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Moment Features Weighting for Image Retrieval

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Abstract: *Feature selection is an effective tool to improve the performance of content based image retrieval systems. This paper presents an effective moment weighting method according to image reconstruction and retrieval accuracyto reduce the dimensionality of moment-based features. Weighting algorithms are important group of feature selection schemes. Among features employed in content based image retrieval systems, orthogonal moments are shape features which have been used to distinguish objects. But in current applications, selecting effective features among momentshas been less considered. The proposed novel weighting algorithm, obtains the weight of moment features by calculating the mean retrieval accuracy over images that are reconstructed by only one kernel coefficient and, selects the top-N features. The performance of the algorithm is compared with well-known ReliefF feature weighting and selection algorithm. Experimental results, applied on Coil-20 shape dataset, show the confidence and superiority of this feature weighing scheme over ReliefF algorithm.*
Keywords: *Content Based Image Retrieval, Feature Selection, Feature Weighting, Exact Legendre Moments.*

I. Introduction

Content-Based Image Retrieval (CBIR) is one of important and rapidly growing fields of research that concerned with searching and browsing digital images from database collections. The main reason of increasing demands for such systems is rapidly growing the size of digital image collections in various domains such as personal photos, medical imaging, education, crime prevention, geographical information and remote sensing, and the need for effective tools for searching, browsing and retrieval of images with attention to instantaneous accessibility and transmission of images throughInternet. CBIR systems use the low level extractable visual feature of images to describe high level semantics. Thus exploitation of useful features that properly characterize the distinguishing contents of images of the datasets, related to particular domain, is very important for such systems. The most commonly used types of features in CBIR include color, texture, shape, spatial location and salient points[11],[10]. One type of image retrieval that deals with retrieval of only shape images is also called shape retrieval.

Shape features, commonly used in shape retrieval, are basic and important group of features which have been used to describe image contents, specially segmented image regions and specific images of man-made objects. Utilizingshape features, similar objects can be efficiently matched among numerous instances of different object types. Some types of shape features are shape signature, signature histogram, shape invariants, moments, curvature, shape context, shape matrix, spectral features[11], [10]. The effectiveness of a shape representation and description is usually evaluated by its retrieval accuracy, feature compactness, computation complexity and robustness respect to deformations[7]. Shape descriptors which are able to effectively find perceptually similar shapes from a database, will have good retrieval performance. Shape features can be mainly categorized into two groups: contour-based descriptors that are computed from the shape boundary only and region-based descriptors that are based on both the boundary and interior content[6].

In most CBIR applications, extracted features are directly used to construct image features vector. But sometimes the number of extracted features grows immoderately that significantly reduces the speed and quality of classification and retrieval. In these cases the size of feature vectors must be efficiently reduced. A solution is feature selection. The objective of feature selection is to choose a subset of features among all features which provides a better classification performance. This can be achieved by removing redundant and irrelevant features. Feature selection methods are categorized into two groupsaccording to subset evaluation method: Filter and Wrapper[1]. Filter methods evaluate features with their intrinsic effects on separating classes while wrapper methods use the accuracy of learning methods to evaluate subsets of features.

Moment feature weighting and selection in various applications which employ moment features,has been less considered. Current applications usually select a maximum order $g = (p + q)$ and use all pairs (p, q) that $(p + q) \leq g$ to build moment kernel functions ($Kernel_{pq}$) and employ the coefficients of these functions (L_{pq}) as features. But selecting a subset of these features has been less addressed. The main reason might be the attention to orthogonality attribute of the moments, because moments can describe an image with a series of non-overlapping codes. This factimposesa vision that feature subset selection is redundant. But this is incorrect, because each feature shows specific property of the shape ofan image and each property has different effect on retrieval accuracy.

This paper presents a novel moment feature weighting and selection algorithm by utilizing reconstruction property of moments to evaluate their effects on retrieval accuracy. At the first step, the algorithm produces a new set of images by extractingpatterns from each image of the datasetby reconstructing it only with one kernel coefficientL_{pq} . Then, it calculates the mean accuracy of querying each image of the dataset and uses it as the weight for each feature. Finally, the algorithm selects the top-k features with higher weights and retrieval accuracy, based on the original database. The proposed algorithm is applied on Coil-20 shape dataset[9].

The organizationof rest of the paper is as follows. Section one describes Legendre moment calculation method to construct feature vectors and describesthe image reconstruction process using moments. Section two, proposes the feature weighting and selection algorithm. Section three talks about the experimental results and, section four is conclusion.

II. Legendre Moments and Image Reconstruction

Moment descriptors are suitable to describe shapes. This is mainly due to their ability to fully describe an image by encoding its contents in a compact way. Orthogonal momentsare widely used as descriptors. The main reason is that orthogonal moments can represent an image with the minimum amount of information redundancy, thus the recovery of an image from its geometric moments is accurate. These moments can be classified into continuous and discrete moments [15]. Examples of continuous orthogonal moments are Legendre, Zernike, Pseudo-Zernike and Fourier-Mellin. Examples of discrete ones are Tchebichef, Krawtchouk,Racah and Dual Hahn moments [12]. Orthogonal moment firstly introduced in [13] as a generalization of geometric moments with using Legendre, Zernike and other polynomials as kernel function.

Legendre moments have been used in many applications in image recognition [3, 4, 14] and analysis [2]. Hosny[5] proposed a fast and accurate method for both binary and gray level images named Exact Legendre Moment (ELM). This section presents ELM and shows the reconstruction property of Legendre moments.

1.1. Legendre Moments Calculation

Legendre moments are continuous and orthogonal and they can represent images with minimum redundancy. The general computational form of an order moment *g=(p+q)* computed on an N×M image having intensity function *f(x,y)*, is defined as follows

$$L_{pq} = NF * \int_{i=1}^{N}\int_{j=1}^{M} Kernel_{pq}(x_i, y_j) f(x_i, y_j) \tag{1}$$

Where $Kernel_{pq}(.)$ corresponds to the moment's kernel consisting of specific polynomials of order *p* and *q*, which constitute the orthogonal basis and NF is a normalization factor. Legendre Momentsare specific type of moments that use Legendre polynomials to construct kernel functions and formulated as follows

$$L_{pq} = \frac{(2p+1)(2q+1)}{4} \int_{-1}^{1}\int_{-1}^{1} P_p(x) P_p(y) f(x,y) dxdy \tag{2}$$

where$P_p(x)$ is the p^{th} order of Legendre polynomial and is defined as

$$P_p(x) = \sum_{k=0}^{p} a_{k,p} x^k = \frac{1}{2^p p!} (\frac{d}{dx})^p [(x^2-1)]^p \tag{3}$$

where x∈[-1,1] and $P_p(x)$obeys the following rule

$$P_{p+1}(x) = \frac{(2p+1)}{(p+1)} x P_p(x) - \frac{p}{p+1} P_{p-1}(x) \tag{4}$$

with $P_0(x) = 1, P_1(x) = x$ and P > 1.

A set of Legendre polynomials constructs a complete set of orthogonal basis in the range [-1, 1] and can be defined as follows[5]

$$\tilde{L}_{pq} = \sum_{i=1}^{N} I_p(x_i) Y_{iq} \quad , Y_{iq} = \sum_{j=1}^{N} I_p(y_j) f(x_i, y_j) \tag{5}$$

where

$$I_P(x_i) = \left(\frac{(2p+1)}{(2p+2)}\right) [x P_p(x) - P_{p-1}(x)]_{U_i}^{U_{i+1}} \tag{6}$$

$$I_q(y_j) = \left(\frac{(2q+1)}{(2q+2)}\right) [y P_q(y) - P_{q-1}(y)]_{V_i}^{V_{i+1}} \tag{7}$$

$$U_{i+1} = x_i + \frac{\Delta x_i}{2} = -1 + i\Delta x \tag{8}$$

$$U_i = x_i - \frac{\Delta x_i}{2} = -1 + (i-1)\Delta x \tag{9}$$

$$V_{j+1} = y_i + \frac{\Delta j}{2} = -1 + j\Delta y \tag{10}$$

$$V_j = y_j - \frac{\Delta y_j}{2} = -1 + (j-1)\Delta y \tag{11}$$

In above equations (U_i, V_j) is the center of a pixel of any image with coordinates (x_i, y_j).

1.2. Reconstruction Property of Legendre Moments

Theoretically, if we have all image moments, we can reconstruct the original image. In the case of Legendre moments the reconstructed image can be calculated as follows

$$f(x,y) = \sum_{p=0}^{\infty}\sum_{q=0}^{\infty} L_{pq} P_p(x) P_p(y) \tag{12}$$

Once a finite number of moments up to a specific order n_{max} are computed, the approximated image can be reconstructed by applying a similar formula:

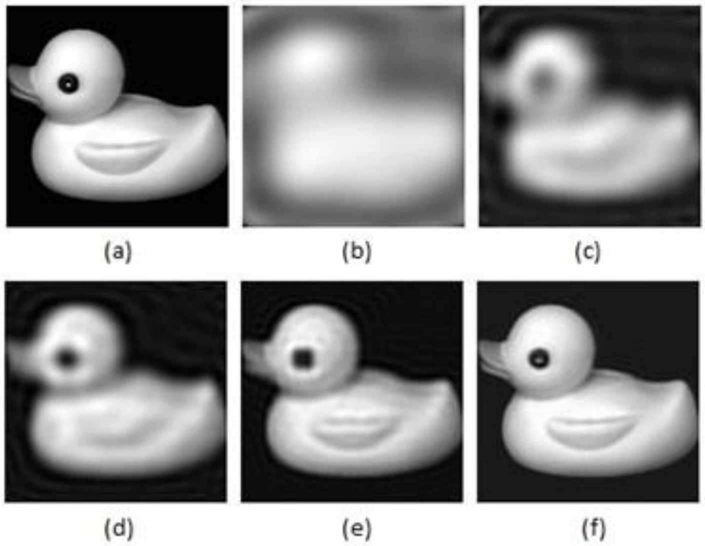

Figure 1. Reconstruction of an image;from(a) to (f): original image, reconstructed by moment orders 10, 20, 30, 60 and 120.

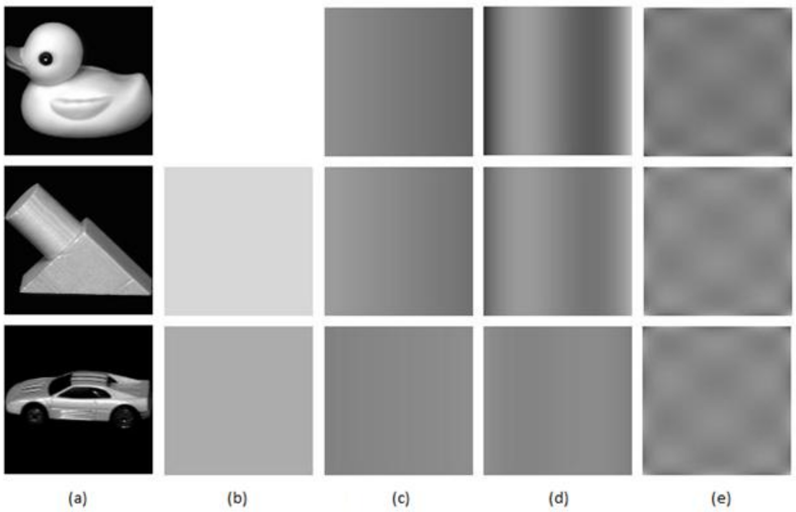

Figure 2. Reconstruction of images using one basis function; from columns (a) to (e): original images, reconstructed images with (0, 0), (0, 2), (0, 9) and (7, 1)

$$\hat{f}(x,y) = \sum_{p=0}^{n_{max}} \sum_{q=0}^{p} L_{p-q,q} P_{p-q}(x) P_p(y) \tag{13}$$

Fig. 1 shows the reconstructed images using (13) with various values of n_{max} as an example.

Each orthogonal basis adds a layer to the reconstructed image and each one demonstrates a specific property of the shape of image. Reconstructed image of each layer can be shown with (14).

$$f_{pq}(x,y) = L_{pq} P_p(x) P_p(y) \tag{14}$$

Fig. 2 presents the reconstructed images using various pairs *(p, q)* in (13) for different images.

III. Proposed Feature Weighting and Selection Algorithm

Assigning weights to each feature according to its effect on classification and retrieval is helpful to select the proper subset of features. This section describesthe novel algorithm for weighting and selection of moment features using image reconstruction property of moments and retrieval accuracy.

1.3. Calculating Weight for Each Moment

As we mentioned before, usually feature vectors are based on the selected moment order (g),that constructs$m = \frac{(g+1)(g+2)}{2}$ basis functions using the specified kernel function and the parameters p and q which $(p+q) \le g$. The effect of each basis function on describing shape feature of an image, is demonstrated by L_{pq} in (1) and is used as a moment feature. Now if we want to know which of these basis functions describesthe feature of the shape of image,which better segregatesthe images from each object category, and thus improves the object retrieval accuracy, we can reconstruct the image with only that basis function and calculate the retrieval accuracy. The procedure is as follows:

- First, considering a pair (p, q) as parameters of a basis function, for each image of the original database, a moment feature L_{pq} by ELM method described in section (2.1) is calculated.
- The reconstructed image dataset considering the basis function is obtained by reconstruction of all images using (14).
- The mean retrieval accuracy for the reconstructed dataset is considered as the weight for the feature L_{pq}.

The mean retrieval accuracy can be obtained by considering each image of the dataset as a query image, calculating Euclidean distances from all other images, sorting the distances in ascending order, retrieving the top-K images and calculating precision of retrieval using (15). Then all retrieval precisions are averaged.

$$Precision = \frac{Number\ of\ relevent\ images\ retrieved}{Total\ Number\ of\ relevent\ images\ retrieved} \tag{15}$$

We can assign weight to each moment feature according to its effect on the retrieval accuracy and, select the best subset of features to construct selected feature vector.

1.4. Feature selection

The simple way of feature selection according to feature weights is to sort the weights in decreasing order and selecting the top-N features with higher weights. But how we can choose N. One way is as follows:

- Sort features according to their weights in descending order.
- Select top-weighted features and calculate their retrieval accuracy.
- Add next feature to selected subset if the retrieval accuracy of new subset is improved in comparison with the previous subset or else omit it.
- If number of omitted features exceeds a specified threshold we can stop the algorithm or we can proceed until the all features are evaluated.

This fast and simple algorithm leads to select a subset of features that probably is the best one, considering the orthogonal moment. But this subset may be suboptimal.

Overall quality of selection can be calculated using the following formula

$$Overall\ Quality = \beta \times Precision\ of\ Retrieval + (1-\beta) \times (1 - \frac{Number\ of\ Selected\ Features}{Total\ Number\ of\ Features}) \tag{16}$$

where, β $(0 < \beta < 1)$ is a balancing factor which adjusts the importance of retrieval accuracy and the length of feature vector.

IV. Experimental results

The proposed method of moment feature weighting and selection are examined on Coil-20 [9] shape dataset that contains 1440 gray level shape images of 20 object classes. Size of images is 128×128 pixels. First, images of the dataset are divided into two groups of training and test images and, 75percent of images in each object category are used as training dataset and the remaining 25 percent of those are used as test dataset. For each image of the training dataset,the order 9 of Legendre moment features are extracted by ELM method explored in Section 2.1. Thus, the length of original feature vector is 55. All images of the training dataset are used for calculating the retrieval accuracy. The number of retrieved images for each query in the training phase is 54 and in test phase is 18 because we have 72 images in each class. For selection of N features with mentioned feature selection method, all features are evaluated, and a subset that has best mean retrieval performance is obtained.

One of the important weighting algorithms is Relief [8], which was devised for two class problems. This algorithm assigns weight to a feature according to its ability to decrease the distance between two instances from the same class and increase the distance between two instances from different classes. ReliefF is an extension of Relief for multi-class problems and has considered as one of the most successful feature weighting methods due to its simplicity and effectiveness. Fig. 3 presents the calculated weights, obtained by the proposed method,compared with the results ofReliefF.The figure shows that, despite the difference in the range of weights and the weight of some features, weight ratio of the majority of features is similar. Thus, the selected subsets, using above mentioned feature selection method, with these twoweighting methods are very similar. Fig. 4 shows the retrieval accuracies with selecting each number of features (1 up to all).The figurepresents the mean accuracies thatare obtained bythe following four retrieval schemes.

Scheme 1: Retrieval with ReliefF based selection and Euclidean distance based retrieval

Scheme 2: Retrieval with ReliefF based selection and weighted Euclidean distance based retrieval

Scheme 3: Retrieval with reconstruction based selection and Euclidean distance based retrieval

Scheme 4: Retrieval with reconstruction based selection and weightedEuclidean distance based retrieval

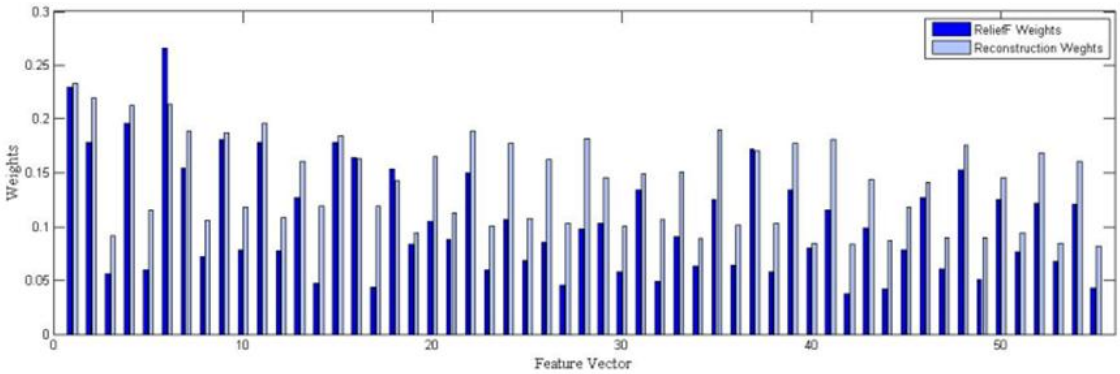

Figure 3: Weights calculated by the proposed method and Relief F algorithm

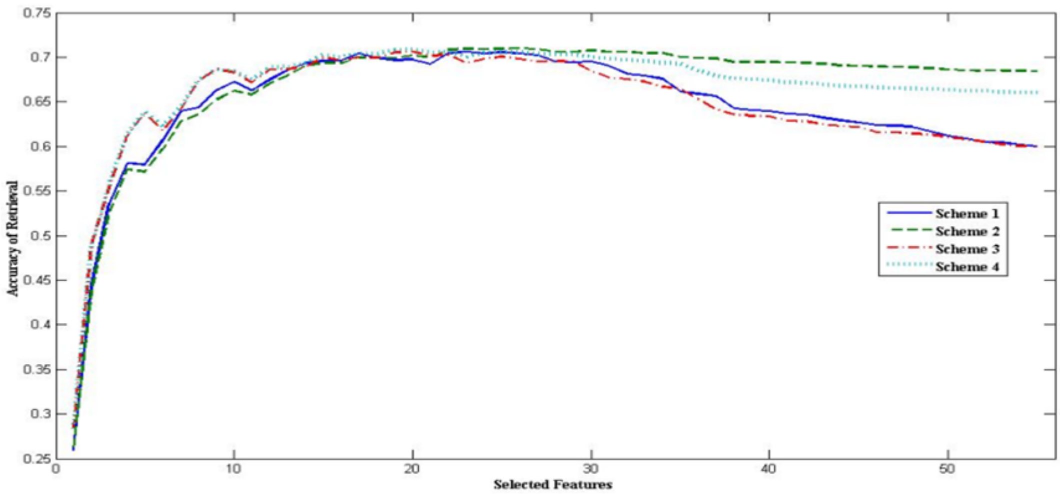

Figure 4: Retrieval accuracies of selection usingthe proposed weighting method and Relief F

Table 1. The number of selected features using each scheme with maximum of mean retrieval accuracy and the classification results on test dataset

Methods of selection and retrieval	Number of features	Maximum of mean retrieval accuracy	Retrieval accuracy over test dataset	Overall Quality
Scheme 1	23	70.63	68.24	63.21
Scheme 2	26	71.00	68.58	60.65
Scheme 3	20	70.60	67.31	65.47
Scheme 4	**20**	**70.89**	**67.73**	**65.68**
Without Selection	55	59.99	60.12	30.06

Table 1 shows the maximum of mean retrieval accuracies, based on the selected and the number of features for each scheme and the final retrieval accuracy.In the table the overall quality of each method is calculated using (16)where β=0.5. The table shows the superiority of the proposed method in terms of retrieval accuracy and feature selection.

V. Conclusion

This article proposed a new method for moment features weighting and selection. The method is based on evaluating the effect of each moment basis function that describes specific shape property of images on performance of image retrieval. It isobserved that the performance of retrieval,is mainly controlled by features that have higher weights and other features could be omitted without degrading the retrieval quality. Also this selection improves the retrieval accuracy, in comparison with the retrieval without feature selection.

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