Logo Recognition Using Shape Descriptors and Fusion of Multiple Classifiers

MatheelEmaduldeen*(Assist.Prof) Ph.D Mohammad Talib Hashim*

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Abstract

An important problem in the field of document image processing is the recognition of graphical items, such as company logos. Logos are mainly used by companies and organizations to identify themselves on documents. Different feature extraction and shape description methods in logo image recognition systems have been studied by several researchers. In this paper, two region-based shape descriptors: Zernike moment descriptors and Geometric moment descriptors are studied and compared. The performance of an ensemble of classifiers, each trained on different feature sets is also evaluated. The recognition results of the individual classifiers are compared with those obtained from fusing the classifiers' output, showing significant performance improvements of the proposed methodology.

Keywords: logo recognition, shape descriptors, multiple classifiers.

*University of Technology

1. Introduction

Logos in documents are widely used visually-salient symbols serving as remarkable identifications of related organizations. The topic of utilizing logo for document retrieval basically involves two aspects: (1) detecting the probable logo from a document image; (2) indexing the detected logo candidate region into a database to classify it or conclude that the region is not of interest. The first matter is referred to as logo detection while the second is logo recognition [1].

This work was focus on the logo recognition phase.From the machine learning point of view, logo recognition is considered a multi-class classification task since each logo category is considered a separate target class. In this view, the classification system involves two main stages: the selection and/or extraction of informative features and the construction of a classification algorithm. In such a system, a desirable feature set can greatly simplify the construction of a classification algorithm, and a powerful classification algorithm can work well even with a low discriminative feature set [1].

There are generally two types of shape descriptors: contour-based shape descriptors and region-based shape descriptors. Contour-based shape descriptors such as Fourier descriptors, curvature scale space and shape signatures exploit only boundary information, they cannot capture shape interior content. Besides, these methods cannot deal with disjoint shapes where boundary may not be available; therefore, they have limited applications [2].

In region based techniques, all the pixels within a shape region are taken into account to obtain the shape representation. Common region based methods use moment descriptors to describe shape. These include geometric moments, Legendre moments, Zernike moments and pseudo Zernike moments [2].

The contribution of this work is two-fold: (1) two region based shape descriptors: Zernike moments descriptors and geometric moments descriptors were studied and compared;(2) improving the recognition performance by utilizing a combination strategy that is appropriate for fusing different sources of information. The principles used for the comparison are the six requirements set by MPEG-7 [3], i.e. good retrieval accuracy, compact features, general application, low computation complexity, robust retrieval performance and hierarchical representation.

2. Related Works

One of the first approaches dealing with logo recognition was the one presented by Doermann et al. in [4]. In that work, the authors decomposed the logos in a set of textual and graphical primitives such as lines, circles, rectangles, triangles, etc. and described them by a set of local and global invariants composing a logo signature which was matched against the logo database. Many other works relying on a compact description of the logos and a subsequent matching step can be found, as examples the work of Eakins et al. [5] where logos are described by a set of features extracted from the shape's boundaries which used in shape retrieval system. In [6], Chen et al. represented logos by line segment drawings which were then matched according to a modification of the Hausdorff distance. In [7], Hodge et al. propose a perceptual logo description, whereas in [8] Leuken et al. describe logos by the layout spatial arrangement of basic primitives. In [9] proposed combining both the magnitude and phase coefficients to form a new shape descriptor, referred to as invariant Zernike moment descriptors for shape recognition and retrieval.

3. Region-based Shape Descriptors

The two region-based shape descriptors to be compared are described in details.

3.1Zernike Moments Descriptors (ZMD)

Teague [10] has proposed the use of orthogonal moments to recover the image from moments based on the theory of orthogonal polynomials, and has introduced Zernike moments, which allow independent moment invariants to be constructed to an arbitrarily high order.

The two-dimensional Zernike moments, A_{nm} of order n with repetition m, of an image $f(\rho,\theta)$ are defined as [11]:

$$A_{pq} = \frac{n+1}{\pi} \sum_{x=0}^{x=M-1} \sum_{y=0}^{y=N-1} f(\rho,\theta) V'_{pq}(\rho,\theta), \rho \leq 1 \qquad (1)$$

where:

(ρ, θ) is a polar coordinate,

V'_{pq} is a complex conjugate,

$$\rho = \sqrt{x^2 + y^2} \qquad (1a)$$

$$\theta = \arctan(y/x) \qquad (1b)$$

$V'_{pq}$is a complex polynomial defined inside a unit circle with the formula:

$$V'_{pq}(\rho, \theta) = R_{pq}(\rho) exp(jm\theta) \qquad (2)$$

where:

$\rho \leq 1$ andj $= \sqrt{-1}$ (imaginary unit).

$R_{pq}(\rho)$ is a radial polynomial, which can be generated using:

$$R_{pq}(\rho) = \sum_{s=0}^{n-\frac{|m|}{2}} (-1)^s . \frac{(n-s)!}{s!\left(\frac{n+|m|}{2} - s\right)!\left(\frac{n-|m|}{2} - s\right)!} . \rho^n - 2s \qquad (3)$$

where:

n is a positive integer, m can be a positive or negative integer,

n - |m| is even, |m| <= n.

In order to make ZMD translation and scaling invariants, image normalization needs to be performed. To achieve translation normalization, the regular geometric moment of each image is used (m_{pq}). Translation invariance is achieved by transforming the image into a new one whose first order moments, m_{01} and m_{10}, are both equal to zero. This is done by transforming f(x, y) into f(x+x, y+y), where x and y are the image centroid point. Scaling invariance is achieved by transforming the original image f(x, y) into a new image f(αx, αy), where $\alpha = \sqrt{\beta/\mathrm{m}_{00}}$, β is a predetermined value, and m_{00} is the zero-th order moment of the original image, which is the object's area in a binary image [11].

3.2 Geometric MomentsDescriptors(GMD)

The technique based on geometric moment invariants for shape representation and similarity measure is extensively used in shape recognition. Moment invariants are derived from moments of shapes and are invariant to 2D geometric transformations of shapes. The central moments of order p+q of a two dimensional shape represented by function f(x, y) are given by [2]:

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y) \qquad p,q = 0,1,2 \ldots. \qquad (4)$$

Where

$\bar{x} = \mu_{10}/m$(4a)

$\bar{y} = \mu_{01}/m$(4b)

m: mass of the shape region.

μ_{pq}: invariant to translation.

The first 7 normalized geometric moments which are invariant under translation, rotation and scaling are given by Hu [2]:

$I_1 = \eta_{20}+\eta_{02}$(5a)

$I_2 = (\eta_{20}-\eta_{02})^2 + 4\,\eta^2_{11}$(5b)

$I_3 = (\eta_{30}-3\eta_{12})^2 + (3\eta_{21}-\eta_{03})^2$(5c)

$I_4 = (\eta_{30}+\eta_{12})^2 + (\eta_{21}+\eta_{03})^2$(5d)

$I_5 = (\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})[(\eta_{30}-\eta_{12})^2-3(\eta_{21}-\eta_{03})^2]+(3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})$
(5e)$[(3\eta_{30}+\eta_{12})^2-(\eta_{21}-\eta_{03})^2]$

$I_6 = (\eta_{20}-\eta_{02})[(\eta_{30}+\eta_{12})^2-(\eta_{21}-\eta_{03})^2]+4\eta^2_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03})$ (5f)

$I_7 = (3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}-\eta_{12})^2-3(\eta_{21}-\eta_{03})^2]+(3\eta_{12}-\eta_{03})(\eta_{21}+\eta_{03})$
(5g)$[(3\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2]$

Where

$\eta_{pq} = \mu_{pq}/(\mu_{00})\gamma$ and (5h)

$\gamma = 1+(p+q)/2$ for $p+q = 2, 3, \ldots.$ (5i)

The advantage of using GMD is it is a very compact shape representation and the computation is low, however, it is difficult to obtain higher order moment invariants.

4. Classification

Image classification methods can be roughly divided into two broad families of approaches: (i) Learning-based classifiers, which require an intensive learning/training phase of the classifier parameters (e.g., parameters of Support Vector Machines, Boosting, and decision trees. These methods are also known as parametric methods. (ii) Nonparametric classifiers, which base their classification decision directly on the data, and require no learning/training of parameters. The most common non-parametric methods rely on Nearest-Neighbor distance estimation [12].

Non-parametric classifiers have several very important advantages that are not shared by most learning-based approaches [12]:

(i) Can naturally handle a huge number of classes.

(ii) Avoid overfitting of parameters, which is a central issue in learning based approaches.

(iii) Require no learning/ training phase. Although training is often viewed as a one-time preprocessing step, retraining of parameters in large dynamic databases may take days, whereas changing classes/training-sets is instantaneous in nonparametric classifiers.

4.1 Nearest Neighbor Classifier

The nearest neighbor classifier relies on a metric or a distance function between points. For all points x, y and z, a metric $D(\cdot, \cdot)$ must satisfy the following properties:

1) Nonnegativity: $D(x, y) \geq 0$. (6a)

2) Reflexivity: $D(x, y) = 0$ if and only if $x = y$. (6b)

3) Symmetry: $D(x, y) = D(y, x)$. (6c)

4) Triangle inequality: $D(x, y) + D(y, z) \geq D(x, z)$. (6d)

The nearest neighbor classifier is used to compare the feature vector of the prototype image and feature vectors stored in the database. It is obtained by finding the distance between the prototype image and the database. Let $C_1, C_2, C_3, \ldots, C_k$ be the k clusters in the database. The class is found by measuring the distance $d(x(q), C_k)$ between $x(q)$ and the k^{th} cluster C_k. The feature vector with minimum difference is found to be the closest matching vector. It is given by [12]:

$d(x(q), C_k) = \min\{\| x(q) - x \| : x \in C_k\}$ (7)

Nearest-Neighbor classifiers provide good image classification when the query image is similar to one of the labeled images in its class [12].

4.2 Multiple Classifier Systems

In such systems, the classification task can be solved by integrating different classifiers, leading to better performance. However, the ensembleapproach depends on the assumption that single classifiers' errors are uncorrelated, which is known as classifier diversity. The intuition is that if each classifier makes different errors, then the total errors can be reduced by an appropriate combination of these classifiers. The design process of a multiple classifier system generally involves two steps: the collection of an ensemble of classifiers and the design of the combination rule [13]. These steps are explained in detail in the next subsections.

4.2.1 Creating an ensemble of classifiers

There are three general approaches to creating an ensemble of classifiers in stateof-the-art research, which can be considered as different ways to achieve diversity.The most straightforward approach is using different learning algorithms for thebase classifiers or variations of the parameters of the base classifiers e.g. different initial weights or different topologies of a series of neural network classifiers.Another approach, which has been getting more attention in the related literature, is to use different training sets to train base classifiers. Such sets are oftenobtained from the original training set by resampling techniques. The third approach is to train the individual classifiers with datasets that consist of differentfeature subsets, or so-called ensemble feature selection [13]. While traditionalfeature selection algorithms seek to find an optimal subset of features, the goal ofensemble feature selection is to find different feature subsets to generate accurateand diverse classifiers [1].

4.2.2 Design of a combination rule

Once a set of classifiers are generated, the next step is to construct a combination function to merge their outputs, which is also called decision optimization. The most straightforward strategy is the simple majority voting, in which each classifier votes on the class it predicts, and the class receiving the largest number of votes is the ensemble decision. Other strategies for combination function include sum, product, maximum and minimum, fuzzy integral, and decision templates [1].

Derivation of the rules: The ultimate goal for a classifier is to correctly estimate the probability that an object belongs to a certain class w_j. This object is represented by a measurement vector x, in which each component is a measurement of a feature. When *R* measurement vectors $x^1,\ldots,x^R$ from different feature spaces are available, this probability$P(w_j|x^1,\ldots,x^R)$has to be approximated.In each of the *R* feature spaces a classifier can be constructed which approximates the true class probability $P(w_j|x^k)$in that feature space [14]:

$$f_j^k(x^k) = P(w_j|\, x^k) + \epsilon_j^k(x^k)(8)$$

A good combination rule uses these $f_j^k(x^k)$ to approximate $P(w_j|\ x^1,\ldots, x^R)$as optimal as possible. The two combination rules will be considered, the mean rule and the product rule [14]:

$$f_j(x^1,\ldots,x^R) = \frac{1}{R}\sum_{k=1}^{R} f_j^k(x^k)(9)$$

$$f_j(x^1,\ldots,x^R) = \frac{\prod_{k=1}^{R} f_j^k(x^k)}{\sum j' \prod_{k=1}^{R} f_{j'}^k(x^k)}(10)$$

4.3 K-Fold Cross-Validation

Given a dataset X, we would like to generate K training/validation set pairs, $\{T_i, V_i\}_{i=1}^{K}$, from this dataset(after having left out some part as the test set).In K-fold cross-validation, the dataset X is divided randomly into K equal sized parts, X_i, i=1,...,K. To generate each pair, we keep one of the K parts out as the validation set and combine the remaining K−1 parts to form the training set. Doing this K times, each time leaving out another one of the K parts out, we get K pairs: [15]

$$\left.\begin{array}{ll} V_1=X_1 & T_1=X_2\cup X_3\cup\cdots\cup X_K \\ V_2=X_2 & T_2=X_1\cup X_3\cup\cdots\cup X_K(11) \\ . & \\ . & \\ V_K=X_K & T_K=X_1\cup X_2\cup\cdots\cup X_{K-1} \end{array}\right\}$$

It has also become possible to have multiple runs of K-fold cross-validation, for example, 10×10 fold, and use average over averages to get more reliable error estimates [15].

The performance measures used is

$$\text{error} = (\text{fp}+\text{fn})/\text{N} \quad (12)$$

$$\text{accuracy} = (\text{tp}+\text{tn})/\text{N} = 1 - \text{error} \quad (13)$$

where:

fp : false positive , fn : false negative

tp : true positive , tn : true negative

N : size of dataset

5. Framework of the proposed logo recognition system

As mentioned earlier, this work focuses on the second step of logo analysis: logo recognition. The problems of image segmentation and logo detection are beyond the scope of this work. Figure 1 shows the framework of the proposed logo recognition system. In the followings, the main phases of the framework are described.

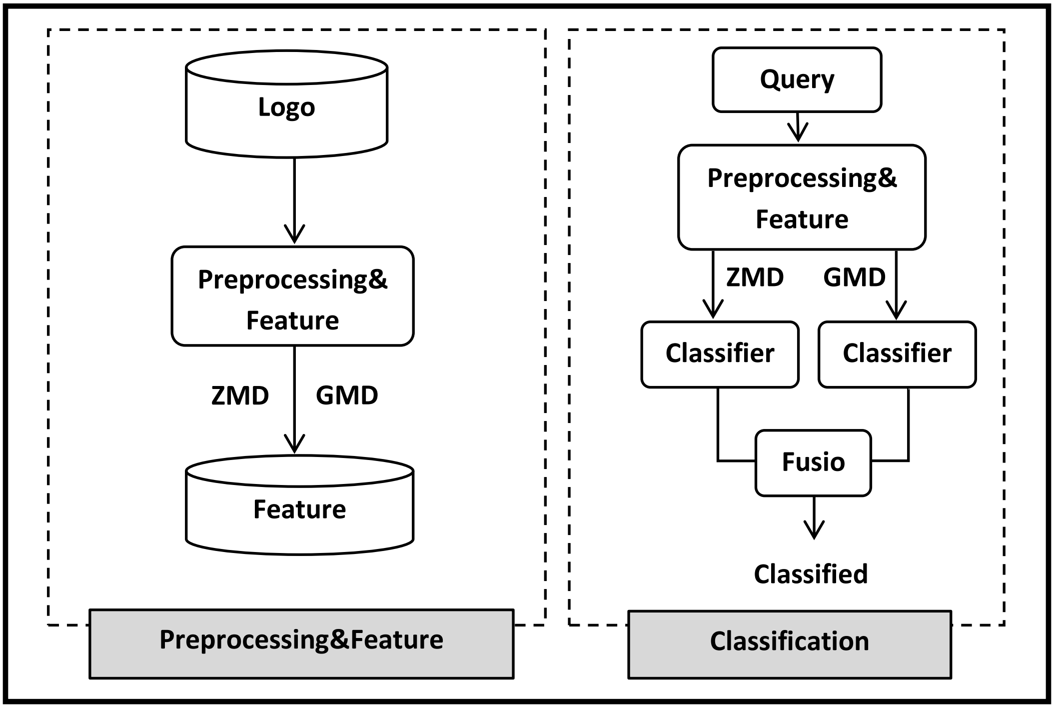

Figure 1: The block diagram of the proposed system.

5.1 Preprocessingand Feature Extraction

In this work, two different image description techniques were employed: ZMD andGMDfeatureswere extracted from each image. The steps of such process are summarized in the following:

Input: An image

Output: ZMD and GMD Features

1. Loading images.

2. Feature extraction: for each image do the following:

i. ZMD Features

a. Since Zernike basis functions take the unit disk as their domain, this disk must be specified before moments can be calculated. In our implementation, all the logos are normalized into a unit circle of fixed radius of 64 pixels. The unit disk is then centered on the shape centroid. This makes the obtained moments scale and translation invariant.

b. The Zernike moments of the image are calculated using equation 1 up to the 8th order. The complex part defines rotation, and using only the real part leads to a rotation invariant representation.

Note that each order of the Zernike polynomial representation includes several coefficients, so in this experiment, 8th order polynomial representation leads to 24 coefficients.

c. The magnitudes are then normalized to [0, 1] by dividing them by the mass of the logo shape.

The block diagram of the whole process of computing ZMD is shown in Figure 2.

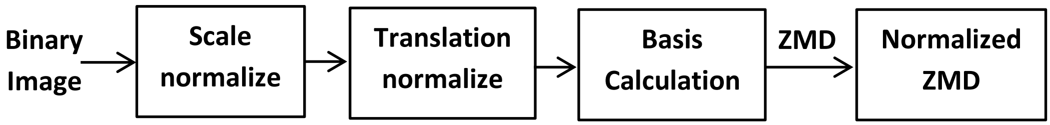

Figure 2: block diagram of computing ZMD

ii. GMD Features

a. calculate seven moment invariants as in equations 1-7

b. all the invariants are normalized into [0, 1] by the limit values of each dimension.

c. the output feature vector GMD = $(I_1, I_2, \ldots I_7)$ is used to index each logo in the database.

3. Repeat steps (1 to 2) for all images in the database.

5.2 LogoClassification

Given a query logo and the aim is to classify the logo image based on the fusion of individual classifiers. The steps of such process are summarized in the following:

Input: Logo image

Output: Classified logo

1. Loading logo image.

2. Feature extraction: repeat steps as in feature extraction process

In thiswork, the number of input features extracted using Hu invariants feature extraction method is 7 while the number of input features extracted using Zernike moments is 24. These inputs are presented to the nearest neighbor classifiers to do matching with the feature values in reference database.

3. Decision fusion: each feature vector is given to the corresponding classifier and the outputs of the nearest neighbor base classifiers are then combined to make an ultimate decision for the test image, using the mean and product combining rules as in equations (9) and (10) respectively.

6. Experiments Analysis and Discussions

Datasets: The logo image database used is extracted from Tobacco-800 dataset [16] and other logo images are added. Figure 3 shows a few of samples for some categories of this dataset. This dataset consists of 20 classes with 20 instances per class, which represents a total of 400 logo images. The image database partitioned into training set (70%) and testing set (30%). The training set is used in the evaluation of the classification performance by means of 10-fold cross-validation, while the testing set is used to evaluate the final classification performance.

Figure 3: Some examples of labeled images in the dataset.

Experiments: The classification of different logo images is based on the fusion of individual classifiers. The combining rules used in the experiments were mean and product rule as in equation (9) and (10) respectively.In these experiments,classification resultsfromsingle classifier trained only on Geometric momentand Zernikemomentsarecompared with the fusion of these individual classifiers. In order to improve the reliability of the results, the experiments are conducted using different numbers of classes, i.e. different numbers of selected logo categories.

Performance evaluation: For evaluation, the classification performance is obtained by means of stratified 10-fold cross-validation over 10 runs.

The summary of the results are reported in Table 1. This table shows the classification accuracy of individual classifiers and the fusion of themwith KNN as the base learners. Figure 4 shows this results diagrammatically.

Table 1: Classification accuracy of using only single classifier (trained only on GMD or ZMD) and using fused classifiers (trained on GMD and ZMD) with KNN as the base learner.

	Single classifier trained only on		Fusion	
Classes	**Zernike moments**	**Geometric moments**	**Mean**	**Product**
5	97.90 %	92.00 %	98.00%	100 %
10	97.56 %	90.00 %	97.80 %	98.20 %
15	96.06 %	88.20 %	95.13 %	97.80 %
20	95.65 %	88.10 %	93.45 %	96.15 %

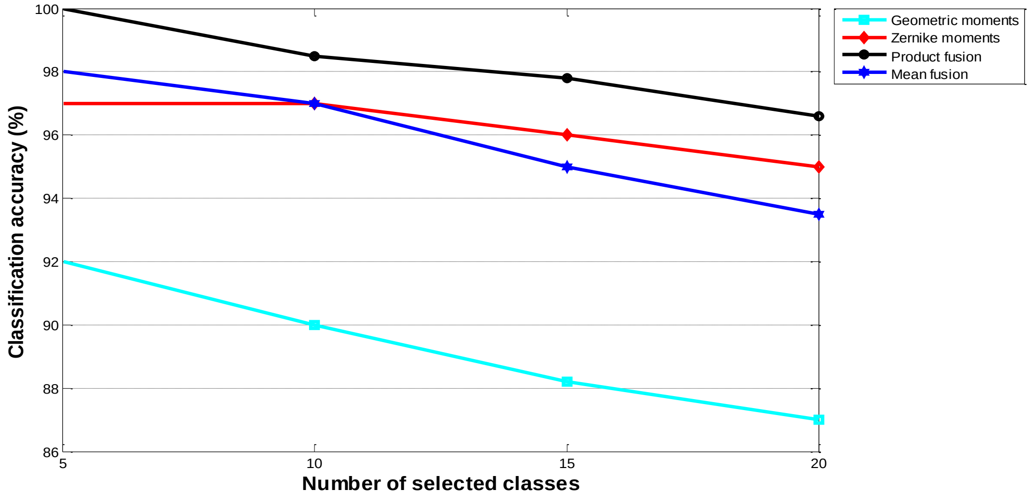

Figure 4: Classification accuracy of single and fused classifiers by different combination methods using KNN as the base learner.

As an additional analysis, we compare classification results of merging classifiers by the two fusion methods using testing dataset for each class. Table 2 show the classification accuracy of the best individual classifier usingZernike moments and the ensemble systems by the two fusion methods.

Table 2: Classification accuracies of different methods using testing dataset for each class.

Class	Zernike moments	Mean	Product
1	96.67 %	98.20 %	99.03 %
2	95.56 %	96.20 %	98.20 %
3	95.89 %	97.80 %	98.20 %
4	98.20 %	96.15 %	99.19 %
5	83.23 %	85.01 %	86.81%
6	89.05 %	86.92 %	90.20 %
7	97.12 %	97.20 %	98.28 %
8	83.64 %	85.36 %	86.15 %
9	97.03 %	97.33 %	97.93 %
10	80.47 %	82.86%	86.67 %
11	95.89 %	96.19 %	97.80 %
12	86.75 %	86.92 %	88.95 %
13	81.89 %	82.06 %	82.67 %
14	94.44 %	93.16 %	98.20 %
15	98.02 %	98.12 %	99.00 %
16	85.12 %	88.12 %	88.82 %
17	86.12 %	87.52 %	89.12 %
18	94.14 %	95.28 %	97.16 %
19	92.38 %	93.38 %	95.08 %
20	81.21 %	81.98 %	82.28 %

It is important to note the outperformance of the fused results in comparison with the individual classifier. This improvement is clearer when the number of classes of the datasets is increased. In that case, the inter-class variability is reduced, and thus, it is easier to confuse patterns from different classes.

The comparison of the two region-based shape descriptors is given in the following:

1. Feature domains. ZMD is extracted from spectral domain while GMD are extracted from spatial domain.

2. Compactness. The dimension of GMD and ZMD is low.
3. Robustness. ZMD is more robust to shape variations than GMD.
4. Computation complexity. The extraction of ZMD involves expensive computation while it is simple to extract GMD.
5. Accuracy. At the same level of recall, the retrieval precision of ZMD is higher than of GMD.
6. Hierarchical representation. ZMD support hierarchical representation. The number of ZMDs can be adjusted to meet hierarchical requirement. GMD does not support hierarchical representation because higher geometric moment invariants are difficult to obtain.

7. Conclusions

In this paper two region-based shape descriptors have implemented and studied. The classification performances of the two region-based shape descriptors are obtained based on logo database. Based on the study, it has been found that ZMD outperforms GMD in terms of robustness, accuracy, and hierarchical representation. There fore, ZMD is the most suitable for effective and efficient logo recognition. The classification results of the individual classifiers were compared with those obtained from fusing the classifiers by the two combination method. Using ensemble methods for the classification of logo images is effective, though different combination methods would show differentperformances.However, as demonstrated by our experiments the classification performance was significantly increased compared with single classifiers trained by a specific set of features.

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تمييزالشعاربإستعمال واصفات الشكل ودمج عدة مصنفات

أ.م.د.مثيل عماد الدين *　　(طالب دكتوراه) محمد طالب هاشم*

المستخلص

احدىاهم المشاكل في حقل معالجة صورالوثائق هي تميزالاشكال الرسومية،مثل شعارالشركات. تستعمل الشعارات بشكل رئيسي من قبل الشركات والمنظمات لتمييزأنفسهم على الوثائق. تم دراسة العديد من طرق إستخلاص الخصائص ووصف الشكل في أنظمة تميزالشعارات من قبل عدة باحثين. في هذا البحث،تم دراسة ومقارنة نوعين من واصفات الشكل أساسها لمنطقة :

Zernike moment descriptors و Geometric moment descriptors

ايضا تم تقييم أداء مجموعة من المصنفات التي تدربكل منهاعلى مجموعة مختلفة من الخصائص ومقارنة نتائج تمييزكل مصنف مع نتائج التمييزالناتجة من دمج ناتج المصنفات، والتي اظهرت تحسن ها م في الأداء للطريقة المقترحة.

الكلمات المفتاحية: تميز الشعار ، واصفات الشكل، المصنفات

*الجامعة التكنولوجية