# A new system for trademark segmentation and retrieval

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## Abstract

With the increase in the number of trademarks, trademark imitation has become a serious problem. Thus, building an efficient trademark retrieval system is imperative. In this paper, such a system is presented. First, a semi-automatic segmentation method is proposed to extract the shapes of those representative objects, called 'masks', in each trademark. Next, some features are selected to describe a mask. These include invariant moments, the histogram of edge directions, and two kinds of transform coefficients that are robust to geometric deformation. Then, based on the rank of the feature distance, a similarity measure is provided to do the similar trademark retrieval. Finally, a feedback algorithm is also proposed to automatically determine the weight of each feature according to the user's response. Furthermore, in order to show the effectiveness of the proposed system, two databases from MPEG-7 test database are used to compare the performances of the proposed system and those methods using chain code, Zernike moments or MPLV as features. The experimental results show that the proposed system is superior to others. © 2001 Elsevier Science B.V. All rights reserved.

*Keywords:* Trademark segmentation; Trademark retrieval; feedback algorithm

## 1. Introduction

Trademarks are specially designed marks that identify companies, products, and services. The imitation of a registered trademark is illegal. However, there are so many trademarks around the world and how to avoid designing a trademark similar to an existing one becomes an important problem. To treat this problem, developing an automatic and fast content-based trademark retrieval system is necessary.

In general, trademarks can be divided into three types: character-in-mark, device-mark and composite-mark (Fig. 1). Since a character-in-mark trademark contains only characters, the traditional character recognition techniques can be applied. The device-mark trademarks contain only geometric shapes, while the composite-mark ones contain both characters and geometric shapes. The QBIC system proposed by IBM [1–3] places more emphasis on the device-mark and composite-mark trademarks. However, the QBIC system does not work very well for some trademarks with geometric deformation or partial change. In addition, if the users do not satisfy the retrieval results,

the QBIC system cannot take the user's response to retrieve again.

Kim [4,5] uses the Zernike moment magnitudes (ZMMs), which are rotation and scale invariant and robust to noise and slight shape deformation, to do retrieval. But for some geometric deformation, such as the sphere transformation, the retrieval result is poor. Mehtre also introduced a retrieval system [6,7]. A color clustering algorithm and a shape clustering algorithm are provided to find connected components in a trademark. Then, some invariant moments of these components are used as the features for trademark retrieval. Since these moments are sensitive to shape deformation, only using these moments as features cannot correctly extract those trademarks with similar shapes.

Some methods [8,9] use the histogram of the edge directions of the shape boundary in a trademark as the feature. However, the histogram does not contain the location information. Zhang [10] proposed a dynamic shape matching algorithm which uses the eight-directional chain code to describe the binary shape. The chain code is robust to scale changes and small, non-rigid deformation. However, chain code is not rotation invariant. The eigenvalues and eigenvectors of each sub-region in an object are used as shape descriptor [11]. They are invariant to rotation and scale, but not invariant to geometric deformation. Some methods use boundary information to do image retrieval. These include the boundary matching algorithm [12],

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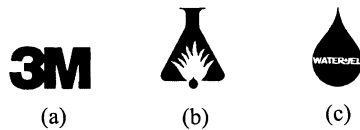*E-mail addresses:* sjl@chu.edu.tw (J.-L. Shih), lhchen@cc.nctu.edu.tw (L.-H. Chen).

Fig. 1. Examples of three types of trademarks: (a) character-in-mark, (b) device-mark, and (c) composite-mark.

Fourier descriptor [13] and multiscale curve matching [14], etc. The performances of these methods depend on the accurate detection of the shape boundary. If there are some small cracks or overlap in the components of a trademark, the retrieving result will be much different. Moreover, the Fourier descriptor and curve matching method are sensitive to boundary pixel number. To treat these problems, we provide a new system for trademark retrieval in this paper. The system includes three phases: the trademark segmentation, feature extraction, and trademark retrieval. In the trademark segmentation phase, a semi-automatic and user-friendly trademark segmentation sub-system is proposed. Using this sub-system, a user can locate those representative masks from a trademark. In the feature extraction phase, four kinds of features are extracted. These include invariant moments, two kinds of transform coefficients and the histogram of edge directions. The invariant moments are invariant to rotation, scaling and translation. Two kinds of transform coefficients are obtained by combining the polar-coordinate transform, an edge detector [15], derivative, and the Fourier transform [15]. They are invariant to rotation, scaling and translation and robust to shape deformation. Besides, the histogram of edge directions is a suitable feature vector to search for those similar masks with different mass centers. In the trademark retrieval phase, based on the extracted features, a similarity measure is first provided to search for similar trademarks in the trademark database. Then, a feedback algorithm is proposed to automatically determine the weight of each feature via the user's response. The information contained in the database includes trademarks, masks, and feature set. Furthermore, in order to show the effectiveness of the proposed system, based on the MPEG-7 test database [11], some experiments have been conducted on the proposed system and other methods using chain code [10], Zernike moments [5], or MPLV [11] as features. The experiment results show that the proposed system is superior to others.

In Section 2, we will introduce the proposed trademark segmentation sub-system. In Section 3, feature extraction methods will be described. The similarity measure and feedback algorithm will be described in Section 4. Section 5 will



Fig. 2. The original trademark and three suggestive masks: (a) an original trademark, (b) the first mask, (c) the second mask, and (d) the third mask.
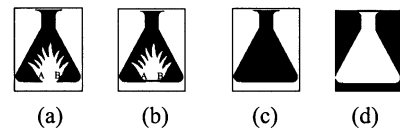


Fig. 3. An example to illustrate the process of segmenting a desired mask from Fig. 2(a): (a) the result of using 'Region-delete' to take off the little black spot from Fig. 2(a), (b) the result of using 'Draw-black-line' to connect points A and B, (c) the result of applying the 'Region-growing' on the interior white area of (b), and (d) the desired mask (white part) obtained by applying the Region-growing on the black bottle of (c).

present the experimental results. Finally, conclusions will be given in Section 6.

## 2. Trademark segmentation

For real world trademarks, those belonging to one company usually are designed as the same shape with various colors. This means that the trademark shape is a more important feature than the color during the retrieval process. Thus, in this paper, the trademark shape will be used to do similar retrieval. For most trademarks, it is hard to extract their representative shapes automatically. One example shown in Fig. 2 is given to illustrate this fact. Fig. 2(a) shows an original trademark in which there are three different subjective representative shapes shown in Fig. 2(b) – (d). From this figure, we can see that developing a segmentation method to automatically extract these three shapes is impossible. Due to this fact, we will propose a semi-automatic (i.e. interactive) trademark segmentation sub-system to extract those desired shapes called 'masks'. Using this sub-system, a trademark will be first segmented into some masks. A mask represents a meaningful object in the trademark. Based on these extracted masks, the features used to do retrieval are extracted.

In the proposed sub-system, some primary functions are provided and described as follows: (1) Thresholding: using binary thresholding method to get a binary image from a given gray level trademark image. (2) Region-growing: using the Region-Growing algorithm [15] to find a connected area. The seed of the Region-Growing algorithm is selected by the user. (3) Region-delete: using the Region-Growing algorithm to delete a connected area. The seed is also selected by the user. (4) Draw-black-line (Draw-white-line): draw a black (white) line segment. It is used to restrict the area of the Region-growing and Region-delete. The starting and ending points of this line are identified by the user. An example is shown in Fig. 3. This interactive sub-system can be operated easily and help the user to get the desired masks.

## 3. Feature extraction

After all masks are extracted from a trademark, users can use one of these masks (called query mask) to search for
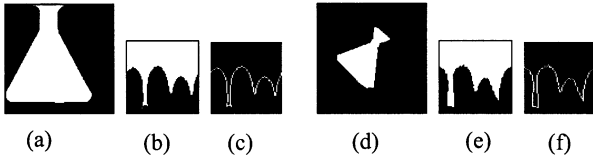
Fig. 4. Two examples to show the results of polar-coordinate transform and edge detector: (a) a mask, (b) the polar-coordinate-transformed image of (a), (c) the edge detection result of (b), (d) a slightly distorted mask formed by applying translation, scaling and rotation to (a), (e) the polar-coordinate-transformed image of (d), and (f) the edge detection result of (e).

those trademarks with a mask similar to the query one. Many kinds of features have been commonly used for searching a similar mask. In general, features used must be invariant to rotation, translation, and scaling. Moreover, these features also have to be insensitive to the shape deformation. In this paper, a composite feature set that is robust for shape deformation will be used for trademark retrieval. For each mask, four feature vectors will be extracted and introduced in Sections 3.1–3.3.

### 3.1. Invariant moments

The seven moments proposed by Hu [16] are invariant to rotation, scaling, and translation. In the proposed system, for each mask $s$, the feature vector formed by its seven moments is denoted as $Mom_s(n)$, $n = 0, 1, ..., 6$. If only these seven moments are used, some shape-deformed masks will not be extracted. Hence, some other features that are robust for shape deformation will be proposed.

### 3.2. Polar-coordinate transform, edge detector, derivative, and Fourier transform

In this section, we will derive two feature vectors that are effective for deformed mask retrieval. The polar-coordinate transform and an edge detector [15] are first applied to make the feature vectors invariant to scaling and rotation. Then, the influence of translation is eliminated by using the Fourier transform [17].

First, through the polar-coordinate transform, the Cartesian coordinates of a pixel at $(x, y)$ are transformed to the polar coordinates $(\rho, \theta)$ with

$$\rho = ((x - x_0)^2 + (y - y_0)^2)^{1/2},$$

$$\theta = \tan^{-1}((y - y_0)/(x - x_0)),$$

where $(x_0, y_0)$ is the mass center of a mask. For each mask

image, we take 64 radial lines with different angle $\theta$, where $\theta = 5.625 \times n$ and $n = 0, 1, 2, ..., 63$. For each radial line, the points with $\rho = \tilde{\rho}(m + 1)/64$ are sampled, $m = 0, 1, 2, ..., 63$, to form a $64 \times 64$ image. $\tilde{\rho}$ is the longest $\rho$ on the mask boundary. An edge detector is then applied to the polar-coordinate-transformed image to find the one-pixel-width edges. Note that a rotation in the Cartesian coordinate plane becomes a translation along the $\theta$-axis. Let $Lap_s(m, n)$ represent the result of the edge detector for mask $s$ and $Lap_s(m, n) = 0$ or 255. Fig. 4 shows the edge detection results for two similar trademark images with different rotation, translation, and scaling. From this figure, we can see that after applying the polar-coordinate transform and the edge detector, the translation and scaling factors are eliminated, but rotation factor still exists and is transformed to translation. To solve this problem, the Fourier transform is applied to $Lap_s(m, n)$. The resulting image is expressed as $F\_Lap_s(m, n)$, which is invariant to rotation, translation and scaling. Moreover, it is insensitive to non-rigid deformation.

Based on $Lap_s(m, n)$, we will find the first derivative of the extracted edge. For a mask $s$, define an edge curve $l_s(n)$ as

$$l_s(n) = \max_m \{m | Lap_s(m, n) = 255\}, \quad \text{for } n = 0, 1, ..., 63.$$

The first derivative of $l_s(n)$ is then defined as

$$Der_s(n) = l_s(n) - l_s(n + 1).$$

$Der_s(n)$ is the novel feature proposed in this paper. In our experimental results, we find that $Der_s(n)$ is more robust to rigid deformation with mass center fixed than other features.

In general, the shapes shown in Fig. 5(a) and (b) can be regarded as similar shapes. A major difference between these two masks is that they have different mass centers. The mass center of Fig. 5(a) is on the top of the lower rectangle, while the mass center of Fig. 5(b) is in the bottom of the higher triangle. For these kinds of similar masks, their polar-coordinate-transformed images will be different. Thus, another feature vector to deal with this situation will be provided in Section 3.3.

### 3.3. Histogram of edge directions

In this section, we will use the histogram of edge directions as a feature vector to search for similar masks, which may have different mass centers. To get the histogram, the edges of a mask should be extracted first. Then a $3 \times 3$ mask is used to find the direction, $\alpha_{\omega_0}$, of each edge point $\omega_0$. The eight neighbors of $\omega_0$ are used to evaluate $\alpha_{\omega_0}$. Define the number of edge pixels among these eight neighbors as NE. If NE = 2, the edge direction $\alpha_{\omega_0}$ can be evaluated by

$$\alpha_{\omega_0} = \tan^{-1}\left(\frac{y' - y''}{x' - x''}\right),$$

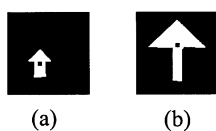where $(x', y')$ and $(x'', y'')$ are the coordinates of the two



Fig. 5. Two similar masks with different mass centers marked by black points: (a) a small arrowhead mask, and (b) a large arrowhead mask with the mass center different from (a).

neighboring edge points of $\omega_0$. If $NE \geq 3$, the edge direction of $\omega_0$ is not considered. In our experiments, the edge direction $\alpha_{\omega_0}$ is approximated by one of the following eight directions: $-63, -45, -26, 0, 26, 45, 63,$ and $90°$. The edge direction histogram is defined as $\text{Edge}_s(h)$, $h = 0, 1, ..., 7$. Note that $\text{Edge}_s(h)$ is especially efficient for searching polygonal masks such as triangles, rectangles and those similar masks with different mass centers. $\text{F\_Lap}_s(m, n)$ and $\text{Der}_s(n)$ are suitable for retrieving non-polygonal shape masks and those deformed masks with similar mass centers.

## 4. Trademark retrieval

Based on the four kinds of feature vectors introduced in Section 3, the similar trademark retrieval will be conducted. To do retrieval, a similarity measure is first proposed to evaluate the similarity between two masks. Since the scales of these four kinds of feature vectors are different, the traditional similarity measure that uses the summation of all the differences of the feature vectors between query and matching masks is unsuitable in this paper. Thus, a new similarity measure is proposed. For a query mask $q$ and any matching mask $s$, define the difference of the $n$th moment as

$$\text{Dis\_Mom}_{q,s}(n) = |\text{Mom}_q(n) - \text{Mom}_s(n)|,$$

where $n = 0, 1, ..., 6$. Then for each $n$, sort $\text{Dis\_Mom}_{q,s}(n)$, $s = 1, 2, ..., k$ ($k$ is the total number of matching masks) in an increasing order. For the top $g$ masks, we define their grades for the $n$th moment, $\text{G\_Mom}_{q,s}$, as $g$, $g - 1$, $g - 2, ...,$ and 1, respectively. In addition, $\text{G\_Mom}_{q,s}$ of all other masks are defined as zero. Based on these seven grades $\text{G\_Mom}_{q,s}(n)$, $n = 0, 1, ..., 6$, the total grade of the moments for mask $s$ is defined to be

$$\text{GT\_Mom}_{q,s} = \sum_{n=0}^{6} \omega_{M_n} \text{G\_Mom}_{q,s}(n),$$

where $\omega_{M_n}$, $n = 0, 1, ..., 6$, is the weight for the $n$th moment. For the remaining three feature vectors, the distance between the query mask $q$ and a matching mask $s$ can be defined in a similar way:

$$\text{Dis\_Lap}_{q,s} = \sum_{m=0}^{63} \sum_{n=0}^{63} | \text{F\_Lap}_q(m, n) - \text{F\_Lap}_s(m, n)|,$$

$$\text{Dis\_Der}_{q,s} = \min_t \sum_{n=0}^{63} |\text{Der}_q(n) - \text{Der}_s(n')|,$$

where $n' = (n + t) \bmod 64$, $t = 0, 1, 2, ..., 63$,

$$\text{Dis\_Edge}_{q,s} = \min_t \sum_{h=0}^{7} |\text{Edge}_q(h) - \text{Edge}_s(h')|,$$

where $h' = (h + t) \bmod 8$, $t = 0, 1, 2, ..., 7$. These distances are also sorted in an increasing order and the grades for these feature vectors are expressed as $\text{G\_Lap}_{q,s}$, $\text{G\_Der}_{q,s}$,

and $\text{G\_Edge}_{q,s}$. For each matching mask $s$, the summation of grades is defined as

$$\text{Grade}_{q,s} = \omega_1 \text{GT\_Mom}_{q,s} + \omega_2 \text{G\_Lap}_{q,s} + \omega_3 \text{G\_Der}_{q,s}$$
$$+ \omega_4 \text{G\_Edge}_{q,s},$$

where $\omega_1$, $\omega_2$, $\omega_3$, and $\omega_4$ are the weights. Finally, $\text{Grade}_{q,s}$ is used as the similarity measure between two masks. According to this measure, a group of trademarks, which have a mask similar to the query one, can be retrieved. Note that the four weights will affect the retrieval results, and it is impossible to determine a set of fixed weights that is appropriate for any kind of shapes. For example, for a polygon-shape mask, the weight for $\text{G\_Edge}_{q,s}$ should be increased. Here, we will propose a feedback algorithm through the user's response to automatically determine the weights. That is, some initial weights are first given to get a rough retrieval result. Then, a user can choose $r$ similar masks, $l_1, l_2, ..., l_r$, from the query results. Based on the grades of these masks, a feedback algorithm is provided to adaptively modify these weights. The new $\omega_1$, $\omega_2$, $\omega_3$ and $\omega_4$ are calculated by

$$\omega_1 = \sum_{j=1}^{r} \text{GT\_Mom}_{q,l_j},$$

$$\omega_2 = \sum_{j=1}^{r} \text{G\_Lap}_{q,l_j},$$

$$\omega_3 = \sum_{j=1}^{r} \text{G\_Der}_{q,l_j},$$

$$\omega_4 = \sum_{j=1}^{r} \text{G\_Edge}_{q,l_j}.$$

The feedback algorithm can also be used to modify the local weights for the seven moments. Using these new weights, a user can get a new retrieval result. The new retrieval result will be more similar to what the user really wants. Users can interactively search for similar masks until the retrieval result is satisfactory.

## 5. Experimental results

To evaluate the performance of the proposed trademark retrieval system, experiments have been conducted based on the MPEG-7 test database [11]. There are two major test databases, D1 and CE1 in our experiment. In order to obtain a larger test database, D1 is partly provided by the United States Patent and Trademark Office (USPTO) and partly from CE2 in MPEG-7 test material ITEM S8. Based on D1, we implement three other methods using chain code [10], Zernike moments [5] and MPLV [11] as features, to compare their performances with ours. On the other hand, some papers have provided the retrieval results of using

| Trademark | Representative masks | trademark | Representative masks |
|---|---|---|---|
| | | | |
| | | | |

Fig. 6. Some trademarks and their representative masks in the database D1.

Zernike moments [5] and MPLV [11] on CE1; thus, we also apply our methods on CE1 to compare the performances.

### 5.1. Experimental results on database D1

Applying the proposed semi-automatic segmentation system to D1, we can get several masks for each trademark. There are 3543 device-mark type trademarks and 6541 corresponding masks. Fig. 6 shows several trademarks and their corresponding masks. Users can use one of these masks (called query mask) to search for those trademarks with a mask similar to the query one.

A test database D1-A is established to test the performance of our system for the geometric deformed shape. To form D1-A, 100 masks are first randomly selected from the D1 as the seed masks. Then, each seed mask is deformed by the following transformation: pinch 20°, pinch 40°, pinch −20°, pinch −40°, twirl 30°, twirl −30°, ripple 50, scaling, and rotation 180° (Fig. 7). Thus, there are 1000 deformed masks in D1-A. In the experiments, each image in D1-A is submitted as a query image to D1-A. The performance is measured by the recall and precision. Note that recall is defined as

$$\text{Recall} = \frac{\text{Number of relevant images that are retrieved}}{\text{Total number of relevant images}}.$$

Precision is defined as

$$\text{Precision} = \frac{\text{Number of retrieved images that are relevant}}{\text{Total number of retrieved images}}.$$

In order to compare the performances of the proposed method and others using chain code [10], Zernike moments
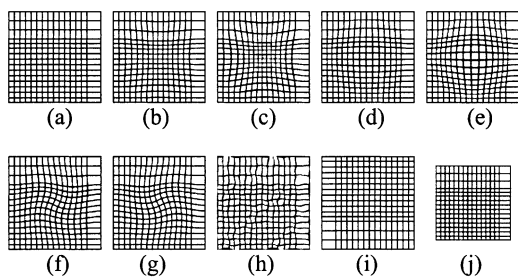


Fig. 7. The geometric deformation for database D1-A: (a) an original image, (b) pinch 20°, (c) pinch 40°, (d) pinch −20°, (e) pinch −40°, (f) twirl 30°, (g) twirl −30°, (h) ripple 50, (i) rotation 180°, and (j) scale.

[5], and MPLV [11] as features, we also implemented those methods and have shown the experimental results in Fig. 8. We can see that only using the Der feature has better performance than using one of the other features. Moreover, the combination of the four features provided has the best performance. Since we want to know what kind of deformation will dramatically affect the retrieval performance, the detail performance comparison of using different features for each kind of deformed masks in D1-A is shown in Fig. 9. We can see that all the features have bad performance for the deformation of pinch −40°, except the Der feature. Since the chain code feature is not rotation invariant, it has bad performance for the rotation deformation. Each deformed trademark of D1-A is submitted as a query image to the original trademark database, D1, to examine whether the original ones can be retrieved. If the original mask can be retrieved among the total number of retrieved image, the recall for this deformed mask is 100%, otherwise 0%. The recall comparison between different features is shown in Fig. 10. We can see that the Der feature also provides better performance than any other feature. Besides, the combination of the provided four features still has the best performance.

### 5.2. Experimental results on database CE1

Zernike moments [5] and MPLV [11] have been used to do shape retrieval on database CE1 and the performances have been shown in Refs. [5,11]. In order to do objective comparison, we also use the same database, CE1, to do retrieval. Each image in CE1 is a single-closed contour shape. CE1 has two test sub-databases. One has 2100 images (70 classes) consisting of the digitally rotated and scaled images obtained from the MPEG-7 core experiment participants; the other has 1300 fish images including 200 Bream fish images taken from the MPEG-4 test image sequence. Fig. 11 shows the various classes used in CE1 and Fig. 12 shows an example of variations within a class.

The evaluation is performed in four parts called A1, A2, B and C. Part A1 will test scale invariance. An image of each class is scaled by five kinds of factors. Therefore, there are 420 images called CE1-A1 and the number of relevant images for each image is six. Each image in CE1-A1 is submitted as a query image to CE1-A1. Part A2 will test rotation invariance. An image of each class is rotated by 9,
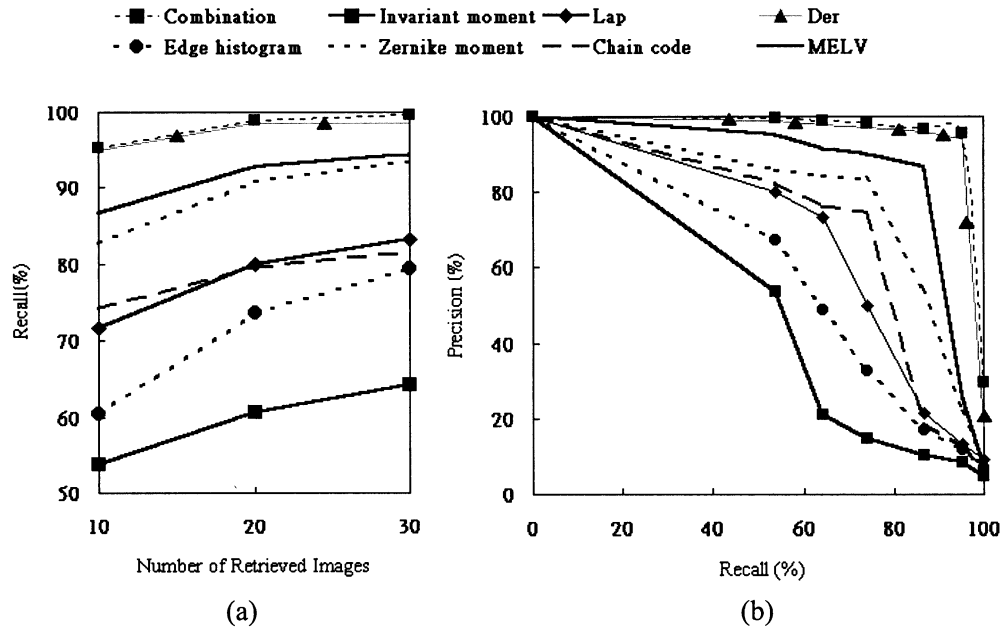
Fig. 8. The performance comparison of using different features for database D1-A. "Combination" means to use invariant moment, Lap, Der and Edge histogram: (a) the recall curve, and (b) precision vs. recall curve.

36, 45, 90, and 150°. Hence, there are 420 images called CE1-A2. Each image in CE1-A2 is submitted as a query image to CE1-A2 and the number of relevant images for each image is six. The performance is measured by the recall among six retrieved images.

Part B is designed to evaluate similar retrieval. 1400 images (70 classes) called CE1-B are used as the query images to CE1-B. Bull's eye performance (BEP) is used to measure the performance. BEP is defined as the recall with 20 relevant images and 40 ($2 \times 20$) retrieved images.

Part C is designed to test the robustness of retrieval to small non-rigid deformations. 1300 fish images including 200 Bream fish images are called CE1-C. The performance is measured by the recall with 200 retrieved images.

Table 1 shows the performance comparison of using our proposed features and other features for the database CE1. Since the results of using other features have been provided in Refs. [5,11], we do not implement those methods. In addition, the feedback algorithm is applied in the database CE1-B to prove its efficiency. Seven persons select several similar shapes based on the current query result to recalculate the new performance. Note that, for the CE1-A1, CE1-A2 and CE1-B, only using the Der feature can result in better retrieval performance. That is, Der is more efficient than others. However, if we combine the provided four features and use the feedback algorithm to automatically adjust the weight of each feature, the best performance can be obtained. Finally, we can see that based on the
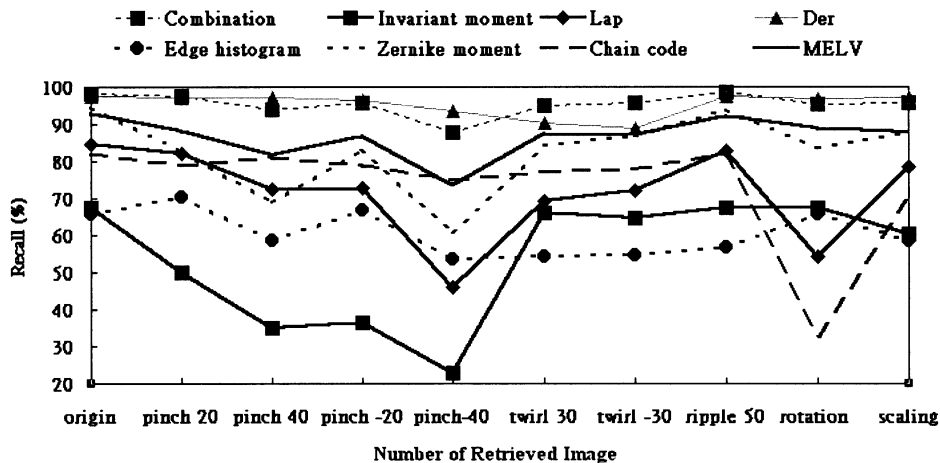


Fig. 9. The recall comparison of using different features for various deformations of D1-A with retrieved image number 10.
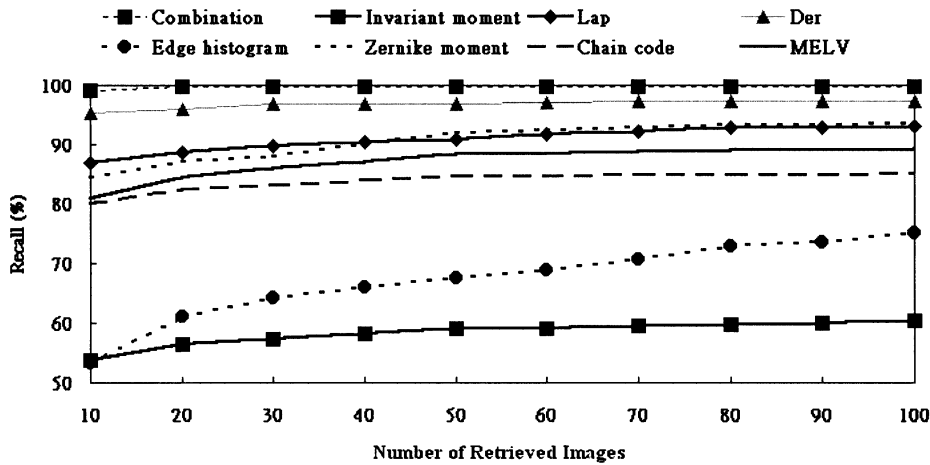
Fig. 10. The recall comparison of using different features for the deformed masks in D1-A to retrieve the original one from D1.



Fig. 11. Some simple closed contour shapes in CE1.



Fig. 12. An example of some shapes in the same class of CE1.

feedback algorithm, the advantage of each feature can be enhanced.

## 6. Conclusions

In this paper, an efficient and effective trademark retrieval system is proposed. In the beginning, we have proposed a user-friendly and semi-automatic trademark segmentation sub-system to extract the desired masks from a trademark image. Then, four features are presented. Invariant moments are used to treat rotation, scaling and translation invariant. Lap and Der features are robust to geometric deformation with similar mass center. The histogram of edge directions is especially effective for searching polygonal masks with

different mass centers. In the retrieval process, a grade evaluation method is provided to measure the similarity between a query mask and each matching mask. Finally, we have introduced a feedback algorithm to automatically and interactively determine the weights of features according to the user's response. Based on the feedback algorithm, the advantage of each feature can be enhanced. The experimental results show that the proposed system has a better performance than the other methods. In addition, our system is also efficient in time complexity. For example, the time of extracting all the proposed features for D1-A is about 20 min by using the Pentium III 800. However, to calculate the MPLV for D1-A needs about 4 h.

Table 1
The recall for CE1

|                            | A1 (%) | A2 (%) | B (%) | C (%) |
|----------------------------|--------|--------|-------|-------|
| Invariant moments          | 79.0   | 94.0   | 37.8  | 95.0  |
| Lap                        | 87.9   | 86.6   | 41.5  | 84.0  |
| Der                        | 95.5   | 99.2   | 71.3  | 90.0  |
| Edge histogram             | 53.0   | 29.3   | 36.6  | 72.0  |
| Combination                | 94.2   | 99.0   | 68.4  | 94.5  |
| Combination with feedback  |        |        | 76.8  |       |
| MLEV                       | 92.4   | 100    | 70.3  | 88.0  |
| Zernike moments            | 100    | 93.2   | 70.6  | 94.5  |

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