexing, searching and integration.

Liang and Kuo [5] proposed a wavelet-based system, WaveGuide, which integrated a set of image features including texture, color and shape in the wavelet domain for image description and indexing. Although the system successfully handled the two components of data representation and content description in a unified framework, it adopted a fixed image feature selection scheme and applied pre-defined criteria for similarity measures. The recent MARS (Multimedia Analysis and Retrieval System) project [6] aims to bridge the gap between the low-level features to high-level semantic concepts such as complex objects and scenes by utilizing image understanding techniques. However, the selection of features and indexing structure are fixed in MARS.

To achieve flexibility and multiple feature integration, we propose to construct a decision tree for the retrieval task where a statistically based feature selection criterion is used to guide the selection and integration of the most relevant features for similarity measurement in a hierarchical structure.

Furthermore, we introduce a data warehousing structure and a feature component code scheme to facilitate dynamic image indexing, multiple feature integration, flexible similarity measures and guided search.

This paper is organized in the following sections. Section 2 presents a dynamic image indexing scheme which embraces multiple features in conjunction with the statistically based feature selection scheme and the feature component codes for large collection of images based on the proposed image data warehousing structure. Section 3 describes a coarse-to-fine search algorithm for image retrieval. The comprehensive experimental results are reported in Section 4. Finally the conclusions are summarized in Section 5.

2 Dynamic Image Indexing

2.1 Image Data Warehouse and Multi-dimensional Feature Cube

Unlike the traditional image databases which focus on only image data (content), the proposed image data warehouse extends its capacity for data mapping and summarization. By mapping different image features to the data warehouse and generating summary tables based on the dimension data, the retrieval for similar feature data is guided by directing a query to the right tables for fast searching. This search is much faster as the size of these tables and the number of feature components is much smaller. Further, as these tables are materialized views, information stored in them is pre-computed. The reference to different summary tables will result in the selection of different indexing schemes and similarity measurement. Thus, the use of the data warehouse will facilitate dynamic indexing to speed up the retrieval task. Fig. 1 illustrates the hierarchy of multi-dimensional data cubes.

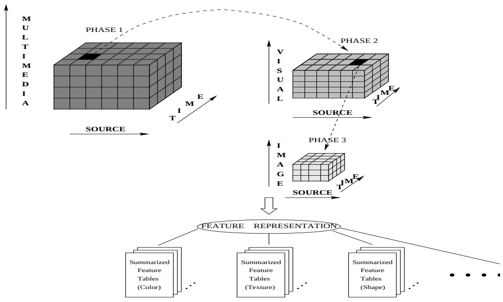


Fig. 1. A hierarchy of multi-dimensional data cubes

In our proposed image data warehouse system, the fact table defines the image content with three major image features: color, texture and shape. For each image feature, the representation of the particular item is further described in the subsequent dimension table. Each of the fields in the current dimension table can be considered as facts at a lower level and the details are summarized in the associated dimension table. Fig. 2 shows an example of such multi-level dimension tables for the representation of shape feature, where Level 1 describes the major fields of an image content (fact table), Level 2 shows the further description of shape feature details in a corresponding dimension table at a lower level (dimension table) and Level 3 lists the further details of the subsequent moment information for shape feature measurement at the next lower level. Note that the amount of information stored in one of the lower tables is much less than in the original fact table, which makes it easier to handle. For other image features such as color, texture and salient feature points, the corresponding dimension tables can be constructed in a similar manner.

With the proposed hierarchies of the image data warehousing structure, a multi-dimensional feature cube can be used to visualize the image data warehouse and its OLAP (On-line Analytical Processing) data, where the cells hold the quantifying image feature components (often referred to as facts), while the qualifying feature indices describe the axes of the cube and can be used for addressing individual feature components or groups of multiple features. The proposed multi-dimensional structure of the image feature cube offers flexibility to access and manipulate the image data from different perspectives. Such a structure allows quick data summarization at different levels for dynamic image indexing and multiple feature integration. The statistical data resulting from the OLAP operation is used to discover the hidden patterns or implicit knowledge to speed up the task of CBIR. For example, a statistically based feature selection criterion can be adopted to determine the importance of individual features in indexing and similarity measurement. A comparison of our proposed approach with the existing techniques is summarized in Table 1 and more details are reported in the following sections.

2.2 Dynamic Feature Selection and Multiple Feature Integration

Most of the existing CBIR systems pre-define the features for the retrieval task in a conventional database structure. In this paper, we propose to use a statistically based

LEVEL 1: The major fields of an image content (fact table)

Image ID	Category	Color	Texture	Shape
image #1	feature component code	color dimension table	texture dimension table	shape dimension table
image #2	feature component code	color dimension table	texture dimension table	shape dimension table
......	......	......	......	......
image #N	feature component code	color dimension table	texture dimension table	shape dimension table

LEVEL 2: The major fields of shape feature description (dimension table)

Image ID	B-spline Description	Moment Description	Salient Points
image #1	B-spline coefficients	moment feature vector	feature point list
image #2	B-spline coefficients	moment feature vector	feature point list
......	......	......	......

LEVEL 3: The data fields of invariant moments (dimension table)

Image ID	Invariant Moment (Order 0)	Invariant Moment (Order 1)	Invariant Moment (Order 2)
image #1	moment measurement	moment measurement	moment measurement
image #2	moment measurement	moment measurement	moment measurement
......	......	......	......

Fig. 2. A hierarchy of multi-level dimension tables for shape representation

feature selection criterion to determine the most appropriate feature dimension table for dynamic feature selection and indexing.

Recently feature selection criteria based on statistical measures have been extensively studied. These include the Chi-square criterion, Asymmetrical Tau and Symmetrical Tau [9]. A comprehensive description and comparison of these criteria is given in [9]. In this paper, we extend the use of the Symmetrical Tau criterion [9] to guide the selection and combination of multiple image features for content-based image retrieval within the framework of image data warehousing structure. The key features of our approach include: 1) apply Symmetrical Tau criterion to determine the importance of each individual image features; 2) use partitioning and aggregation technique to generate the most appropriate feature dimension table for dynamic image indexing; 3) adopt a flexible similarity measurement to integrate multiple features with different weights. In addition, we apply a training procedure to determine the most appropriate weights for multiple feature integration. Instead of using individual features to calculate the corresponding Tau as initially defined, we use the combined feature vector to obtain the relevant Tau. Such a process is iteratively repeated by dynamically adjusting the weights associated with each feature component. A higher weight is assigned to the component for strong emphasis and a lower weight reflects less emphasis on the non-relevant component. The set of weights with the maximum Tau is used to combine multiple features for similarity measures. More specifically, we conduct the calculation throughout the following major steps: 1) Identify all of the individual features to be used for retrieval and obtain their feature vectors. For n features $\mathbf{f}_i$ $(i = 0, 1, ..., n-1)$, there will be n individual feature vectors $\mathbf{V}_i$ $(i = 0, 1, ..., n-1)$. 2) Apply Gaussian normal-

Table 1. Comparison of different CBIR systems

Name of the System	System Structure	Data Representation	Similarity Measurement	Search Method	Query Process
QBIC [7]	single database	image modeling	pre-defined measures	one-to-one comparison	user interactive
Garlic [8]	multiple databases	image&text features	fuzzy set technique	object oriented	user interactive
MARS [6]	traditional database	image/video features	fixed measurement	hierarchical structure	user interactive
WaveGuide [5]	traditional database	wavelet-based multiple features	fixed measurement	weighted ranking	user interactive
Mediahouse (proposed approach)	data warehouse	multiple features	flexible measurement	hierarchical search	user interactive

ization to the above feature vectors. 3) Initialize a set of weights α_i $(i = 0, 1, ..., n-1)$ and obtain its corresponding combined feature vector $\mathbf{V}_c = \sum_{i=0}^{n-1} \alpha_i \mathbf{V}_i$. 4) Calculate the corresponding Tau using the following formula:

$$Tau = \frac{\sum_{j=1}^{J} \sum_{i=1}^{I} \frac{P(ij)^2}{P(+j)} + \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{P(ij)^2}{P(i+)} - SUM}{2 - SUM} \quad (1)$$

where the contingency table has I rows and J columns; $P(ij)$ is the probability that a variable belongs both to row category and to column category j; P(i+) and P(+j) are the marginal probabilities in row category i and column category j, respectively, and $SUM = \sum_{i=1}^{I} P(i+)^2 + \sum_{j=1}^{J} P(+j)^2$. 5) Adjust the set of weights, and obtain a new combined feature vector $\mathbf{V'}_c$ and calculate the corresponding Tau. 6) Repeat Step 5 for all of the given adjustment weight sets. 7) Find the maximum value of Tau from the sequences of Tau obtained in the previous stage. 8) Choose the combined feature with the maximum Tau value.

3 Coarse-to-Fine Search

We propose a coarse-to-fine search scheme in conjunction with feature component code and selective matching criteria to speed up the process in a hierarchical fashion. Our approach is characterized as follows: 1) we use image feature component code to identify the major feature components in an image; 2) we apply statistically based feature selection criterion to rank the importance of each feature component and access to the corresponding feature dimension table to group the potential candidates at coarse level; 3) we use different similarity measurements to conduct matching at the fine level. Our proposed system will support two types of queries: a) to pose a query by image sample, and b) to use a simple sketch as a query.

In the case of query by image sample, the search follows multiple feature extraction and image similarity measurement described in the previous sections. Based on the nature of the query image, the user can add additional component weights during the combination of image features for image similarity measurement.In the case of query by a simple sketch provided a user, we will apply a B-spline based curve matching scheme to identify the most suitable candidates from the image database. In the case of a query by sample image, we will use the proposed image component code to guide the search for the most appropriate candidates in terms of color, texture and shape from data warehouse at a coarse level and apply image matching at fine level for the final output. A fractional discrimination function is used to identify object boundaries for coarse-to-fine matching.

3.1 Feature Component Code

In this paper, we adopt a general wavelet based scheme for image feature extraction and representation. Three features – color, texture and shape are considered and each is associated with an individual feature vector. To organize the index structure with these features to facilitate image query, we propose a three-bit feature component code to characterize the status of each individual image, where the left bit C represents color status (1 for a color image and 0 for a black and white image), the middle bit T represents texture status (1 for a texture image and 0 for a non-texture image), and the right bit S represents shape status (1 for an image with clear objects and 0 for an image without any objects).

Fig. 3 shows four image samples representing an outdoor scene, a texture, a sketch, and a textured object respectively. The component code will facilitate the hierarchical structure of indexing and searching. Each individual image is classified into different image groups according to its component code. Within each group, images are further ranked with respect to their individual feature vectors or measurements. The relevant data is pre-processed and stored in the corresponding summary tables in the warehouse structure. The search process will start with the image group which has the same component code as the query image, which speeds up the processing by filtering out irrelevant images from the image collection.

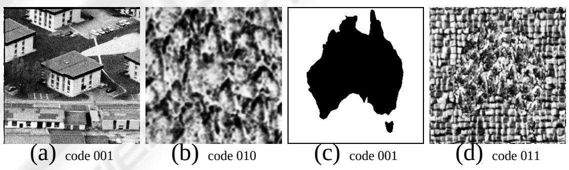


Fig. 3. Image feature component coding

3.2 A Multi-level Curve Matching Scheme

To avoid the blind searching for the best fit between the template pattern and all of the sample patterns stored in the image data warehouse, a guided search strategy is essential to reduce computation burden. In a conventional data warehouse, various methods of partitioning have been developed to improve the efficiency for query processing. Most of the existing methods fall into two major categories – horizontal partitioning and vertical partitioning. In general, the way in which a fact table will be split up depends on the type of a query. In this paper, we adopted partitioning along a dimension to facilitate a coarse-to-fine curve matching scheme for similar shape retrieval. As illustrated in Fig. 2, B-spline curve and invariant moments coefficients are associates with the shape feature in two dimensions and can be further partitioned into a lower level.

The initial search for the best similar shape matching starts with the dimension of invariant moments. The similarity measurement is based on the comparison of the Cosine distance of the proposed shape moment feature vectors for different samples after Gaussian normalization. The candidates with small distance differences will be considered for fine matching based on 2D polygonal arc matching and B-spline curve matching. The goal here is to match and recognize shape curves for the final retrieval output. The curve candidates which are selected from the 2D polygonal arc match will be further compared based on their B-spline models. Traditionally the judgment is made by the comparison of their control points, where the ordered corner points from boundary tracing are used. The sample is allocated to the class with minimum difference distance. However, the problem with this approach is that it cannot handle occluded curves although it is straightforward to estimate the residual errors for similarity measurements. Based on [10], we are able to use the Hausdorff distance algorithm to search for portions, or partial hidden objects [11]. In the work reported here, we further extend our previous research by using contour corner points as a basis for curve matching in terms of the Hausdorff distance. It aims to reduce the computation required for a reliable match and be able to find partially hidden curves. The Hausdorff distance is a non-linear operator which determines the degree of the mismatch between a model and an object by measuring the distance of the point of a model that is farthest from any point of an object and vice versa. Therefore, it can be used for object recognition by comparing two images which are superimposed on one another. For the curve matching, set A and B contain the contour points of two curves respectively; and the best matching occurs when its Hausdorff distance is minimal. To speed up the searching for the best fit between the two given curves, once again, we adopt a hierarchical scheme. The Hausdorff distance at coarse level is determined by the B-spline control points of each curve, and the more neighboring contour points are considered to determine the Hausdorff distance at a fine level.

4 Experimental Results

4.1 System Description

Our MediaHouse system applies data warehousing technique to handle important issues of CBIR for a large collection of image samples from different sources. The 6,228 images used in our experiments include 3,834 palmprint samples of size 384×284 for the case study of personal identification via palmprint retrieval, 1,266 face images of size 384×284 for the case study of face recognition based on similar shape retrieval, and 1,128 natural images collected from various websites and public domains. The preprocessing includes: 1) wavelet transforms of image samples; 2) multiple image feature representation with respect to color, texture and shape; 3) generation of feature dimension tables. The Oracle data warehousing tool is used for data analysis and processing.

The operation of our system includes two basic phases: dynamic feature selection and integrated similarity measures for phase I; and hierarchical search for the best match for phase II. Our system supports query-by-example which compares the target image with the possible candidates in the image data warehouse throughout the proposed guided search procedure. Fig. 4 shows the diagram of the system structure.

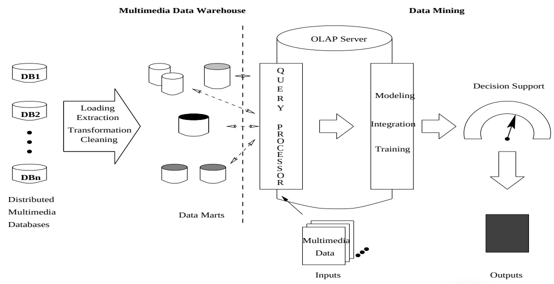
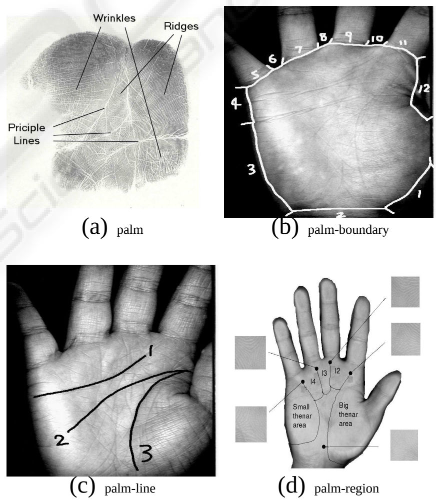


Fig. 4. System structure of MediaHouse image data warehouse

4.2 Dynamic Feature Selection and Multi-level Similarity Measures

The dynamic selection of image features is demonstrated by multi-level palmprint feature extraction for personal identification and verification (see our previous work [12]). The experiment is carried out in two stages. In stage one, the global palmprint features are extracted at coarse level and candidate samples are selected for further processing. In stage two, the regional palmprint features are detected and a hierarchical image matching is performed for the final retrieval. Fig. 5 illustrates the multi-level extraction of palmprint features.



(a) palm (b) palm-boundary

(c) palm-line (d) palm-region

Fig. 5. Multi-level feature extraction

In our system, we consider multiple palmprint features and adopt different similarity measures in a hierarchical manner to facilitate a coarse-to-fine palmprint matching scheme for personal identification. Four palmprint features are extracted – Level-1 global geometry feature, Level-2 global texture energy, Level-3 local “interest” lines, and Level-4 local texture feature vector. More specifically, the palm boundary segments are used as Level-1 global geometry feature and they can be extracted by a boundary tracking algorithm. The ‘tuned’ mask based texture energy measurement is used for Level-2 global texture feature representation [12]. The dominant feature lines such as principal lines, wrinkles, ridges in palmprint are extracted as Level-3 local ‘interest’ feature lines. A 2D Gabor phase coding is used to form Level-4 local texture feature vector. We begin initial searching for the best similar palmprint matching group with Level-1 global geometry feature. Our similarity measurement method is based on the comparison of the boundary segment with respect to its length and tangent for different samples. The candidates with small distance differences will be considered for further coarse-level selection by global texture measurement. The selected candidates will be subjected to fine matching based on 2D polygonal arc matching and comparison of local texture feature vector.

The proposed fine matching algorithm starts with 2D polygonal arc matching by using a subgroup of the unit quaternions. For palmprint samples which consist of the best matched arcs will go through the final fine matching in terms of their local texture feature vectors. The final matching is based on the comparison of local texture feature vectors via 2D Gabor coding. The best match is the candidate with the least normalized Hamming distance.

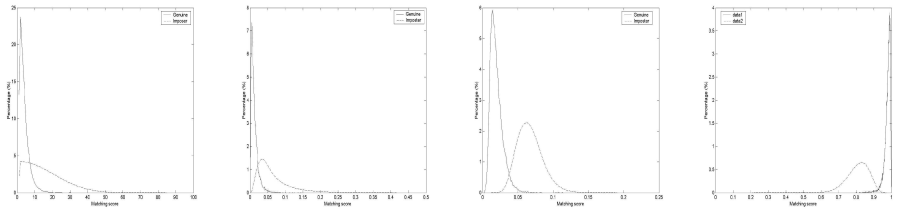
The palmprint image samples used for the testing are size of 384×284 with the resolution of 75 dpi and 256 gray scales. In our palmprint image database, 3834 palmprint images from 193 individuals are stored. These palmprint samples are collected from both female and male adults with the age range from 18 to 50. A series of experiments have been carried out to verify the high performance of the proposed algorithms.

The verification accuracies at different levels are shown in Fig 6. Fig 6 A-1,A-2, A-3 and A-4 present the probability distributions of genuine and imposter at different feature levels. The corresponding *receiver operating curves* (ROC), being a plot of genuine acceptance rate against false acceptance rate for all possible operating points are demonstrated in Fig 6 B-1, B-2, B-3 and B-4. Based on ROCs, we conclude that Level-4 local texture feature performs better than our hierarchical palmprint approach when the false acceptance rate is large, such as 5%. However, a biometric system should always operate in the condition of low false acceptance rate. Therefore, our hierarchical palmprint approach is better than fine-texture with low false acceptance rates. The false rejection and correct rejection rates of the first three levels are given in Table 2. The improvement of system efficiency by the use of hierarchical scheme is illustrated in Fig. 7 of system performance.

4.3 Multi-level Similar Shape Retrieval

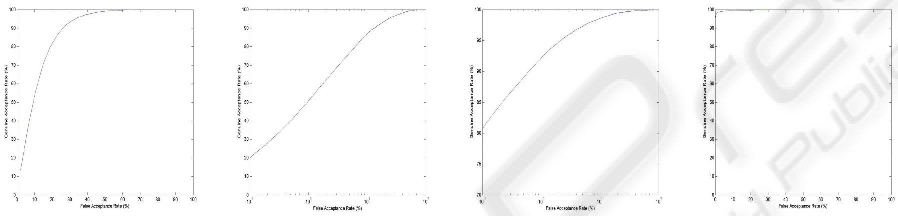
The problem of similar-shape retrieval concerns retrieving or selecting all shapes or images that are visually similar to the query shape or the query image’s shape. The proposed coarse-to-fine curve matching approach is demonstrated in the test of face

A. Genuine and imposter distributions for different features



(a) Level-1 (b) Level-2 (c) Level-3 (d) Level-4

B. Receiver operator curve (ROC) distributions for different features



(e) Level-1 (f) Level-2 (g) Level-3 (h) Level-4

Fig. 6. Palmprint verification test using multi-level features

Table 2. The system performance of accuracy

	False Reject Rate	Correct Reject Rate
T_a	1.69%	92.47%
T_b	1.10%	86.62%
T_c	0.73%	79.27%

recognition for personal identification. At the coarse level, a fractional discrimination function is used to identify the region of the interest of an individual's face. At fine curve matching level, the active contour tracing algorithm is applied to detect the boundaries of interest face regions for the final matching. Fig. 8 illustrates the tracing of face curves for face recognition. Fig. 8(a) is an original image, Fig. 8(b) shows the boundaries of interest regions on the face and Fig. 8(c) presents the curve segments for hierarchical face recognition by curve matching.

To verify the effectiveness of our approach, a series of tests are carried out in a database of 1,266 face collections from different individuals under various conditions such as uneven lighting, moderate tilting and partial sheltering. Fig. 9 shows the detected regions of different individuals detected by the proposed algorithm and Table 3 lists the correctness rate of the coarse-level detection.

To show the robustness of the proposed algorithm for face detection invariant of perspective view, partial distortion and occlusion, the fine-level curve matching is applied

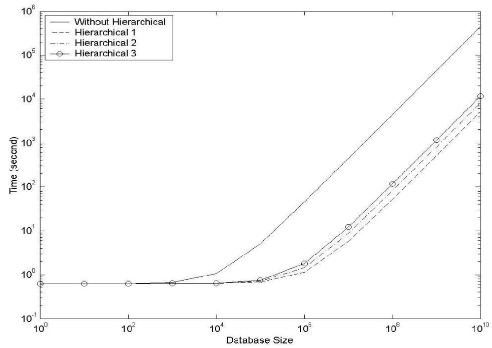


Fig. 7. The system performance

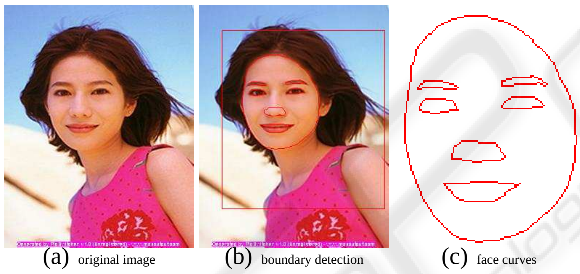


Fig. 8. Face curve extraction

to face images with different orientations and expressions. Fig. 10 illustrates face samples of the same person at various perspective views and Table 4 summarizes the testing result for 100 testing cases. Fig. 11 shows face samples of the same person at different conditions such as face expression, partial occlusion and distortion. The testing result for 100 cases is listed in Table 5.

5 Conclusion

Image feature extraction, indexing and search are essential issues in content-based image retrieval. In contrast to the existing techniques which mostly apply a fixed mechanism for feature extraction and indexing, we have proposed a statistically based feature

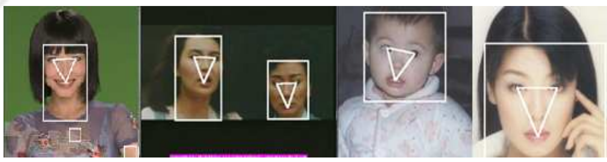


Fig. 9. The detection of face region of interest

Table 3. Performance of face detection at coarse-level

Face Condition	Correct Detection Rate
unevenness of lighting	98%
multiple faces	95%
moderate tilt of faces	97%
partial sheltering	85%

Fig. 10. The face samples at different orientations

selection scheme for dynamic multiple feature extraction and integration within the image data warehousing structure. This method is characterized as a flexible but simple approach to extract multiple features for similarity measures. In addition, the introduction of fractional discrimination function is powerful for multi-level feature extraction and the proposal of image feature component code facilitates guided search for the best matching. The experimental results provide the basis for the further development of an effective and efficient content-based image retrieval system. For future research, it would be of considerable interest to investigate the following issues. Firstly, we would like to develop a comprehensive interactive query interface with the full support of user feedback. Secondly, we would like to include more image samples of diversity in our image data warehouse and apply data mining techniques for image understanding and feature clustering. Thirdly, we would like to develop a general scheme for performance evaluation in terms of accuracy and efficiency in addition to the current measurement of precision and recall.

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Table 4. Performance of face recognition at different orientations

Viewing Perspective	Correct Classification Rate
-20^0 (vertical)	84%
-10^0 (vertical)	86%
$+10^0$ (vertical)	86%
$+20^0$ (vertical)	83%
-20^0 (horizontal)	85%
-10^0 (horizontal)	87%
$+10^0$ (horizontal)	87%
$+20^0$ (horizontal)	84%

Fig. 11. The face samples at different conditions

Table 5. Performance of face classification with different conditions

Face Condition	Correct Classification Rate
partial occlusion	77%
various expressions	81%
wearing glasses	82%

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