Combined Local and Global Features for Improving the Shape Retrieval

Mohamed Eisa

Computer Science Department, Port Said University
42526 Port Said, Egypt

Abstract

Content-based image retrieval (CBIR) is playing an important role in multimedia information retrieval. This paper proposes an effective solution for IR by combining shape description and feature matching. First, an effective shape description method which includes two shape descriptors is presented. Second, an effective feature matching strategy to compute the dissimilarity value between the feature vectors extracted from images is proposed. Finally, we combine the shape description method and the feature matching strategy to realize our solution.
A large number of experiments are carried out to evaluate the system performance over five standard databases, which represent various kinds of images. The results reveal that the proposed descriptors and the strategy of distance measure outperform the existing methods of image retrieval.

Keywords: *content-based image retrieval, features extraction, similarity measures*.

1. Introduction

During the last decade, a huge growth in the multimedia information systems involving both the images and videos is observed, which necessitates the requirement for the accurate retrieval of multimedia content from large archives/databases. Here, we are concerned with content based image retrieval, which means that the retrieval of images from the database is based on their features instead of their manual annotations [1]. Content-based image retrieval system has many applications such as medical diagnosis, crime prevention, military services, architectural and engineering design, geographical information, trademark matching, etc. The key task of an image retrieval system is to extract appropriate features from images that can describe their visual contents. Low level features such as texture, color, and shape are used to describe image contents. However, texture features do not provide semantic information [2] and retrieval using color is achieved using color histograms, which identifies the proportion of each pixel holding specific values. The shape feature is associated with a particular object in an image. Therefore, shape semantic features are more effective than texture [3]. Thus, in this paper we concentrate on the shape based image retrieval. A lot of research has been performed on the image retrieval system based on the shape. Shape based image retrieval is usually organized into two parts: contour based shape descriptors and region based shape descriptors. Contour based descriptors are associated with the outline or boundary of the shape, which represents the local structure of an image. On the other hand, region based descriptors provide the global structure of an image. Some of the effective contour based shape descriptors are wavelet descriptors [4], curvature scale space [5], Fourier descriptors (FD) [6], chain codes [7], Weber local descriptor (WLD) [8], contour point distribution histogram (CPDH) [9]. Region based shape descriptors include geometric moments [10], moment invariants (MI) [11], generic Fourier descriptors (GFD) [12].
For realization of IR, two important issues must be addressed. One is how to extract appropriate feature vectors to represent image content correctly, and the other is how to carry out the image retrieval based on the extracted feature vectors effectively. For images, the shape feature vectors are usually used to represent image content, so in this paper we concentrate on shape- based solution for IR. Jain et al. [13] proposed the weight-based solution (WBS), in which the extracted feature vector includes two shape features: edge directions and invariant moments and a weight-based strategy were presented for feature matching. Wei et al. [14] proposed the two-component solution (TCS), in which centroid distances, contour curvature and Zernike moments were selected as the shape features, while a two-component strategy was applied in feature matching. Qi et al. [15] proposed the trademark image retrieval system, the local features are extracted using relationship among two adjacent boundary points and the global features are extracted using spatial distribution of feature points. Singh et al. [16] proposed the image retrieval system using combined features, the local features is presented by computing histograms of distances from edge lines to the centroid of edge image and the Zernike moments are used to extract the global features.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

In this paper, an effective solution for IR is proposed, which consists of both shape description and feature matching. The main contribution of this paper as follows: An effective shape description method to extract the feature vector from images is proposed. In our method, two shape descriptors are used. The contour-based shape descriptor not only represents the feature of every boundary points but also consider the relationship among two adjacent boundary points and the centroid. The region-based descriptor based on improved feature points matching to avoid the complex calculation of Zernike moments.
An effective feature matching strategy to compute the dissimilarity value between a query image and an arbitrary image in the database is presented.
One of the fundamental ways of describing objects in an image is by mathematical functions that describe the adjacency among the edge points. A highly effective way of utilizing this kind of information is the Hough transform. The Hough transform is a robust technique to link edge points in predetermined shapes: lines, curves, circles, ellipses, etc. It links all edge points that are closest to the given shape and hence it is based on the summation operations. We know that an image processing operation based on summation or integration is robust to noise and thus Hough transform provides consistent results under noisy conditions [17]. The main difficulty with Hough transform is its high computation complexity, therefore, normally the lowest order curve, i.e., linear edges (lines) are preferred over high order curves. In addition, fast algorithms exist for line detection [18], which reduces the high time requirement of Hough transform. The features derived from the normalized distances of linear edges to the centroid of edge image can be made invariant to affine transformations. Thus, in this paper, we employ two types of features: the local features representing the adjacency using Hough transform to detect linear edges and the global features using the spatial distribution of feature points-feature points matching SDFP-FPM. For computing similarity between images, an effective similarity measure known as Bray–Curtis [19] is applied, which we observe to be more effective than Euclidean distance. Bray–Curtis distance provides normalized similarity values as it is computed using summation of the absolute differences divided by summation of their absolute additions, hence their values always lie in the range of [0,1]. As a result, features with higher magnitudes will not dominate features with lower magnitudes. We perform extensive experiments over five databases representing various aspects of images. The results of experiments authenticate that the proposed method outperforms the existing methods in terms of accuracy and top relevant retrievals.

In shape description, features are generally classified into two types. One is the contour-based shape feature, and the other is the region-based shape feature. Contour-based shape feature is the feature extracted from the shape boundary points only, while region-based shape feature is the feature extracted from the shape interior points.
In general, the feature matching strategies are proposed to compute the similarity value or the dissimilarity value of images based on the combination of the contour-based shape features and the region-based shape features.
The rest of this paper is organized as follows. Section 2 provides an overview of the proposed system architecture. Section 3 presents the algorithms proposed for extracting shape descriptors. Section 4 presents Bray–Curtis similarity measure to compute the similarity value.
Detailed experimental results and performance evaluations are given in Section 5 and Section 6 provides conclusion.

2. Overview of the proposed system

Image retrieval system consists of an offline database construction part and an online image retrieval part as shown in Fig. 1. The offline database construction part is intended to ensure high retrieval efficiency by extracting a feature set for each of the images in the database in an offline manner and storing the feature set along with its corresponding image in the database so that when a query image is presented to the system, the system does not have to perform online feature extraction on each database image.
To access the database, the user initiates the online image retrieval process by providing a query image as input, and then the system starts with extracting the features from the query image. Afterwards, the system measures the similarity between the feature set of the query image and those of the images stored in the database. Finally, the system ranks the relevance based on the similarity and returns the results to the user.

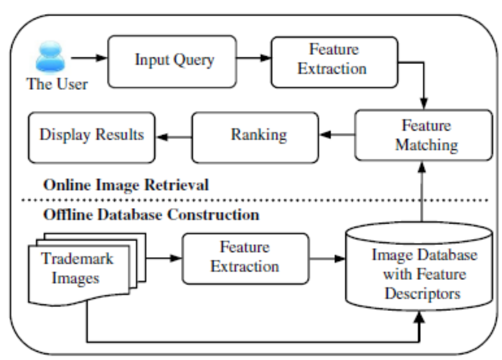

Fig. 1. The architecture of the proposed image retrieval system

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

3. Shape descriptors

The extraction of significant features from shape is one of the principal responsibilities of an effective shape descriptor. An image can be described either by its local features, which are associated with the contour of the shape or by global features that describe the region of the shape. Both local and global features have their own advantages and disadvantages. However, if we utilize them together, they can provide better results because they are complimentary to each other. Moreover, an effective classifier is needed to realize better performance of a retrieval system, which exploits the full potential of the features. Therefore, we use both local and global features to describe images and combine them with the help of Bray–Curtis similarity measure.

In this section, a shape descriptors are proposed, which characterizes local and global features extraction. Local features are extracted using Hough transform for describing the contour of the shape and global features extraction is done by using SDFP-FPM for describing the region of the shape.

3.1.Hough Transform: Contour-based shape descriptor

Hough transform is an effective technique for detecting lines from an edge image, which is widely used in computer vision and pattern recognition. Hough transform maps a line in the spatial domain to a point in the Hough parametric domain [20]. The Hough parametric space is a 2-D space and is described in the form (m, b) in the Cartesian coordinates system, where m and b represent the slope and intercept of the line, respectively, passing through the point (x_i, y_i). The transform is represented by

$$b = -mx_i + y_i \tag{1}$$

Eq. (1) refers to the equation of a single line for an edge point (x_i, y_i) in parameter space, i.e., in $m - b$ plane. If there finds another edge point (x_k, y_k) satisfying Eq. (1) then the edge points are collinear as shown in Fig. 2. Hough transform is implemented by a voting method in which all edge points voting to a given point (m, b) are said to belong to the same line. Thus, one of the parameters say m is chosen and its value is varied in a given interval $[-1, +1]$ and the other parameter is computed using Eq. (1) for an edge point (x_i, y_i). The process is repeated for all the edge points. The order of complexity of the method is $O(ES)$ where E is the total number of edge points, and S is the total values of the parameter m between -1 and +1. The dynamic range of both the parameters m and b is $[-\infty, \infty]$, it is restricted to the finite domain by splitting the range of m in two parts: $|m| \le 1$ and $|m| > 1$, as given by the following equations:

$$b = \begin{cases} -mx_i + y_i, & |m| \le 1 \\ -my_i + x_i, & |m| > 1 \end{cases} \tag{2}$$

This is done to keep the absolute value of the slope less than or equal to 1. This approach is adopted to avoid slope taking very high or infinite values. The complete procedure of local features extraction is described as follows:

-A threshold edge image is acquired by applying the Canny edge detector [21]. It finds the discontinuities in an image and produces a binary edge map, which preserves the crucial structural properties and significantly reduces the amount of data in an image. The resulting edge map represents the contour of the original image.

-The edge points detected using Canny operator are linked using Hough transform to detect lines from the edge image, and to create an association among adjacent edge points. We select all the lines with $n \ge 3$ points, where n is the number of points on a line, so that, the complete contour of the image can be described

-The centroid (x_c, y_c) of the edge image is computed

-The perpendicular distance of each linear edge from the centroid (x_c, y_c) of the edge image is computed as

$$d_i = \frac{|m_i x_c + b_i - y_c|}{\sqrt{1 + m_i^2}} \tag{3}$$

Where m_i and b_i are the slope and intercept of the ith linear edge.

All the distances are normalized between [0, 1] by dividing d_i by $d_{\max}$, where $d_{\max} = \max\{d_i\}$, $0 \le i < L$, where L is the total number of lines. This makes the edge line feature translation, scale, and rotation invariant. Histograms are generated by quantizing the normalized values into 10 bins [0-0.1], [0.1-0.2], …, [0.9-1]. The normalized histograms are presented in percentile, i.e. $p_i = l_i / \sum_{i=0}^{9} l_i$, where l_i is the frequency of the ith bin.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

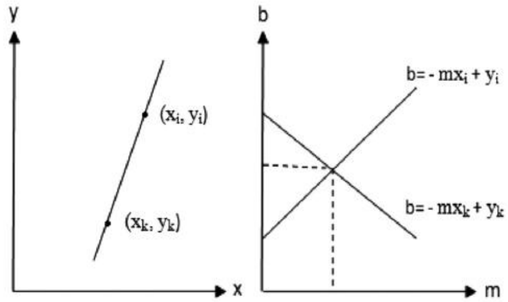

Fig. 2. Hough transform demonstration

3.2. SDFP-FPM: region-based shape descriptor

The moment shape descriptors are used in the weight-based solution and the two-component solution to represent the region-based shape feature. Among these moment descriptors, Zernike moments are better than others, which have been adopted by MPEG-7 as a region-based shape descriptor [22]. But the computation of Zernike moments is very complex. To the best of our knowledge, feature points matching (FPM) is used in image retrieval only recently, e.g., medical image search based on FPM [23]. In FPM, the spatial distribution of feature points (SDFP) is seldom considered. An improved descriptor described by SDFP-FPM, which combines the feature points matching and the spatial distribution of feature points to represent the region-based shape feature is proposed.

In the process of feature points matching, we use the Kanade– Lucas–Tomasi feature tracker [24] to extract feature points for a given image. After extraction of feature points, the similarity value between two images can be calculated. Suppose that a is the query image and b is an arbitrary image in the database, N_a denotes the number of feature points extracted from a, M_{ab} denotes the number of feature points which are extracted from a and traced on b, so we have $M_{ab} \le N_a$. S_{ab} , the similarity value between a and b can be calculated as follows:

$$S_{ab} = \frac{M_{ab}}{N_a} \tag{4}$$

The final retrieval results are sorted by the descending order of S_{ab} . To represent the spatial distribution of feature points, we build the histogram of feature points. The process is described as follows:

- For each image, using the open source tool KLT, which is an implementation of the Kanade–Lucas–Tomasi feature tracker, to extract feature points.

- In this open source tool the upper-left corner of the image is used as the origin. To reduce the complexity of computation, we do not change the position of origin. We can compute the distance between the origin and each feature point.

- After computing the corresponding distances of all feature points, the values are normalized to build the histogram.

When we get the histogram of feature points, the Bray-Curtis is used to compute the dissimilarity value between any two histograms. According to the above analysis, we can obtain S_{ab} which denotes the similarity value between two images based on the FPM and D_{ab} which denotes the dissimilarity value between two images based on the SDFP. Because we have $0 \le S_{ab} \le 1$, we can define $D'_{ab} = 1 - S_{ab}$ to represent the dissimilarity value based on FPM. In our method, if the dissimilarity value of the region-based shape features between two images is denoted by D^r_{ab}, we have $D^r_{ab} = D'_{ab} + D_{ab}$.

Based on the analysis in this section, we can see that the proposed shape description method consists of two effective shape descriptors: H.T and SDFP-FPM. By H.T detecting lines from an edge image are extracted as the contour-based shape feature, while feature points and their spatial distribution are extracted by SDFP-FPM as the region-based shape feature. As the result of our shape description method, the shape feature vector includes the contour-based feature and the region-based feature.

4. Effective similarity measure

In this section, an effective feature matching strategy to compute the dissimilarity value between feature vectors is proposed. The smaller the global dissimilarity value between feature vectors of any two images is, the more similar these two images are. For a query image and an arbitrary image in the database, we can use our shape description method to extract their feature vectors. Then, the global dissimilarity value between their feature vectors is computed by our feature matching strategy. Finally, we sort the images in the database based on these dissimilarity values to get retrieval results of the query image.

In the past, Euclidean distance measure is commonly used to calculate the similarity value between images. However, Euclidean similarity measure does not normalize the feature values. Eventually, some features exhibiting higher magnitudes dominate features with lower magnitudes. Therefore, contribution made by lower magnitudes may become insignificant irrespective of their effectiveness. Moreover, the distances in each dimension are squared before summation, which lays greater

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

emphasis on those features for which the dissimilarity is large.

We propose Bray–Curtis [25] similarity measure, which normalizes the feature values by dividing the absolute difference of corresponding feature values by the absolute value of their sum. The Bray–Curtis similarity measure for the proposed contour based descriptor is given as

$$d_c(Q,D)=\frac{\sum_{i=0}^{N-1}\left|f_i(Q)-f_i(D)\right|}{\sum_{i=0}^{N-1}\left|f_i(Q)+f_i(D)\right|} \tag{5}$$

Where $f_i(Q)$ and $f_i(D)$ represent the feature vectors of the query and the database images, respectively, which is 10 for contour based features. The Bray–Curtis similarity measure for the proposed region based descriptor is given as

$$d_r(Q,D)=\frac{\sum_{i=0}^{n-1}\left|H_i(Q)-H_i(D)\right|}{\sum_{i=0}^{n-1}\left|H_i(Q)+H_i(D)\right|} \tag{6}$$

Where $H_i(Q)$ and $H_i(D)$ are the feature vectors of the query and the database images, respectively, and n is the number of features. As we take into account both local and global features to describe the shape, Bray–Curtis distance of both local and global features are combined to compute the overall similarity given as

$$d(Q,D)=w_c d_c(Q,D)+w_r d_r(Q,D) \tag{7}$$

Where w_c and w_r represent the weight factors of the contour based and region based similarity measures, respectively.

5. Experiments and performance evaluation

The objective of our experiments is to demonstrate the effectiveness of the proposed system and its enhanced performance over other methods. In order to evaluate the performance of the proposed system, we carry out extensive set of experiments in which our results are compared with four recent approaches, WBS, TCS, QLS and HZS. All the methods are implemented using the approaches mentioned in their research papers.

The experiments are performed on a computer which has an Intel Pentium Dual-Core processor (2.30 GHz) with 2.00 GB memory. Our solution and other compared solutions are implemented in Matlab and C++ languages. Some popular open source libraries for image processing are used in the experiments, including IPL98 [26], FOURIER 0.8 [27], KLT [28]. We consider five standard databases to review the system performance under various conditions such as rotation, scale, image type, 3D objects, complex structured, and texture images, which are described as follows:

Kimia-99: it contains 9 classes of binary images with 11 instances in each class. The variations include distortions, partial occlusion by other objects, different poses, styles.

Columbia Object Image Library (COIL-100): this database contains color images of 100 classes of 3D objects with 72 samples in each class, taken with pose variation from 0° to 360° with interval of 5°.

Trademark: 20 trademark images with complex inner structure are collected from the Internet, which are then resized and oriented to five different sizes (64×64, 80×80, 96×96, 112×112, and 128×128) and to five different orientations (0°, 36°, 72°, 108°, and 144°). Thus, the database consists of 25 instances per class and a total of 500 images.

MPEG-7 CE shape-1 part B: it consists of 1400 images having 70 classes of images with 20 instances in each class. This database represents variations in instances of same class.

Brodatz: this database consists of 64 classes of texture. The database is expanded by resizing the images to five different sizes (64×64, 80×80, 96×96, 112×112, and 128×128) and to five different orientations (0°, 36°, 72°, 108°, and 144°). Thus, the database consists of 25 instances per class and a total of 1600 images.

5.1. Measurement of retrieval performance

Two performance evaluation tests to measure the retrieval accuracy of the system are used. The first one is precision (P) and recall (R) to evaluate the retrieval performance of the proposed and the current state of the art approaches. The other test is the Bull's Eye Performance (BEP), which measures the retrieval accuracy of the system. These tests are described as follows:

5.1.1. Precision and Recall (P–R)

Precision measures the retrieval accuracy and recall measures the ability to retrieve relevant images from the database. Precision and recall are inversely proportional to each other as the precision reduces, the recall increases. We use average precision and average recall for all the

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

retrieval results. For a test image t we calculate precision and recall in percentage as follows:

$$P = \frac{n_t}{T_t} \times 100, \quad R = \frac{n_t}{D_t} \times 100 \tag{8}$$

Where n_t represents the number of similar images retrieved from the database, T_t represents the total number of images retrieved, D_t represents the number of images in database similar to test image t.

5.1.2. Bull's Eye Performance (BEP)

BEP is measured by the correct retrievals among the top 2R retrievals, where R is the number of shapes, which are relevant to the test image in the database. We use average percentage value to measure BEP.

5.2. Performance comparison and results

In the proposed solution, after deriving local and global features using HLTC and SDFP-FPM, respectively, Bray–Curtis similarity measure is applied to compute the similarity values. These values are then sorted in ascending order and images with the smallest distances to the test image are considered as relevant images. The proposed method is examined against the approaches shown in Fig. 3. In order to assess the system performance for each type of image, all the images in the database are served as test images. For this purpose, we perform five set of tests. In the first set of tests, we compare the results of the proposed system for Kimia-99 database. The performance is evaluated using P–R curves, The P-R comparisons with approaches, WBS, TCS, QLS and HZS, are given in Fig. 3, which shows that the proposed method performs better than other approaches.
The second test is performed over COIL-100 database, which contains 3D objects and the P-R comparisons over this database is given in Fig. 4. The proposed method still has the best performance.
The third test is performed over Trademark dataset, which contains images of complex structures and several connected regions. The P-R performance is given in Fig. 5. It is observed from the graph that the performance of the proposed solution still preserves its effectiveness over other approaches.
The fourth test is performed over MPEG-7 database, and the performance is depicted in Fig. 6. It can be seen from the graph that the performance of the proposed descriptor is superior to other methods.
In the fifth test, the performance of the proposed system is analyzed for Brodatz texture database as displayed in Fig. 7. It is observed that the proposed solution have the highest retrieval accuracy.

The proposed system outperforms all other methods due to its effective descriptors and by the use of high number of features with an effective similarity measure.
We compute the retrieval rate of all the methods using BEP over five databases, which is presented in Table 1.
The average retrieval rate of all the methods is also presented in the last row of the table. We observe that by considering databases representing various transformations, the performance of the proposed system is extremely effective and provides the highest average retrieval rate. Therefore, the retrieval results under various conditions demonstrate the effectiveness of the proposed system over the other approaches. Some of the retrieval results by the proposed system for all the five standard databases are presented in Fig. 8-12, which is all relevant to their respective test images.

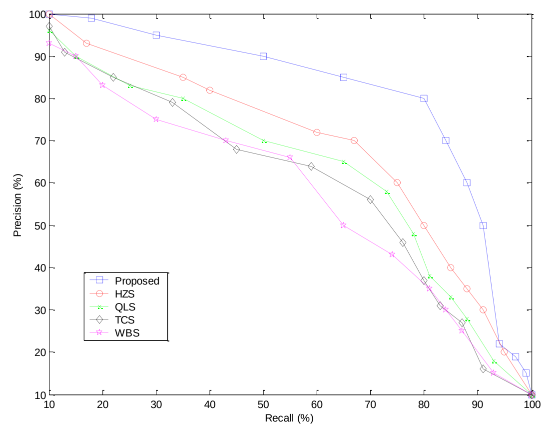

Fig. 3. P-R comparisons for Kimia-99 database against other approaches

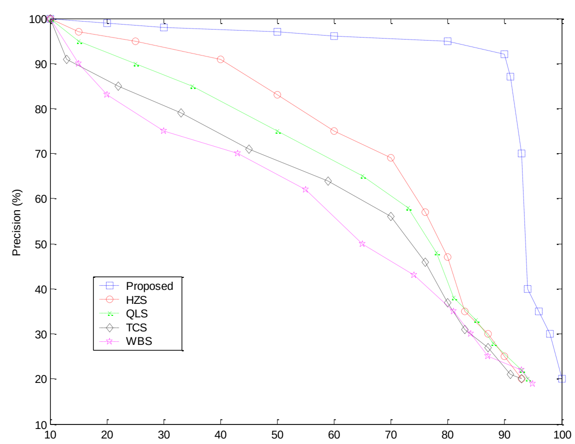

Fig. 4. P-R comparisons for COIL-100 database against other approaches.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

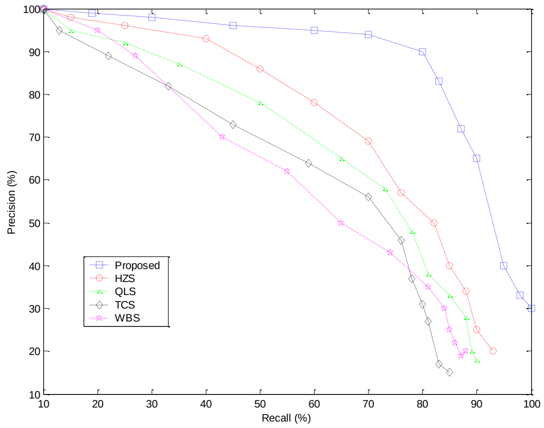

Fig. 5. P-R comparisons for Trademark database against other approaches.

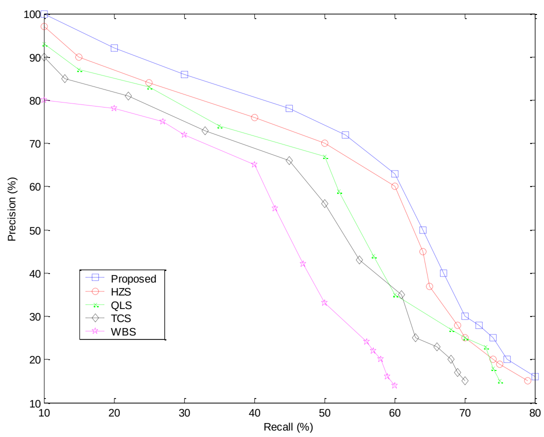

Fig. 6. P-R comparisons for MPEG-7 database against other approaches

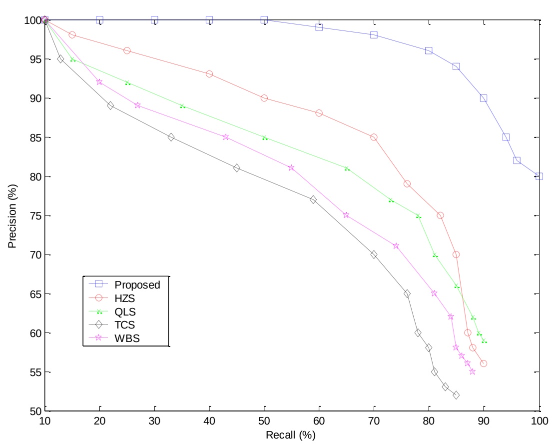

Fig. 7. P-R comparisons for Brodatz database against other approaches

Table 1. Comparison of average BEP of the proposed and other approaches.

	WBS	TCS	QLS	HZS	Proposed
Kimia-99	61.92	59.21	72.81	81.30	94.53
COIL-100	64.11	67.52	79.73	85.61	99.22
Trademark	63.17	55.12	76.13	88.01	97.68
MPEG-7	53.86	62.71	69.94	80.49	81.19
Brodatz	72.19	63.80	80.06	89.16	99.73
Average	63.05	61.67	75.73	84.91	94.47

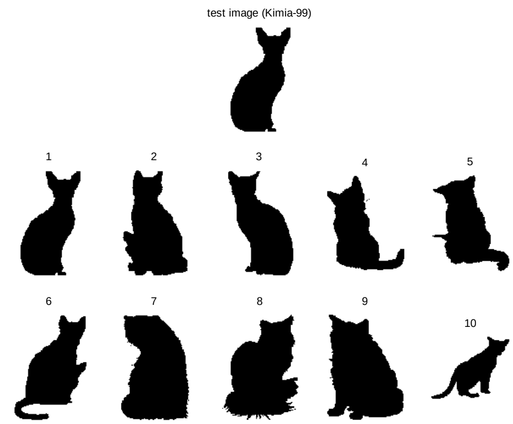

Fig. 8. Retrieval results for Kimia-99 database by the proposed system

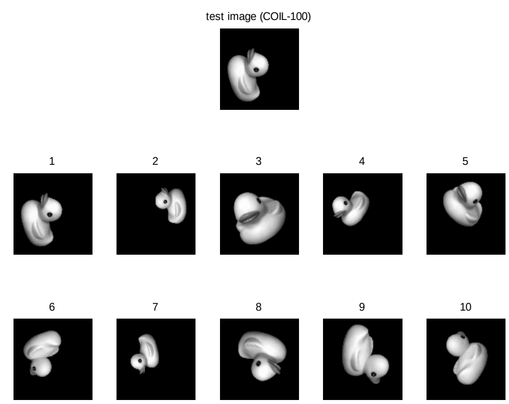

Fig. 9. Retrieval results for COIL-100 database by the proposed system

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

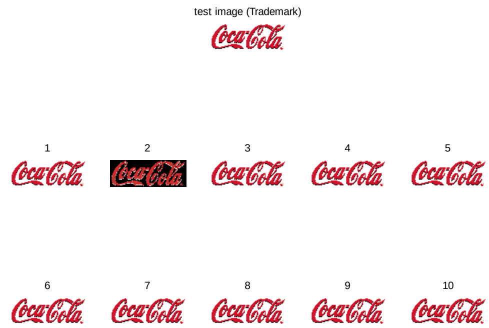

Fig. 10. Retrieval results for Trademark database by the proposed system

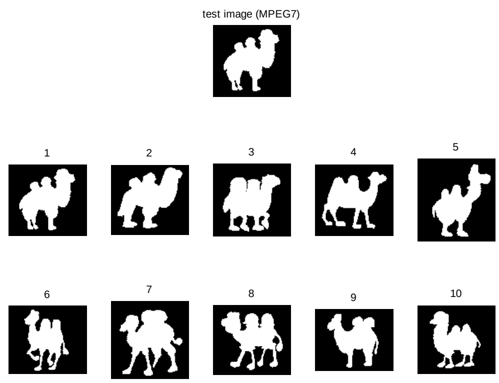

Fig. 11. Retrieval results for MPEG-7 database by the proposed system

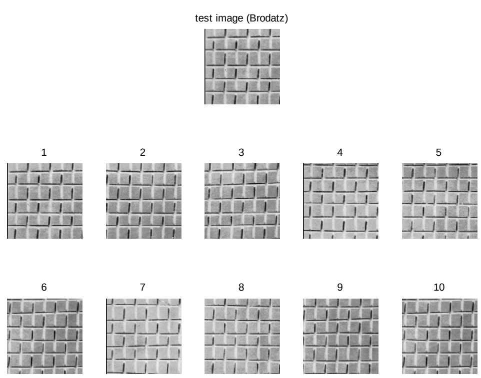

Fig. 12. Retrieval results for Brodatz database by the proposed system

6. Conclusions

In this paper, a novel solution which consists of an effective shape description method and an effective feature matching strategy is proposed. In the shape description method, two feature descriptors are presented. Local features are extracted by detecting linear edges of the edge map of the image using Hough transform and then computing the normalized histograms of distances of lines from the centroid of the edge image. The region-based feature descriptor includes the feature points matching and the spatial distribution of feature points.
As for the image retrieval stage, a two-component matching strategy was used in feature matching. With this strategy, the images can be compared with the query image with their local and global features taken into account separately, and therefore enabling the system to be insensitive to noise or small regional changes. The performance of the proposed algorithm was evaluated in terms of the precision and recall rates. The precision–recall graphs and the extensive experimental results demonstrate the robustness and effectiveness of the proposed solution, which outperforms other conventional algorithms.

References

[1] Schietse J, Eakins JP, Veltkamp RC. "Practice and challenges in trademark image retrieval". In: Proceedings of the sixth ACM International conference on image and video retrieval; 2007.
[2] Chun YD, Kim NC, Jang IH. "Content-based image retrieval using multiresolution color and texture features". IEEE Trans Multimedia; 10(6), 1073–84, 2008.
[3] Manjunath BS, Salembier P, Sikora T. "Introduction to MPEG-7: multimedia content description Interface". Chichester: Wiley; 2002.
[4] Atta Elalfi, Mohamed Eisa and Hosnia Ahmed, "Artificial Neural Networks in Medical Images for Diagnosis Heart Valve Diseases", (IJCSI) International Journal of Computer Science Issues, Vol. 10, Issue 5, No 1, Sep. 2013, 83-90
[5] Mokhtarian F, Mackworth AK. "A theory of multiscale, curvature based shape representation for planar curves". IEEE Trans Pattern Anal Mach Intell, 14: 789–805, 1992.
[6] Wimmer A, Ruppert GS, Sidla O, Konard H, Gretzmacher F. "FFT descriptors for shape recognition of military vehicles". Proc SPIE Int Soc Opt Eng, 2000.
[7] Dubois SR, Glanz FH. "An autoregressive model approach to two dimensional shape classification". IEEE Trans Pattern Anal Mach Intell; 8: 55–65, 1986.
[8] Chen J, Shan S, He C, Zhao G, Pietikainen M, Chen X, et al. WLD: "a robust image local descriptor". IEEE Trans Pattern Anal Mach Intell; 32(9): 1705–20, 2010.
[9] Shu X, Wu X-J. "A novel contour descriptor for 2D shape matching and its application to image retrieval". Image Vis Comput, doi: 10.1016/j.imavis.2010.11.001, 2011.
[10] A. Amanatiadis, V.G. Kaburlasos, A. Gasteratos, S.E. Papadakis, "Evaluation of shape descriptors for shape-based image retrieval", IET Image Process. 5 (5) (2011) 493-499.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.

[11] V. Abdul Hameed and S. Mariyam Shamsuddin, "Generalized Rotational Moment Invariants for Robust Object Recognition", Int. J. Advance Soft Compu. Appl, Vol. 15, No. 3, Nov. 2013.
[12] Zhang D, Lu G. "Shape-based image retrieval using generic Fourier descriptor". Sig Process: Image Commun; 17: 825–48, 2002.
[13] A.K. Jain, A. Vailaya, "Shape-based retrieval: a case study with trademark image database", Pattern Recognition, 31: 1369–1390, 1998.
[14] C.H. Wei, et al., "Trademark image retrieval using synthetic features for describing global shape and interior structure", Pattern Recognition 42: 386-394, 2008.
[15] Qi H, Li K, Shen Y, Qu W. "An effective solution for trademark image retrieval by combining shape description and feature matching". Pattern Recognition; 43: 2017–27, 2010.
[16] Singh C, Pooja. "Improving image retrieval using combined features of Hough transform and Zernike moments". Optics and Lasers in Engineering 49: 1384-1396, 2011.
[17] Rahmdel, P.S., Shi, D.M., Comley, R., "Comment on Collinear Segment Detection Using HT Neighborhoods", IP(23), No. 2, Feb. 2014, pp. 952-955.
[18] Singh C, Bhatia N, Kaur A. "Hough transform based fast skew detection and accurate skew correction methods". Pattern Recognition, 41: 3528–46, 2008.
[19] Deza MM, Deza E. "Encyclopedia of distances". Berlin, Heidelberg: Springer-Verlag; 2009.
[20] Gonzalez RC, Woods RE. Digital image processing. Prentice Hall; 2008.
[21] Canny J. "A computational approach for edge detection". IEEE Trans Pattern Anal Mach Intell, 8(6): 679–98, 1986.
[22] D. Zhang, G. Lu, "Review of shape representation and description techniques", Pattern Recognition, 37: 1–19, 2004.
[23] D. Unay, A. Ekin, R. Jasinschi, "Medical image search and retrieval using local binary patterns and KLT feature points", in: IEEE International Conference on Image Processing, 2008.
[24] Shanmugapriya, N. and R. Nallusamy, "A NEW CONTENT-BASED IMAGE RETRIEVAL SYSTEM USING GMM AND RELEVANCE FEEDBACK", Journal of Computer Science 10 (2): 330-340, 2014.
[25] Kokare M, Chatterjee BN, Biswas PK. "Comparison of similarity metrics for texture image Retrieval". IEEE Conf Convergent Technol Asia-Pacific Reg; 2: 571–5, 2003.
[26] http://www.mip.sdu.dk/ipl98.
[27] http://www.lsus.edu/faculty/~ecelebi/fourier.htm.
[28] http://www.ces.clemson.edu/~stb/klt/index.html.

Copyright (c) 2014 International Journal of Computer Science Issues. All Rights Reserved.