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Integrated probability function and its application to content-based image retrieval by relevance feedback

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Abstract

In the last few years, we have seen an upsurge of interest in content-based image retrieval (CBIR)—the selection of images from a collection via features extracted from images themselves. Often, a single image attribute may not have enough discriminative information for successful retrieval. On the other hand when multiple features are used, it is hard to determine the suitable weighing factors for various features for optimal retrieval. In this paper, we present a relevance feedback framework with Integrated Probability Function (IPF) which combines multiple features for optimal retrieval. The IPF is based on a new posterior probability estimator and a novel weight updating approach. We perform experiments on 1400 monochromatic trademark images have been performed. The proposed IPF is shown to be more effective and efficient to retrieve deformed trademark images than the commonly used integrated dissimilarity function. The new posterior probability estimator is shown to be generally better than the existing one. The proposed novel weight updating approach by relevance feedback is shown to be better than both the existing scoring approach and the existing ratio approach. In experiments, 95% of the targets are ranked at the top five positions. By two iterations of relevance feedback, retrieval performance can be improved from 75% to over 95%. The IPF and its relevance feedback framework proposed in this paper can be effectively and efficiently used in content-based image retrieval.

Keywords: Pattern recognition; Image database; Content-based image retrieval; Relevance feedback; Trademark image retrieval; Integrated probability function

1. Introduction

Content-based image retrieval (CBIR) has become one of the most active research areas in the past few years [1–7]. Generally speaking, primitive visual features representing color, shape, and texture are extracted from an image to represent its content. Similar images can be retrieved from a collection of images on the basis of primitive features—either singly or in combination. Successful content-based image retrieval systems require the integration of various techniques in the fields of pattern recognition, image processing, and information retrieval.

Recently, people are interested in combination techniques in pattern recognition for various application domains. Xu et al. [8] made a systematic investigation on methods of combining the classification powers of several classifiers and made applications to handwriting recognition. Kittler et al. [9] developed a common theoretical framework for combining classifiers and demonstrated that the sum rule outperforms other classifier combination schemes. Moreover, a weight assignment method in dissimilarity function using Genetic Algorithm was proposed in trademark image retrieval and in Chinese cursive script character image retrieval [7,10].

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Relevance feedback in information retrieval is an automatic process for query reformulation [11–14]. Both a query vector moving technique and a re-weighting technique to estimate the ideal query parameter are introduced in MARS [12]. Rui et al. [13] present a relevance feedback-based interactive retrieval approach, which effectively takes into account the following two distinct characteristic of CBIR systems: the subjectivity of human perception of visual content and the gap between high-level concepts and low-level features. A novel global optimization framework for relevance feedback is proposed in Ref. [15]. Most relevance feedback techniques in CBIR have only utilized information of the relevant retrieved images, and have failed to make use of information of the irrelevant retrieved images. In our opinion [16], both the relevant retrieved images and the irrelevant retrieved images contain much information of features that are being used.

In some applications, content-based image retrieval is generally agreed to be more ideal due to the difficulty in formulating meaningful queries using image features that try to capture perceptual similarity. Trademark image retrieval would seem to be an ideal application area for CBIR. Trademarks play an important role in providing unique identity for products and services in the marketing environment. Effective trademark retrieval systems should be able to ensure that the existing trademarks are distinct to avoid confusion. It should necessarily be able to retrieve images which humans perceive as similar. Traditionally, classification of trademarks is based on limited vocabulary descriptions such as human beings, animals, or geometrical figures. The Vienna classification system developed by the World Intellectual Property Organization is widely used for trademark categorization. Trademarks are manually assigned classification codes, but there is a large portion of images with little or no representational meaning making such a classification scheme extremely difficult to use. This motivates the need to investigate the potential use of content-based image retrieval techniques to solve this problem.

There are various systems that deal with trademark image retrieval based on contents. The Query By Image Content (QBIC) system [2,17] by IBM allows users to perform pattern matching on a set of trademark images from the US patent and Trademark Office registry. Eakins et al. [3] presented the Automatic Retrieval of Trademark Images by Shape Analysis (ARTISAN) system and evaluated the retrieval effectiveness on more than 10,000 images from the UK Trade Marks Registry. In other systems, invariant moments, Fourier descriptors [4,18] can be extracted from manually isolated objects. Zernike or pseudo-Zernike moments can be used as visually salient features [5] that represent the global shape of the trademark. Mehtre et al. [19] used outline-based features, region-based features and combined features in trademark retrieval. Mehtre et al. [20] proposed a composite feature measure which combines the shape and color features of an image based on clustering. The histogram of edge angles [6], the boundary-based shape feature [21], radial basis function (RBF) network [22], gestalt features and correlation matrix memory (CMM) neural network [23] have been used in content-based trademark image retrieval systems. In these systems, it is typical to extract multiple features, but little has been done on combination techniques to improve the retrieval performance.

This paper presents a combination technique for image retrieval. It is organized as follows. Section 2 proposes an idea of integrated probability function based on a new posterior probability estimator. A relevance feedback framework with IPF is proposed in Section 3. In Section 4, experiments on trademark images are conducted. Finally, conclusions are given in Section 5.

2. Integrated probability function

2.1. Definition

Suppose an image database, S, is composed of c distinct images $\{I_1, I_2, \ldots, I_c\}$. For a query I_q, image retrieval decision can be made according to the dissimilarity between the query image I_q and any image $I \in S$. This dissimilarity can be called as a kind of decision function.

Decision function: A decision function between two images I and I_q is defined as

$$D(I, I_q) : \Re^{|I|} \times \Re^{|I_q|} \to \Re^1, \tag{1}$$

where $|\cdot|$ indicates the number of elements of a matrix.

In general, the decision function of two images I and I_q can be determined with their features.

Feature extraction: A feature extraction function F for any image I is defined as

$$F(I) : \Re^{|I|} \to \Re^d, \tag{2}$$

which extracts a real-valued d-dimensional feature vector.

Integrated dissimilarity function: Assume that there are M feature extraction functions $\{F_i\}_{i=1}^M$. The dimension of the ith feature extraction function F_i is supposed to be d_i. The integrated dissimilarity function is the commonly used decision function, which is defined as follows:

$$D_{idf}(I, I_q) = \sum_{i=1}^{M} w_i \|F_i(I) - F_i(I_q)\|, \tag{3}$$

where $\|F_i(I) - F_i(I_q)\|$ is the Euclidean distance between the ith feature vectors of images I and I_q, and w_i is the weight assigned to the ith feature extraction function F_i with $w_i \geqslant 0$ and $\sum_{i=1}^{M} w_i = 1$.

When $M = 1$, a single feature is extracted and used for image retrieval. Often, a single feature may not have enough discriminant information for successful retrieval. When $M > 1$, multiple features are extracted and used for image retrieval, it is required to assign adequate weights w_i in Eq. (3).

Weight assignment problem: It may be difficult to assign weights w_i in Eq. (3) because the multiple features may have different scales. One idea is to perform normalization of different feature values. Generally speaking, some discriminant information of features may be lost by this process. Another idea is to use a better combination technique with multiple features in content-based image retrieval since the integrated dissimilarity function is a kind of combination technique.

Combination technique: Combination techniques in pattern recognition problems have been extensively investigated in recent years. Consider a pattern recognition problem where a pattern Z is to be assigned to one of the c possible classes $(\omega_1, \omega_2, \ldots, \omega_c)$. Assume there are M distinct measurement vectors $\{x_i\}_{i=1}^M$. Kittler et al. [9] demonstrated that under some assumptions, the following sum rule outperforms other classifier combination schemes:

$$Z \to \omega_j \quad \text{with } \arg\max_j P(\omega_j|Z) \equiv \frac{1}{M}\sum_{i=1}^{M} P(\omega_j|x_i), \quad (4)$$

where $P(\omega_j|x_i)$ is the posterior probability for the ith measurement vector x_i of the pattern Z.

In Eq. (4), $1/M \sum_{i=1}^M P(\omega_j|x_i)$ can be regarded as an estimator of a posterior probability $P(\omega_j|Z)$ with equal weights assigned to M measurements. Generally, a weighted average $\sum_{i=1}^M w_i P(\omega_j|x_i)$ with $\sum_{i=1}^M w_i = 1$ can be used as an estimator of a posterior probability $P(\omega_j|Z)$, where w_i is the weight assigned to the ith measurement. Therefore, we can introduce a new idea as follows.

Integrated probability function: Assume that there are M feature extraction functions $\{F_i\}_{i=1}^M$ and $\hat{P}(F_i(I)|F_i(I_q))$ is the estimator of the posterior probability of any image I matching with the query image I_q on the feature extraction function F_i. A new decision function can be defined as the following integrated probability function (IPF):

$$D_{ipf}(I, I_q) = \sum_{i=1}^{M} w_i \hat{P}(F_i(I)|F_i(I_q)), \quad (5)$$

where $w_i \geqslant 0$ is the weight assigned to the ith feature extraction function F_i with $\sum_{i=1}^M w_i = 1$.

The proposed IPF will not be affected by the scales of multiple features. The discriminant information of multiple features is used in estimating the posterior probability $\hat{P}(F_i(I)|F_i(I_q))$. Because of the same attribute of M probabilities for M features, it may be much easier to update the interweights in Eq. (5). The following two problems on IPF must be solved: (1) how to estimate the posterior probabilities $\hat{P}(F_i(I)|F_i(I_q))$ and (2) how to update weights w_i, respectively.

2.2. Posterior probability estimator

Now, let us try to estimate the posterior probability $P(\omega_j|x)$ for a given measurement vector x of the pattern Z. Given the representative measurement vectors x^j for the class ω_j $(j = 1, 2, \ldots, c)$, the dissimilarity between two vectors x and x^j can be measured by the Euclidean distance $\|x - x^j\|$, where $\|\cdot\|$ indicates the Euclidean distance.

A function of $\|x - x^j\|$ can be designed to derive the posterior probability $P(\omega_j|x)$. Generally speaking, the smaller the distance value $\|x - x^j\|$, the larger the posterior probability $P(\omega_j|x)$. Xu et al. [8] proposed an estimator, which is defined as

$$\hat{P}_{Xu}(x^j|x) = \frac{1/\|x - x^j\|}{\sum_{k=1}^{c} 1/\|x - x^k\|}. \quad (6)$$

There are two issues with the existing estimator of Eq. (6). First, $\|x - x^k\|$ is required to be non-zero in Eq. (6). When $\|x - x^k\|$ is zero, which occurs easily in practice, Eq. (6) becomes singular. Second, it is not linearly dependent on the values of $\|x - x^k\|$; hence, it is more sensitive to the smaller values of $\|x - x^k\|$. Now, we propose a new estimator of the posterior probability $P(\omega_j|x)$ as follows:

$$\hat{P}_{new}(x^j|x) = \frac{1}{c-1}\left\{1 - \frac{\|x - x^j\|}{\sum_{k=1}^{c} \|x - x^k\|}\right\}, \quad (7)$$

where $1/(c-1)$ is a normalization factor of probabilities.

In Eq. (7), $\sum_{k=1}^c \|x - x^k\|$ will have a non-zero value for any effective feature used. Thus, Eq. (7) will not suffer from the singularity problem. Furthermore, it is linearly dependent on the values of $\|x - x^k\|$, and thus it is not sensitive to the smaller values of $\|x - x^k\|$.

By replacing x^k and x with $F_i(I)$ and $F_i(I_q)$ in Eqs. (6) and (7), respectively, we obtain the following two posterior probability estimators with multiple features:

$$\hat{P}_{Xu}(F_i(I)|F_i(I_q)) = \frac{\frac{1}{\|F_i(I) - F_i(I_q)\|}}{\sum_{I \in S} \frac{1}{\|F_i(I) - F_i(I_q)\|}}, \quad (8)$$

$$\hat{P}_{new}(F_i(I)|F_i(I_q)) = \frac{1}{c-1}\left\{1 - \frac{\|F_i(I) - F_i(I_q)\|}{\sum_{I \in S} \|F_i(I) - F_i(I_q)\|}\right\}. \quad (9)$$

Both Eqs. (8) and (9) can be used in the integrated probability function in Eq. (5). More experimental comparisons between them will be given in Section 3.

3. Relevance feedback

In this section, a relevance feedback framework with IPF is proposed to improve image retrieval performance.

3.1. Relevance information

In a CBIR system, for a query image I_q, the images in the database, S, are sorted according to a decision functions, such as Eq. (3) in non-decreasing order or Eq. (5) in non-increasing order. The K most similar ones, $\mathfrak{R} = \{R_1, R_2, \ldots, R_K\}$, are returned to the user, where K is the number of images the user wants to retrieve. Suppose for any retrieved image $R_k \in \mathfrak{R}$, a degree of relevance is given by user according to his information need and perception subjectivity. In this paper, it is assumed that for any retrieved image $R_j \in \mathfrak{R}$, the user marks it as `relevant`, `neutral`, or `irrelevant`.

Let $\mathfrak{R}^+$ be the set of all the relevant retrievals and $\mathfrak{R}^-$ be the set of all the irrelevant retrievals. They can expressed as follows:

$$\mathfrak{R}^+ = \{R_j \mid R_j \text{ is relevant}, \ R_j \in \mathfrak{R}\}, \tag{10}$$

$$\mathfrak{R}^- = \{R_j \mid R_j \text{ is irrelevant}, \ R_j \in \mathfrak{R}\}. \tag{11}$$

The idea is to use the relevance information of both Eqs. (10) and (11) to improve retrieval performance. The following three problems are taken into account:

(1) How to estimate the query distribution by using relevance information;
(2) How to improve the posterior probability estimation formula of Eq. (5) by using relevance information and
(3) How to update the weights w_i of IPF by using relevance information.

3.2. Query distribution estimation

Without loss of generality, only a single feature extraction function $F(I)$ defined in Eq. (2) is discussed. Because of the similarity, we assume that the query image I_q and the corresponding similar images are clustered in the d-dimensional feature space $\mathfrak{R}^d$ with a distribution function, $P(x)$. We define $P(x)$ as a *query distribution function* (QDF).

It is sometimes preferable to adopt a less complete, but more computable, characterization to describe the QDF, $P(x)$. The most important parameters are the mean, μ, and the covariance matrix, Σ, which are defined, respectively, as

$$\mu = \int x P(x)\,\mathrm{d}x, \tag{12}$$

$$\Sigma = \int (x-\mu)(x-\mu)' P(x)\,\mathrm{d}x. \tag{13}$$

An estimation for the query mean μ can be proposed on the relevance information:

$$\hat{\mu} = \frac{1}{|\mathfrak{R}^+|} \sum_{R_j \in \mathfrak{R}^+} F(R_j). \tag{14}$$

Eq. (14) is commonly used as a query moving technique in content-based image retrieval.

Moreover, the query covariance matrix, Σ , can be estimated as follows:

$$\hat{\Sigma} = \frac{1}{|\mathfrak{R}^+|-1} \sum_{R_j \in \mathfrak{R}^+} (F(R_j)-\hat{\mu})(F(R_j)-\hat{\mu})'. \tag{15}$$

Obviously, the rank of $\hat{\Sigma}$ is no more than $|\mathfrak{R}^+| - 1$. Only when $|\mathfrak{R}^+|$ is much larger than d, the dimension of the feature extraction function $F(I)$, the query covariance matrix Σ can be estimated to be somewhat accurate and can be used in image retrieval. However, the dimension of the feature vector is needed to be large enough to provide sufficient discriminant information in content-based image retrieval. Therefore, since there are a small number of relevant retrievals, the estimated query covariance matrix $\hat{\Sigma}$ will be singular because $|\mathfrak{R}^+| - 1$ is often much less than d, the dimension of the feature vector.

In order to manage with only a small number of relevant retrievals, we assume that the feature vector used is composed of independent components. For an independent feature vector, the query covariance matrix, Σ, is an d-dimensional diagonal matrix expressed as

$$\Sigma = \mathrm{diag}\{\sigma_1^2, \ldots, \sigma_d^2\}, \tag{16}$$

where $\sigma_i (i = 1, \ldots, d)$ is the standard deviation. In this case, an estimation of the diagonal matrix Σ can be obtained directly from the estimation formula of Eq. (15).

3.3. Posterior probability estimation by relevance feedback

When no information on the query distribution is available, only the Euclidean distance can be used in estimating the posterior probability in Eq. (9). By using relevance information, the query distribution can be estimated. Suppose that for the fixed ith feature extraction function F_i, the estimated query mean $\hat{\mu}_i$, and the estimated query covariance matrix $\hat{\Sigma}_i$ are determined by using relevance information according to Eqs. (14) and (15). Thus, a more accurate estimation formula for the posterior probability can be given as follows:

$$\hat{P}_{rf}(F_i(I)|F_i(I_q)) = \frac{1}{c-1}\left\{1 - \frac{(F_i(I)-\hat{\mu}_i)'\hat{\Sigma}_i^{-1}(F_i(I)-\hat{\mu}_i)}{\sum_{I \in S}(F_i(I)-\hat{\mu}_i)'\hat{\Sigma}_i^{-1}(F_i(I)-\hat{\mu}_i)}\right\}. \tag{17}$$

It is noted that the given query I_q can be used in computing the query mean estimation $\hat{\mu}_i$ and the query covariance matrix estimation $\hat{\Sigma}_i$ for any fixed i with Eqs. (14) and (15).

3.4. Weight updating with relevance feedback

In order to evaluate the importance of the ith feature F_i, $\hat{P}_{rf}(F_i(I)|F_i(I_q))$ of Eq. (17) can be used to retrieve the corresponding K most similar images $\mathfrak{R}^{(i)} = \{R_1^{(i)}, R_2^{(i)}, \ldots, R_K^{(i)}\}$, respectively.

Now, two efficiency values can be introduced to describe the importance of the ith feature F_i as follows:

$$u_i^+ = |\{R_j^{(i)} \mid R_j^{(i)} \in \mathfrak{R}^+\}|, \tag{18}$$

$$u_i^- = |\{R_j^{(i)} \mid R_j^{(i)} \in \mathfrak{R}^-\}|, \tag{19}$$

where $|\cdot|$ indicates the number of elements of a set.

Obviously, the ith feature extraction function F_i is good if and only if u_i^+ is as large as possible and u_i^- is as small as possible. If both u_i^+ and u_i^- are large, the feature F_i cannot be regarded as a good one. If both u_i^- and u_i^+ are small, the feature F_i cannot be regarded as a good one, also. Thus, the ith feature F_i is good if and only if $u_i^+ - u_i^-$ is as large as possible.

Let

$$\Delta u_i = u_i^+ - u_i^-. \tag{20}$$

If Δu_i is large, the feature F_i can be regarded as a good one. Otherwise, it can be regarded as a poor feature. Generally speaking, the weight w_i in IPF of Eq. (5) depends on how good or how important of the ith feature F_i. One idea is to update the weight w_i by using Δu_i in Eq. (20).

Scoring approach: In Rui et al. [13], 5 degrees of relevance, {`highly relevant, relevant, neutral, irrelevant, highly irrelevant`} were used, and a scoring approach was proposed to update the raw weights w_i.

In the case of no highly relevant retrievals and no highly irrelevant retrievals, the existing scoring approach for updating raw weights w_i is defined as

$$w_i = \Delta u_i, \tag{21}$$

where raw weights w_i are needed to be normalized. It is noted that if $w_i < 0$, set it to 0.

Eq. (21) is valid if there are more relevant retrievals than irrelevant retrievals. Otherwise, it may not have good performance. Now, we can discuss it in detail as follows.

Obviously, we have that $u_i^+ \leqslant |\mathfrak{R}^+|$ and $u_i^- \leqslant |\mathfrak{R}^-|$. When $|\mathfrak{R}^+|$ is much smaller than $|\mathfrak{R}^-|$, for any fixed i, u_i^+ will be likely to be much smaller than u_i^- and Δu_i will be more likely to be less than 0. Thus, Eq. (21) will become invalid as all the weights w_i are set to be 0.

For example, suppose that $|\mathfrak{R}^+|$ be 1 and $|\mathfrak{R}^-|$ be 9, then u_i^+ will be in $\{0, 1\}$ and u_i^- will be in $\{0, 1, \ldots, 9\}$. In this case, Eq. (21) will be invalid because it cannot make great use of information of all the retrieved images. It is easy to understand that in the above example with $|\mathfrak{R}^+| = 1$ and $|\mathfrak{R}^-| = 9$, if for a given i, u_i^+ be 1 and u_i^- be 2, the ith feature can be said to be more effective than all M features to be used with known weights, i.e., w_i should be updated to be greater than 0, which should be assigned according to Eq. (21).

Ratio approach: In order to make greater use of information of all the retrieved images, w_i should be dealt with the relative ratios of $u_i^+/|\mathfrak{R}^+|$ and $u_i^-/|\mathfrak{R}^-|$. Taking into account the situations of zero relevant retrieved images or zero irrelevant retrieved images, an updating formula of raw weights w_i was presented as follows [16]:

$$w_i = \exp\left\{\alpha\left(\frac{u_i^+ + 1}{|\mathfrak{R}^+| + 1} - \frac{u_i^- + 1}{|\mathfrak{R}^-| + 1}\right)\right\}, \tag{22}$$

where $\alpha > 0$ is a constant.

Obviously, w_i will increase as u_i^+ increases for a fixed u_i^-, and it will decrease as u_i^- increases for a fixed u_i^+. If for any fixed ith feature, $u_i^+ = |\mathfrak{R}^+|$, and $u_i^- = |\mathfrak{R}^-|$, we have $w_i = 1$, which means that the ith feature is as effective as all M features to be used with known weights.

The exponential function $\exp(\cdot)$ changes slowly on the interval $(-1, 1)$, a large parameter α is needed in the Eq. (22). It is experimentally to be assigned an adequate value.

Novel approach: Now, we propose a novel approach to update weights w_i in IPF of Eq. (5) by using all relevance information. The novel formula is:

$$w_i = \exp\{\Delta u_i\}. \tag{23}$$

Not only it can deal with the situation of $\Delta u_i \leqslant 0$, but also it does not contain any unknown parameter.

4. Experiments and analysis

Our aim is to develop a CBIR system that is insensitive to variations on image deformations. In this section, we conduct two sets of experiments:

(1) Evaluate IDF of Eq. (3) and IPF of Eq. (5) with both the new posterior probability estimator of Eq. (9) and the existing posterior probability estimator of Eq. (8);
(2) Evaluate the novel weight updating approach of Eq. (23), the existing scoring approach of Eq. (21), and the existing ratio approach of Eq. (22).

The experiments are performed on a Sun Ultra 5/270 machine with 128 RAM under Solaris 2.6 using C++.

4.1. Trademark database

There are 1400 trademark images with 111 × 111, 10 samples of which are shown in Fig. 1. According to 10 deformed transformation as shown in Fig. 2, 100 deformed images are generated from 10 samples and shown in Fig. 3.

Seven kinds of features are extracted to represent a trademark image. They are eccentricity and invariant moments [24,25], circularity and Fourier descriptors of approximated boundary [7], Legendre moments, Zernike moments and

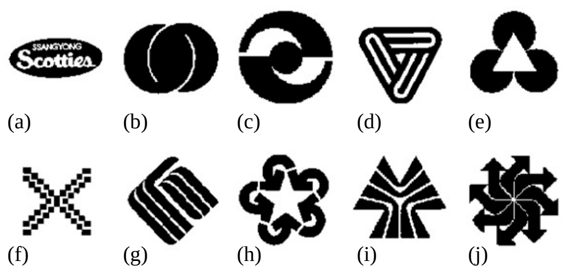

Fig. 1. Trademark samples.

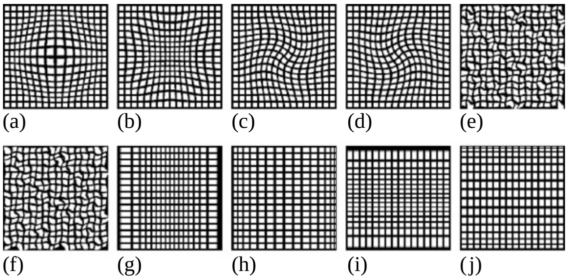

Fig. 2. Deformed transformation include pinch: (a) and (b); twirl: (c) and (d); ripple: (e) and (f); horizontal extension: (g) and (h); and vertical extension (i) and (j).

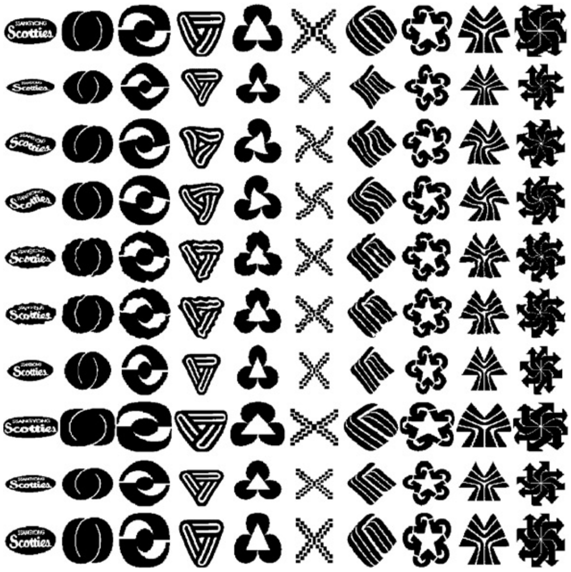

Fig. 3. Deformed images.

pseudo-Zernike moments [26–28]. These features and their dimensions are listed in Table 1. The first four kinds of features are from Chan [7], and the last three kinds of features are computed on 55×55 low resolution trademark images.

Table 1
Seven kinds of features for an image

No.	Description of feature
x_1	1-dimensional eccentricity
x_2	1-dimensional circularity of approximated boundary
x_3	7-dimensional invariant moment
x_4	63-dimensional Fourier descriptors of approximated boundary
x_5	36-dimensional Legendre moment $\lambda_{mn}(0 \leqslant m, n \leqslant 5)$
x_6	36-dimensional Zernike moment $Z_{nk}(0 \leqslant k \leqslant n \leqslant 9,\ n-k=$ even$)$
x_7	36-dimensional pseudo Zernike moment $Z_{nk}(0 \leqslant k \leqslant n \leqslant 7)$

Table 2
Nine combination schemes

No.	Scheme description
C_1	Combining x_6 with x_7
C_2	Combining x_5 with x_7
C_3	Combining x_5 with x_6
C_4	Combining x_5, x_6 with x_7
C_5	Combining x_4, x_5 with x_7
C_6	Combining x_4, x_5, x_6 with x_7
C_7	Combining x_3, x_4, x_5, x_6 with x_7
C_8	Combining x_2, x_3, x_4, x_5, x_6 with x_7
C_9	Combining $x_1, x_2, x_3, x_4, x_5, x_6$ with x_7

4.2. Evaluation of IDF and IPF

We first evaluate the retrieval performances of IDF of Eq. (3) and IPF of Eq. (5) with the new posterior probability estimator of Eq. (9) and the existing posterior probability estimator of Eq. (8) under the following conditions:

- Hundred deformed images shown in Fig. 3 are submitted as query images to our retrieval system to examine whether the deformed images can retrieve their original images in Fig. 1, which are called target images.
- Ten combination schemes are considered and listed in Table 2. For each scheme, identical weights are assigned to the features used in the scheme.

Accumulative frequency and mean: The retrieval performance is measured using following accumulative frequency (AF) and mean of retrieval positions:

$$AF(n) = \frac{\text{target images within } n \text{ positions}}{N}\, 100\%, \tag{24}$$

$$MEAN = \frac{\text{sum of positions of } N \text{ target images}}{N}, \tag{25}$$

where $N = 100$ is the number of test images.

Experimental results and analysis: For each scheme listed in Table 2, 100 retrieval positions are obtained for 100 queries. Then, the accumulative frequency and mean of these 100 retrieval position is computed.

The experimental results of IDF of Eq. (3) are listed in Table 3. The experimental results of IPF of Eq. (5) based on the new posterior probability estimator of Eq. (9) and the existing posterior probability estimator of Eq. (8) are listed in the Tables 4 and 5, respectively.

From Tables 3 to 5, we have the following observations and discussions:

- IPF of Eq. (5) is shown to outperform IDF of Eq. (3), especially when the new posterior probability estimator of Eq. (9) is used.

Table 3
Combination results of IDF

Accumulative frequency	Schemes								
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
1	72	68	65	72	68	72	72	72	71
2	78	75	72	78	75	78	78	78	78
3	81	82	80	81	82	81	81	81	81
4	83	84	81	83	84	83	83	83	83
5	85	84	83	85	84	85	85	85	85
10	92	95	88	92	95	92	92	92	92
20	94	98	91	94	98	94	94	94	94
70	99	100	98	99	100	99	99	99	99
Mean	4.40	3.28	7.17	4.40	3.28	4.40	4.40	4.40	4.40

Table 4
Combination results of IPF with new estimator

Accumulative frequency	Schemes									Chan [7]
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	
1	71	87	84	86	88	86	83	84	79	47
2	78	91	90	89	92	89	90	90	86	
3	81	93	93	93	94	94	93	93	89	
4	84	$\boxed{95}$	93	93	94	94	93	93	90	
5	85	95	94	95	95	95	94	93	90	73
10	92	96	95	95	98	97	96	96	96	
20	94	98	97	97	98	98	98	98	96	
70	99	$\boxed{100}$	99	100	99	100	100	100	99	96
Mean	4.23	$\boxed{2.23}$	3.60	2.46	3.50	2.32	2.39	2.65	3.54	

Table 5
Combination results of IPF with existing estimator

Accumulative frequency	Schemes								
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
1	70	86	86	86	73	78	38	10	4
2	76	88	89	89	80	87	61	26	13
3	80	90	91	94	88	91	73	42	26
4	84	92	92	94	89	92	77	58	37
5	85	94	92	94	89	92	79	63	50
10	91	94	94	95	91	95	92	82	69
20	94	95	95	95	94	96	95	95	92
70	99	99	97	99	97	100	100	100	100
Mean	4.54	3.48	4.80	3.36	2.70	2.46	4.39	6.81	8.62

- The new posterior probability estimator of Eq. (9) is shown to be superior than the existing posterior probability estimator of Eq. (8). Except for the scheme C_5, the new estimator of Eq. (9) has smaller means of retrieval positions than the existing estimator of Eq. (8). Because the experimental results on Eq. (8) are shown to be easily

Table 6
ARP in percentage grouped for trademark samples

Trademark sample	0 rf	Scoring		Ratio		Novel	
		1 rf	2 rf	1 rf	2 rf	1 rf	2 rf
(a) 1	60	100	100	100	100	100	100
2	80	90	90	90	100	90	90
3	60	90	100	90	100	90	100
4	60	90	90	90	100	90	100
5	70	90	100	100	100	100	100
6	70	90	100	100	100	100	100
7	80	100	100	100	100	90	100
8	70	90	90	100	100	100	100
9	80	90	90	90	100	90	90
10	10	60	80	60	80	60	80
(b) 11	80	100	100	100	100	100	100
12	60	100	100	90	90	90	90
13	80	90	100	100	100	100	100
14	70	90	100	100	100	100	100
15	70	90	100	100	100	90	90
16	80	90	100	90	100	90	100
17	60	90	90	90	90	90	90
18	90	100	100	100	100	100	100
19	50	90	90	90	90	90	90
20	20	50	80	40	80	40	80
(c) 21	70	90	90	90	90	90	90
22	40	90	90	90	90	90	90
23	80	90	90	90	90	90	90
24	80	90	90	90	90	90	90
25	60	90	90	90	90	90	90
26	70	90	90	90	90	90	90
27	70	90	90	90	90	90	90
28	$\boxed{0}$	0	$\boxed{0}$	50	$\boxed{90}$	60	$\boxed{100}$
29	70	90	90	90	90	90	90
30	70	90	90	90	90	90	90
(d)	86	100	100	100	100	100	100
(e)	85	93	93	93	93	93	93
(f)	82	98	100	98	100	91	93
(g)	60	97	100	98	100	97	100
(h)	83	91	93	92	93	94	99
(i)	89	98	98	98	98	97	98
(j)	74	86	86	90	93	90	93
ARP in total	$\boxed{75.0}$	92.4	$\boxed{94.1}$	94.2	$\boxed{96.0}$	92.9	$\boxed{95.7}$

affected by the threshold for machine zero, the existing posterior probability estimator of Eq. (8) can be said to be sensitive to the smaller value of all the distance values. In experiments with Eq. (8), a threshold for machine zero is taken to be e^{-20}. Moreover, as the number of features in a scheme is larger than 5, the existing posterior probability estimator has a much more worse mean of retrieval positions than the new posterior probability estimator.

- Among the nine combination schemes, the scheme C_2, the combination of Legendre moment and pseudo-Zernike moment, outperforms the other combination schemes with a minimum mean of retrieval position. Ninety-five percent of the targets are ranked at the top 4 positions and no targets are behind the top 70 position. Thus, we can propose a retrieval system based on the combination of Legendre moments and pseudo Zernike moments.
- The last column of Table 4 lists the experimental results of an existing trademark system [7]. From the accumulative frequency, it is obvious that our system based on IPF in the scheme C_2 performs much better than the existing system, which was based on IDF with four features.

4.3. Evaluation of the weight updating approaches

Now, we compare the retrieval performance by our novel weight updating approach of Eq. (23), the existing scoring approach of Eq. (21), and the existing ratio approach of Eq. (22). For each trademark sample shown in Fig. 1, 10 deformed images are shown in Fig. 3. These 11 images are regarded as highly relevant images. One hundred deformed images shown in Fig. 3 are numbered from 1 to 100 and submitted as query images. Our retrieval system aims at retrieving as many as relevant images from a collection of all the 1400 trademark images and the other 99 deformed images, in which there are 10 relevant image in total, i.e., one original trademark image and the other nine deformed images.

Average retrieval precision: The retrieval performance is measured using the following Average Retrieval Precision (ARP):

$$ARP = \frac{\text{relevant retrieved}}{K} 100\%, \qquad (26)$$

where $K = 10$ is the number of total retrieved images.

Experiments with the novel weight updating approach of Eq. (23), the existing scoring approach of Eq. (21), and the existing ratio approach of Eq. (22) have been performed, respectively. The initial weights w_i $(i = 1,\ldots,7)$ are given to be $\frac{1}{7}$. The parameter α in Eq. (22) is chosen to be 5.

Experimental results on the ARPs in percentage for the first 30 query images are listed in Table 6. The ARPs in percentage for all the 100 query images are grouped in Table 6 according to the 10 trademark samples. It is noted that the symbol "*rf*" denotes the number of iterations of relevance feedback in these two tables.

From Table 6, we can have some observations:

Efficiency: In Table 6, the novel approach of Eq. (23) and the existing ratio approach of Eq. (22) are shown to make great use of information of both relevant retrieved images and irrelevant retrieved images in the situations of no relevant retrieved images for the 28th query than the existing scoring approach of Eq. (21).

Effectiveness: Three weight updating approaches of Eqs. (21)–(23) are successful in improving retrieval performance. The ARP for 100 queries are shown to be increased from 75% to over 94% within two iterations of relevance feedback in the last line of Table 6.

In experiments, the existing ratio approach of Eq. (22) performs a little better than the proposed novel approach of Eq. (23). Taking into account that a parameter α should be assigned an adequate value with the existing ratio approach of Eq. (22), the proposed novel approach of Eq. (23) can be said to be more ideal in applications.

5. Conclusion

This paper presents an idea of integrated probability function (IPF) and a relevance feedback framework based on a new posterior probability estimator and a novel weight updating approach. Experiments on trademark images show that the proposed IPF is superior to the commonly used IDF and the new posterior probability estimator performs better than the existing estimator. The proposed trademark image retrieval system is shown to be superior to the existing system [7]. Ninety-five percent of the targets are ranked at the top 5 positions in a database containing 1400 images. The proposed posterior probability estimator of Eq. (17) by relevance feedback is shown to be able to make great use of relevance information. Experimental results also show that the proposed novel weight updating approach by relevance feedback outperforms both the existing scoring approach and the ratio approach. By two iterations of relevance feedback, retrieval performance can be improved from 75% to over 95%. The IPF and its relevance feedback framework proposed in this paper can be effectively and efficiently used in content-based image retrieval.

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