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Image retrieval based on shape similarity by edge orientation autocorrelogram

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Abstract

This paper introduces a new feature vector for shape-based image indexing and retrieval. This feature classifies image edges based on two factors: their orientations and correlation between neighboring edges. Hence it includes information of continuous edges and lines of images and describes major shape properties of images. This scheme is effective and robustly tolerates translation, scaling, color, illumination, and viewing position variations. Experimental results show superiority of proposed scheme over several other indexing methods. Averages of precision and recall rates of this new indexing scheme for retrieval as compared with traditional color histogram are 1.99 and 1.59 times, respectively. These ratios are 1.26 and 1.04 compared to edge direction histogram.

Keywords: Image retrieval; Image indexing; Shape-based indexing; Non-segmentation based indexing

1. Introduction

Visual information retrieval has become a major research area due to the ever-increasing rate at which images are generated and applied in many fields. Image databases are becoming larger and more widespread, and there is a growing need for effective and efficient content-based image retrieval (CBIR) systems [1]. Color histograms are a popular solution, and many CBIR systems employ this feature vector [2–5]. Color histograms are computationally efficient, and generally insensitive to small changes in viewing position. However, they ignore spatial information, nd therefore are not robust to large appearance changes in images.

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Color-spatial schemes incorporate spatial information with color [6–11]. These approaches offer more effectiveness in comparison with the primary method with little efficiency reduction. Despite the achieved advantage, they suffer from sensitivity to color and illumination changes. For example, Fig. 1 shows a building with two different illumination conditions, but the color-spatial based feature vectors of these images are significantly different. Therefore, they are branded dissimilar by color-spatial approaches. In other words, these approaches are particularly ineffective for image retrieval by shape similarity. This disadvantage results in research on color independent CBIR methods; shape-based image retrieval schemes.

The shape-based scheme is retrieval based on the shape similarity of images. This requires achieving some information related to approximate shape of the objects in images. This information is the basis of feature vector generation. We can divide the shape-based algorithms from segmentation point of view; segmentation and non-segmentation

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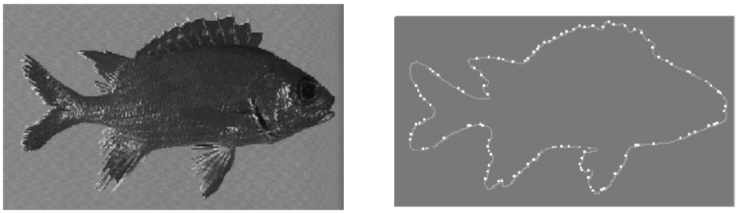
(a) (b)

Fig. 1. An example of two images with different illumination.



(a) (b)

Fig. 2. An example of segmentation-based indexing.

based methods. The segmentation-based methods [12–20] detect the homogeneous regions of images, and then compute the feature vector with some region information like surface, contours, corners, etc. For example, Mokhtarian et al. [15,18,19] detected contours of the main object in image shown in Fig. 2 and generated the feature vector with computing curvature. These methods are effective and compatible with human perception. However, they suffer from three following difficulties: (1) segmentation is never perfect; (2) they are unable to identify high frequency images; and (3) they have high computational overhead. These difficulties constrain segmentation-based methods to some special domains, for example, face identification.

The non-segmentation based methods extract shape factors of an image and generate feature vector without image segmentation [21–30]. For example, Zheng and Leung [24] presented a method using approximate segmentation, in order to avoid complete segmentation computational overhead. This method converted the image into a binary image, extracted 12 shape factors, and employed them as a feature vector. Since a binary image cannot detect homogeneous regions perfectly and regions merge together, this method is ineffective particularly in large image databases. Jain and Vailaya [22,26,27] introduced edge direction histogram (EDH). This method finds the image edges, and with grouping them on the quantized edge directions, generates the EDH. This method is relatively effective and performs retrieval independent of translation, scaling, and viewing position variations. Since this method uses the edges individually and ignores correlation between neighboring edges, its effectiveness is limited. Mahmoudi et al. [28,30] overcame this problem and introduced direction histogram of similar edges (DHSE), a feature vector more effective than EDH. DHSE considers the correlation between neighboring edges using a weighting function and adds this extra information to the edge direction histogram.

This paper proposes a new non-segmentation shape-based image retrieval method called the *edge orientation autocorrelogram* (EOAC). The highlights of this approach are: (1) it includes the correlation between neighboring edges in a window around the kernel edge; (2) it describes the global distribution of local correlation of edges; (3) it describes shape aspects of an image and thus it is not sensitive to color and illumination variation; (4) it acts independent of translation, scaling, and small rotation; (5) it is easy to compute, and (6) the size of the resulting feature vector is small. Our experiments show that this new feature outperforms non-segmentation based methods in retrieval by shape similarity.

The organization of the rest of paper is as follows. Section 2 introduces the edge orientation autocorrelogram algorithm. Section 3 discusses the advantages and disadvantages of normalization algorithms employed to make feature vector invariant with respect to scaling, color, illumination, and rotation. Section 4 describes the retrieval evaluation test-bed, and illustrates the superiority of the new scheme over other similar methods. The final section presents the conclusions.

2. Edge orientation autocorrelogram

Correlogram is a proper tool to express the correlation between image elements [31]. This paper introduces a new approach to Correlogram called edge orientation autocorrelogram (EOAC) for image retrieval. The EOAC classifies edges based on their orientations and correlation between neighboring edges, hence it contains major shape properties of the image. The algorithm of generating EOAC consists of five steps as follows:

(1) *Edge detection*: The *Sobel* operator is less sensitive to noise than other edge detectors [32]. Therefore it has been used for edge detection and making the gradient image. This operator generates two edge components, G_x and G_y. The amplitude and edge orientation is computed as follows:

$$|G| = \sqrt{G_x^2 + G_y^2}, \tag{1}$$

$$\angle G = tg^{-1}(G_y/G_x). \tag{2}$$

(2) *Finding prominent edges*: This step extracts the prominent edges of the gradient image. The prominent edges are extracted by comparing all the edge amplitudes with a threshold value T_1. We have chosen $T_1 = 25$, which is approximately 10% of the maximum intensity value in the 8-bit original images [32].

(3) *Edge orientation quantization*: This step quantizes the edges uniformly into n segments $\angle G_1, \angle G_2, \angle G_3, \ldots, \angle G_n$, and each segment is equal to five degrees.

(4) *Determining distance set*: This step constructs a distance set (D), which shows the distances from the current edge that is used in calculating correlation. It is clear that near edges have high correlation together, thus the number and value of members of D must be low. In our algorithm we have chosen a set with four members as shown below:

$$D = \{1, 3, 5, 7\} \quad \text{and} \quad d = |D| = 4. \tag{3}$$

There is no need to consider the pixels with even numbers, because most of their information is in their adjacent pixels with odd numbers. For example, the correlation information associated with 2 pixels apart can be extracted from 1 and 3 pixels apart.

(5) *Computing elements of EOAC*: In the final stage, the edge orientation autocorrelogram is constructed. This correlogram is a two-dimensional array (a matrix), consisting of n rows and d columns. The $\langle j,k \rangle$element of this matrix ($1 \leqslant j \leqslant n,\ k \in D$) indicates the number of similar edges with the orientation $\angle G_j$, which are k pixel distances apart. Two edges with k pixel distances apart are said to be similar if the absolute values of their orientations and amplitudes differences are less than an angle and an amplitude threshold value, respectively [32].

Fig. 3 illustrates the EOAC matrixes for two sample images as 3D graph. We have used this 3D EOAC as a feature

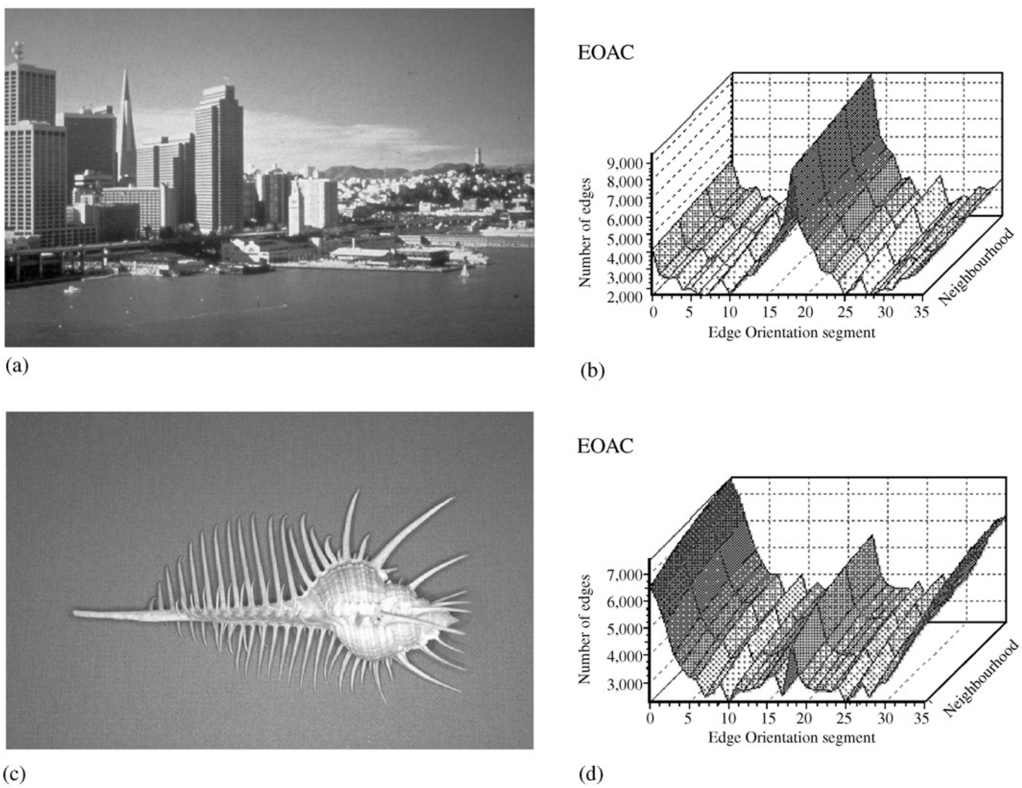


Fig. 3. EOAC graphs for two-image samples.

vector for describing shape content of an image and as an index for shape-based image retrieval.

3. Feature vector normalization

It is desirable that image retrieval similarity-matching algorithm correspond to the human similarity judgment. A human can recognize similar images independent of five factors: translation, rotation, scaling, color, and illumination variations. Therefore, an effective image retrieval system should work the same. This section performs some modifications, called *normalizations*, on the proposed feature vectors to make it invariant with respect to the five mentioned factors. EOAC is naturally translation invariant, because translation has no effect on amplitude and orientation of edges. However this is not the case for the rest of factors.

3.1. Normalization against scaling variation

Since the total number of edge pixels depends to the total number of image pixels, image scaling affects the total number of edges. In contrast, image scaling has no effect on their orientation and amplitude, because edges are constructed on the borders of regions with different colors and when an image is resized its regions relative position and color remain unchanged. For these reasons, the total number of edges is scaled uniformly in the EOAC surfaces. We have illustrated this discussion through an example shown in Fig. 4. Fig. 4a and d show an image of a forest and its EOAC graph, respectively. Fig. 4b and e show the same image after scaling variation and its EOAC graph. These two EOAC graphs are similar with only one difference between them: populations of EOACs bins are changed with a constant ratio. Therefore, feature vector normalization against scaling variation can be simply performed by dividing the population of each EOACs bin by the sum of the populations of all EOACs bins.

3.2. Normalization against color and illumination variations

Image color and illumination variations change relative intensity difference between neighboring regions, so these variations alter edge amplitudes on the borders of the regions. Therefore, by considering T_1 threshold, these variations change the total number of edges. In contrast, image color and illumination variations have no effect on orientation of edges, because edges are constructed on the borders of regions and when color or illumination of an image is varied, its regions relative position remain unchanged. The Statistical data presented in Table 1 confirms these statements. Table 1 shows the total number of edges, edge amplitude averages, and edge amplitude standard deviations change after illumination variation of the forest image. Note that edge orientation averages, and edge

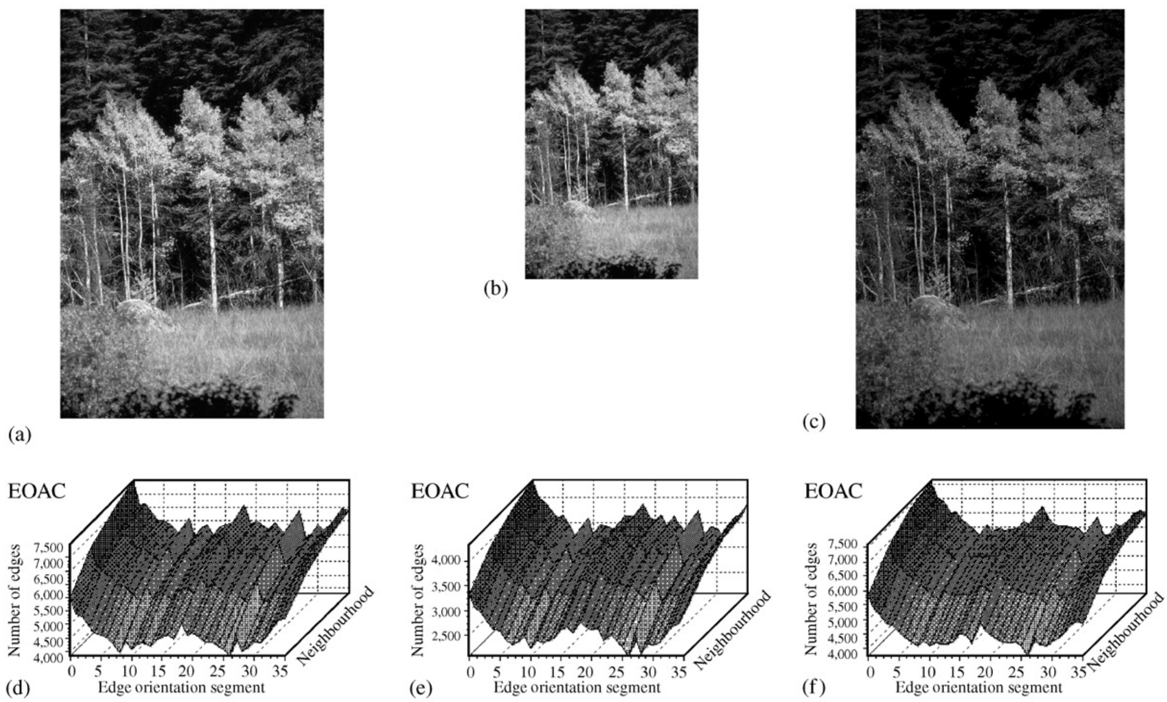


Fig. 4. Effects of scaling and illumination variation on EOAC graphs.

Table 1
Effects of illumination variation on the numbers, amplitudes, and orientations of the forest image

	Forest image	Forest image with illumination variation
Total number of pixels	294,930	294,930
Total number of edges	176,715	130,982
Average of edge amplitudes	212.31	181.07
Standard deviation of edge amplitudes	114.49	92.27
Average of edge orientations	88.92	88.40
Standard deviation of edge orientations	53.00	53.30

orientation standard deviations are approximately the same before and after illumination variation.

For these reasons, the total number of edges is scaled uniformly in the EOAC surfaces. As an example, Fig. 4c and f show the forest image after illumination variation and its EOAC graph, respectively. Comparing two EOAC graph shown in Fig. 4d and f indicates that these two graphs are similar and there is only one difference between them: population of EOACs bins has been changed with a constant ratio. Therefore, the previous feature vector normalization against scaling variation makes feature vector invariant with respect to color and illumination.

3.3. Normalization against rotation

As shown in Fig. 5, rotation of an image only rotates EOACs surfaces, if the following two conditions are satisfied: (1) The shapes of the objects in the image are simple and (2) rotation angle is much greater than orientation quantization level. In this case, normalization process against rotation can be simply accomplished by rotating the surfaces of EOAC so that the peak surface becomes the first surface as shown in Fig. 5. In another case, the normalization process might have undesired effect on feature vector as shown in Fig. 6. This effect causes two dissimilar peak surfaces to coincide, thus it prevents recognizing two relevant images.

4. Experimental results and discussion

This section consists of four subsections as follows: The first subsection describes the image retrieval process. The second subsection presents the specification of the test-bed for retrieval evaluation. The third subsection evaluates the performance of the retrieval scheme. The final subsection shows several retrieval examples and discusses the advantages and disadvantages of the new method.

4.1. Image retrieval process

The EOAC matrixes are precomputed for the entire of the images of the database and stored in a feature database. This reduces the retrieval search time. At retrieval time, query image feature vector is computed in the initial step. Then a linear search is accomplished in the entire feature database and by comparing feature vectors, 12/24 similar images are retrieved in rank order, as shown in Fig. 7. We used $L1$ distance as comparison measures with the following formula:

$$L1(X, Y) = \sum_{i=1}^{n} |x_i - y_i|. \qquad (4)$$

4.2. Retrieval evaluation test-bed

Since there is no standard test-bed for evaluating the performance of image retrieval methods, we have setup a prototype image retrieval evaluation system. We have evaluated EOAC performance and compare it with other schemes by using the evaluation system. The prototype system consists of an image database, a set of benchmark queries, a set of relevant images, and a set of evaluation metrics as described below.

(a) *Image database*: We used 10,000 photos package from Greenstreet (www.gstsoft.com) as an image database. This collection includes 10,000 JPEG color images with different sizes from heterogeneous classes such as: animals, people, sports, recreation, travel, business, holidays, food, textures, cityscapes, natural scene, mountains, caves, clouds, scenic, agriculture, plants, flowers, industries, cars, airplanes, trains, balloons, art, architecture, indoor and outdoor, and so forth.

(b) *Benchmark queries and relevant images*: For the purpose of performance evaluation, we have chosen 65 images from different classes as query images. For each query image, we have considered a set of relevant images and added them to image database. The relevant images are very similar to their query image with some differences on color, illumination, scaling, translation, and viewing position variation. Ideally, when a query is performed all of its relevant images should be retrieved in lower ranks.

(c) *Performance evaluation metrics*: This paper has analyzed the performance in terms of *retrieval accuracy*. This term is concerned with effectiveness of image retrieval. For this purpose, many researchers have computed *precision* and *recall rates* as two accuracy metrics. There is no standard definition for these metrics. Based on the general concepts, different researchers have presented different formulas [9,33–36]. Semantically, recall rate evaluates

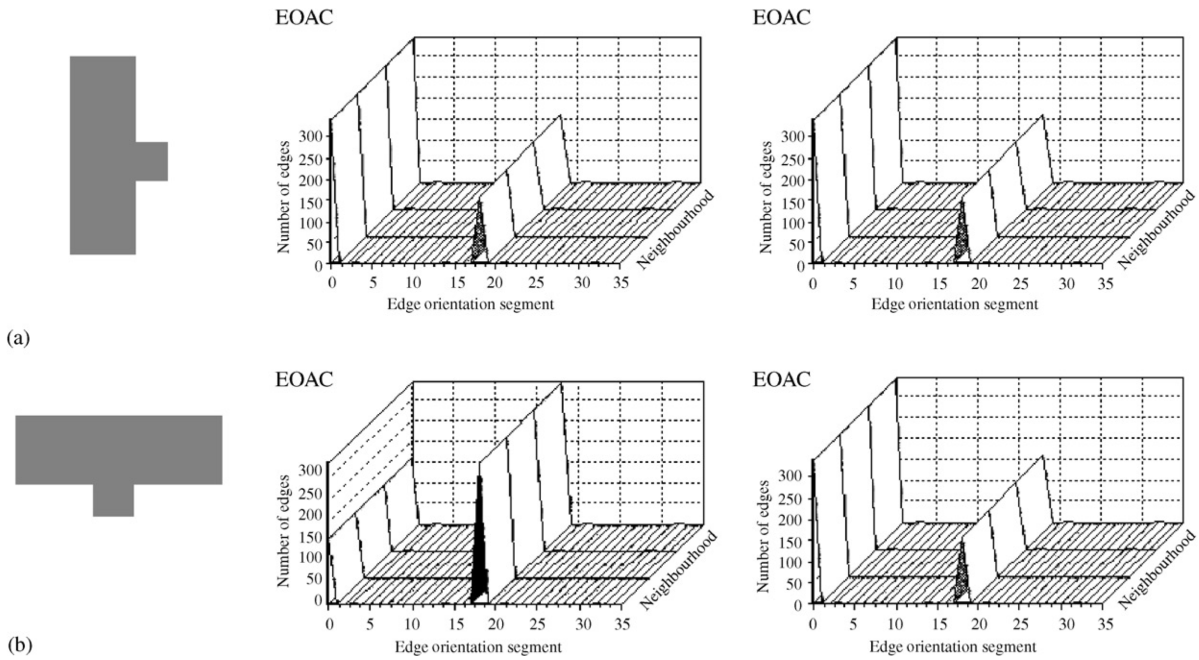


Fig. 5. An example of appropriate effects of normalization against rotation.

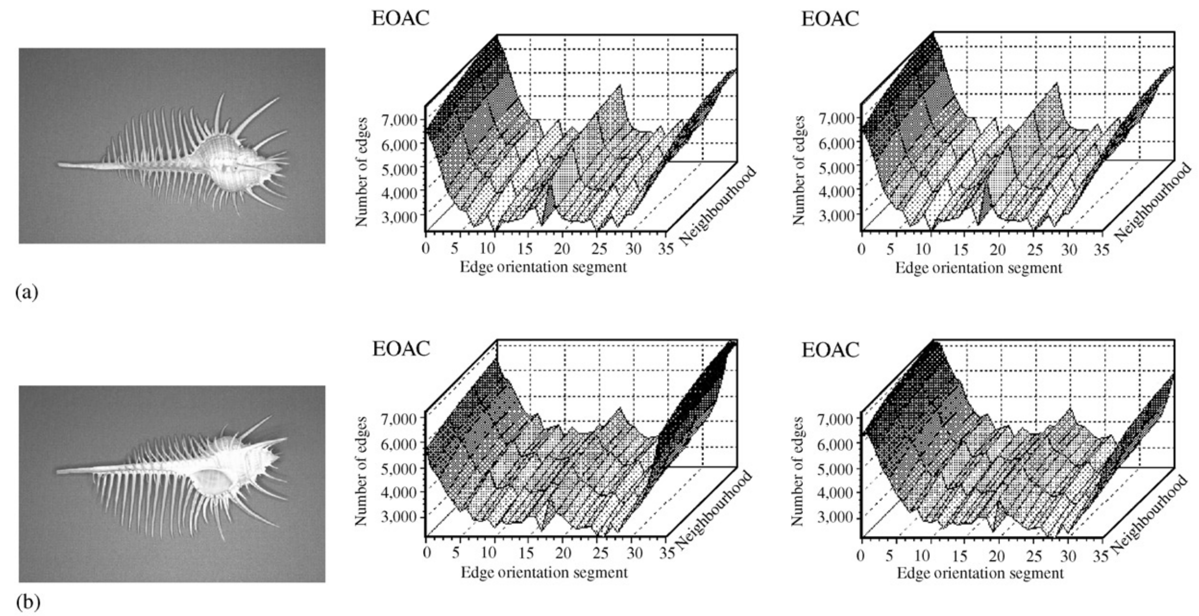


Fig. 6. An example of undesired effects of normalization against rotation.

accuracy of the system by the number of retrieved relevant images and precision rate acts based on the ranks of retrieved relevant images. In the following, by considering formulas introduced in [9], we have employed some formulas for these two metrics. Our metrics are normalized so that they are independent of the number of relevant images. Therefore, the ranges of values for precision and recall rates are between 0 and 1 in all of the cases, and their ideal value is 1. The

Fig. 7. An example of image retrieval based on EOAC, 12 similar images are retrieved in rank order.

precision and recall rates are computed as follows:

$$Y(Q) = |\ \{I_i | Rank(I_i) \leqslant k,\ I_i \in A\}\ |, \tag{5}$$

$$R(Q) = \frac{Y(Q)}{|A|}, \tag{6}$$

$$P(Q) = \frac{\sum_{i-1}^{Y(Q)} fib(Rank(I_i))}{\sum_{i=1}^{|A|} fib(i)}, \tag{7}$$

$$\begin{cases} fib(i) = fib(i+1) + fib(i+2) & if\ 1 \leqslant i \leqslant k-2, \\ fib(k-1) = 2 & \\ fib(k) = 1 & \\ fib(i) = 0 & else, \end{cases} \tag{8}$$

where parameters used in above formulas are: Q is a sample query image, $P(Q)$ the precision rate of Q, $R(Q)$ the recall rate of Q, A the set of relevant images of Q, I_i the ith relevant image of Q, k the number of retrieved images ($k = 24$), $Y(Q)$ the number of retrieved relevant images of Q and fib the fibonacci function that emphasizes on images retrieved in lower ranks.

4.3. Performance evaluation

This section evaluates the performance of new scheme in three subsections. The first subsection describes the role of normalization algorithms in accuracy improvement. The second subsection measures the accuracy of our scheme and compares the results with other color-, color-spatial-, and shape-based schemes. The final subsection investigates the effect of correlation increase in retrieval accuracy.

4.3.1. Role of normalization algorithms in accuracy

We have implemented all of the normalization algorithms on the EOAC, and computed the averages of precision and recall rates for 65 benchmark queries under each of following conditions: without any normalization, normalization against scaling, normalization against rotation, and normalization against both scaling and rotation.

Table 2
The role of normalization algorithms in retrieval accuracy

	Precision rate	Recall rate
Without any normalization	0.762	0.599
Normalization against scaling	**0.911**	**0.780**
Normalization against rotation	0.662	0.519
Normalization against both scaling and rotation	0.836	0.664

Table 2 presents the results. Whereas, there is a gap between low-level visual features and high-level concepts in image, normalization algorithms may have some side effects and cause ineffective retrieval in some cases. But in average, this table shows that the best result is obtained by normalization against scaling. As described in Section 3, this normalization makes the EOAC robust with respect to scaling, color, and illumination variation; but using rotation normalization may generate undesired effects as shown in Fig. 6.

4.3.2. Comparing accuracy of EOAC with other methods

For the purpose of accuracy evaluation, we have measured the averages of precision and recall rates for all 65 benchmark queries. In this subsection, we have considered the EOAC with normalization against scaling. We have also implemented some methods from different categories in our prototype test-bed and measured same metrics for them. These methods are as follows: the color histogram (CH) as the color-based method [2]; the color autocorrelogram (CAC) as the color-spatial-based method [7,8]; the 12 shape factors (SF12), the edge direction histogram (EDH), and the direction histogram of similar edges (DHSE) as the non-segmentation shape-based methods [24,22,26,28,30]. The experimental results presented in Table 3 indicate the superiority of our scheme.

4.3.3. Effects of correlation increase on accuracy

Diagrams shown in Fig. 8 describe the effects of correlation increase on the accuracy of schemes. These diagrams show precision or recall rates for all the benchmark queries sorted by their values. In other words, if n is considered as a point on the horizontal axis and $f(n)$ as its function value on the vertical axis, n is the total number of images that their precision or recall rates are greater than or equal to $f(n)$. In these diagrams, areas under the curves are proportional to, the accuracy of methods.

The graphs of Fig. 8a and c show the CAC and CH curves. Since the CAC algorithm has considered the color correlation between pixels in feature vector and the CH algorithm ignores correlation between pixels, the areas under CAC curves are larger than the areas under CH curves. Therefore, the accuracy of CAC is better than CH. This behavior also exists in shape-based domain. As shown in Fig. 8b and d, since the EOAC algorithm considers correlation between neighboring edges and the EDH ignores it, the accuracy of EOAC is higher than EDH.

4.4. Image retrieval examples and discussion

The experimental results show that, since the EOAC is independent of color and illumination, images with color and illumination variation like those in Fig. 9, are appropriately retrieved. The EOAC is also appropriate for retrieving images with continuous and clear edges particularly images with direct lines, as shown in Fig. 10, because it extracts proper information from correlation between edges on a border. Despite this effectiveness, the EOAC is not appropriate for retrieving texture-based images and images with unclear edges, as shown in Fig. 11.

5. Conclusions

This paper presented a new image feature called the edge orientation autocorrelogram (EOAC). This feature is used for non-segmentation shape-based image indexing and retrieval. The EOAC performs retrieval invariant with respect to translation, scaling, color, illumination, and small viewing position variations. The accuracy comparison studies, conducted using our prototype system, shows superiority of our scheme over the following methods: color histogram, color autocorrelogram, 12 shape factors, edge direction histogram, and direction histogram of similar edges. These schemes used in the comparison studies belong to color-, color-spatial-, and shape-based indexing. The main reason for the superiority of EOAC is further use of correlation between edges in feature vector generation.

Table 3
Comparison of the accuracy metrics of various image retrieval methods

	CH	CAC	SF12	EDH	DHSE	EOAC
Average of $R(Q)$	0.570	0.572	0.130	0.879	0.897	**0.911**
Average of $P(Q)$	0.391	0.413	0.071	0.618	0.752	**0.780**

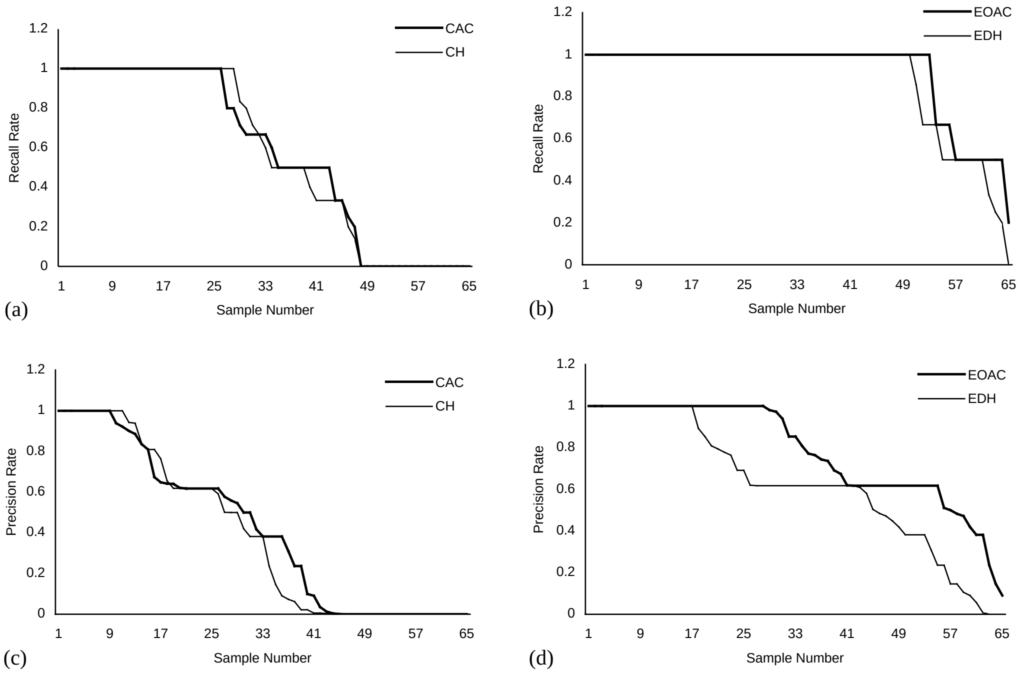


Fig. 8. Performance evaluation of color-based, color-spatial-based, and shape-based methods.

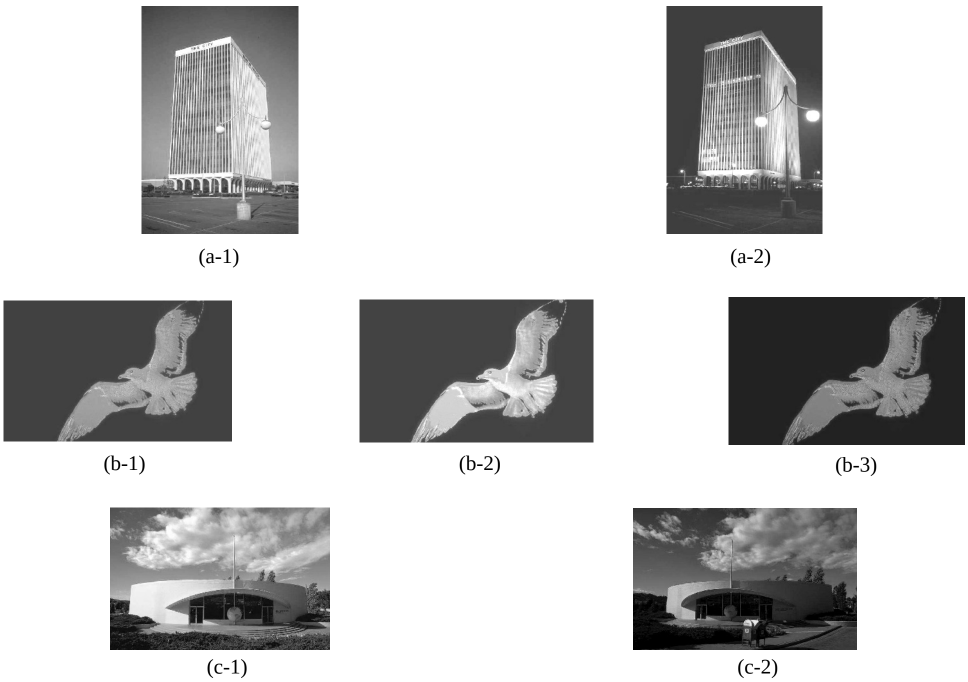


Fig. 9. Several examples of image retrieval by EOAC with color and illumination variations: (a-1) Query image; (a-2) relevant image retrieved in rank 1; (b-1) query image (b-2) relevant image retrieved in rank 1, (b-3) relevant image retrieved in rank 2; (c-1) query image; and (c-2) relevant image retrieved in rank.

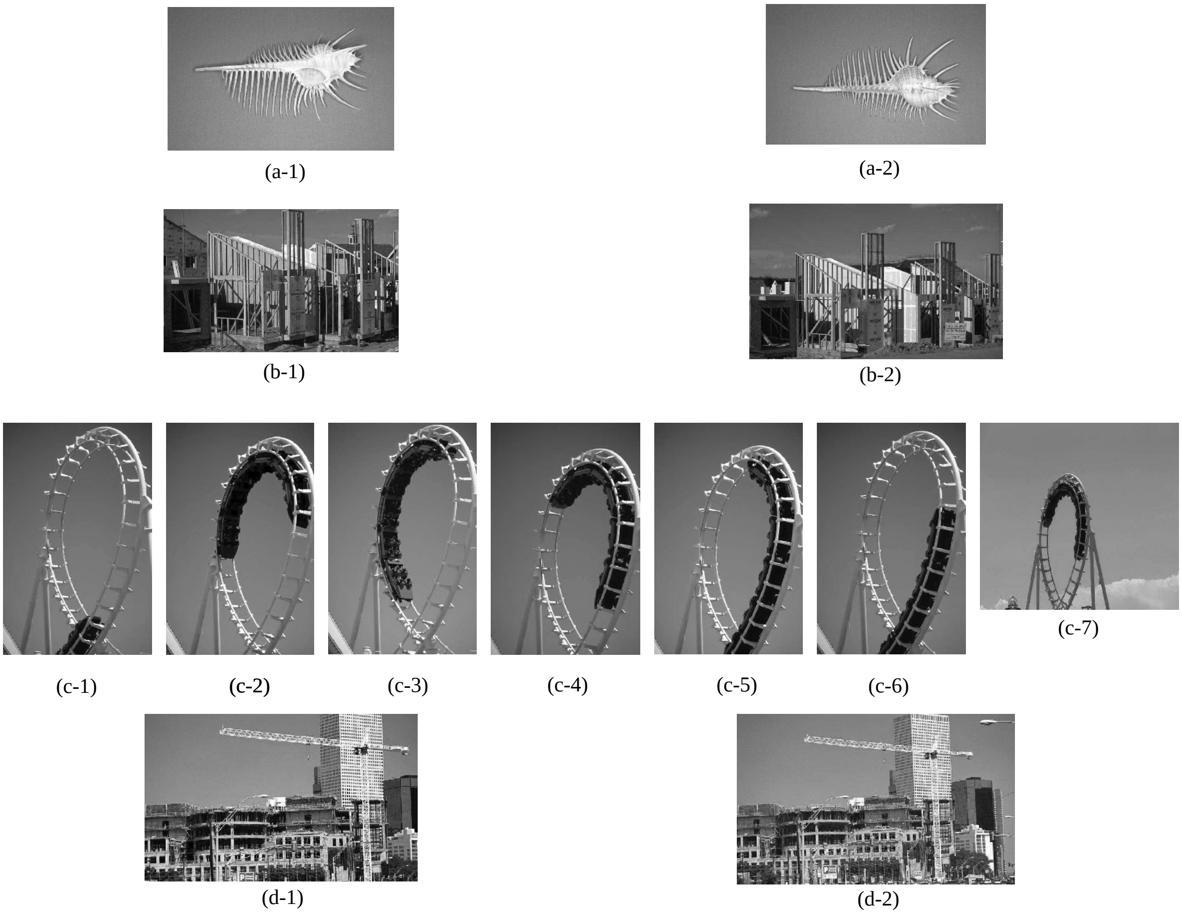


Fig. 10. Several examples of image retrieval by EOAC for images with continuous and clear edges and images with direct lines: (a-1) Query image; (a-2) relevant image retrieved in rank 1; (b-1) query image; (b-2) relevant image retrieved in rank 1; (c-1) query image; (c-2) rank 1; (c-3) rank 3; (c-4) rank 4; (c-5) rank 6; (c-6) rank 7; (c-7) rank 10; (d-1) query image; and (d-2) relevant image retrieved in rank 1.

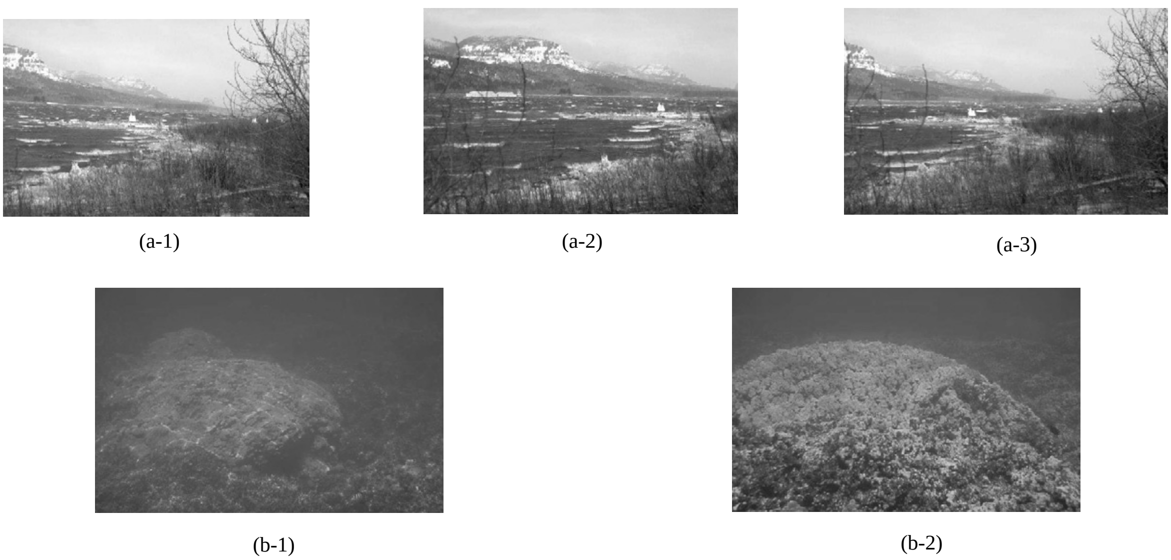


Fig. 11. Two examples of images that the EOAC is not appropriate for retrieving them: (a-1) query image; (a-2) relevant image 1; (a-3) relevant image 2; (b-1) query image; and (b-2) relevant image.

References

[1] J. Shanbehzadeh, A.-M. Eftekhari-Moghadam, F. Mahmoudi, Image indexing and retrieval techniques: past, present and next, Proceedings of the SPIE: Storage and Retrieval for Multimedia Databases 2000, Vol. 3972, San Jose, California, USA January 2000, pp. 461–470.

[2] M. Swain, D. Ballard, Color indexing, Int. J. Comput. Vision 7 (1) (1991) 11–32.

[3] M. Flickner, et al., Query by image and video content: the QBIC system, IEEE Comput. 28 (9) (1995) 23–32.

[4] V.E. Ogle, M. Stonebraker, Chabot: retrieval from a relational database of images, IEEE Comput. 28 (9) (1995) 40–48.

[5] A. Pentland, R. Picard, S. Sclaroff, Photobook: tools for content-based manipulation of image databases, Int. J. Comput. Vision 18 (3) (1996) 233–254.

[6] G. Pass, R. Zabih, Histogram refinement for content-based image retrieval, IEEE WACV (1996) 96–102.

[7] J. Huang, S.R. Kumar, M. Mitra, W.J. Zhu, R. Zabih, Image indexing using color correlograms, Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Juan, Puerto Rico, June 1997, pp. 762–768.

[8] J. Huang, S.R. Kumar, M. Mitra, W.J. Zhu, R. Zabih, Spatial color indexing and applications, International Journal of Computer Vision 35 (3) (1999) 245–268.

[9] Y. Gong, G. Proietti, C. Faloutsos, Image indexing and retrieval based on human perceptual color clustering, Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1998, pp. 578–583.

[10] A. Del Bimbo, M. Mugnaini, P. Pala, F. Turco, Visual querying by color perceptive regions, Pattern Recognition 31 (1998) 1241–1253.

[11] S.Y. Jeong, K. Kim, B.T. Chun, J.Y. Lee, Y.L.J. Bae, Entropy and color correlation features for image indexing, Proceedings of IEEE International Conference on Systems, Man and Cybernetics, Vol. 2, 1999, pp. 895–899.

[12] M.H. O'Docherty, A multimedia information system with automatic content retrieval. Technical Report Series UMCS-93-2-2, Department of Computer Science, University of Manchester, 1993, England.

[13] A. Yoshitaka, S. Kishida, M. Hirakawa, T. Ichikawa, Knowledge-assisted content-based retrieval for multimedia databases, Proceedings of the IEEE International Conference on Multimedia Computing and Systems, Boston, 1994.

[14] J.K. Wu, A.D. Narasimhalu, Identifying faces using multiple retrievals, IEEE Multimedia 1 (2) (1994) 27–38.

[15] F. Mokhtarian, Silhouette-based isolated object recognition through curvature scale space, IEEE Trans. Pattern Anal. Mach. Intell. 17 (5) (1995) 539–544.

[16] W. Niblack, J. Yin, A pseudo-distance measure for 2D shapes based on turning angle, Proceedings of the IEEE International Conference on Image Processing, 1995, pp. 352–355.

[17] G. Iannizzotto, A. Puliafito, L. Vita, Design and implementation of a content-based image retrieval tool, Proceedings of the IEEE PDSE'97, Boston, Massachusetts, USA, May 1997, pp. 304–310.

[18] S. Abbasi, F. Mokhtarian, J. Kittler, Curvature scale space in shape similarity retrieval, Multimedia Systems 7 (6) (1999) 467–476.

[19] S. Abbasi, F. Mokhtarian, Multi-view object representation and recognition through curvature scale space, Proceedings of the Fifth Annual CSI International Conference, Tehran, Iran, March 2000, pp. 467–476.

[20] S. Berretti, A. Del Bimbo, P. Pala, Retrieval by shape similarity with perceptual distance and effective indexing, IEEE Trans. Multimedia 2 (4) (2000) 225–239.

[21] J. Bigun, S.K. Bhattacharjee, S. Michel, Orientation radiograms for image retrieval: an alternative to segmentation, Proceedings of the 13th IEEE International Conference on Pattern Recognition, Vol. 3, 1996, pp. 346–350.

[22] A.K. Jain, A. Vailaya, Image retrieval using color and shape, Pattern Recognition 29 (8) (1996) 1233–1244.

[23] B. Kroepelien, A. Vailaya, A.K. Jain, Image databases: a case study in Norwegian silver authentication, Proceedings of the 13th IEEE International Conference on Pattern Recognition 3 (1996) 370–374.

[24] J. Zheng, C.H.C. Leung, Automatic image indexing for rapid content-based retrieval, Proceedings of the IEEE International Workshop on Multimedia Database Management Systems, Blue Mountain Lake, New York, August 1996, pp. 38–45.

[25] Y. Shinagawa, M. Oga, T.L. Kunii, S. Murakami, Characterizing images based on lines for image indexing, Proceedings of the IEEE Computer Graphics International, Hasselt and Diepenbeek, Belgium, June 1997, pp. 94–102.

[26] A.K. Jain, A. Vailaya, Shape-based retrieval: a case study with trademark image database, Pattern Recognition 31 (9) (1998) 1369–1390.

[27] A. Vailaya, A. Jain, H.J. Zhang, On image classification: city vs. landscape, Proceedings of the IEEE Workshop on Content-Based Access of Image and Video Libraries, June, 1998, pp. 3–8.

[28] J. Shanbehzadeh, F. Mahmoudi, A. Sarafzadeh, A.-M. Eftekhari-Moghadam, Image retrieval based on the directional edge similarity, Proceedings of the SPIE: Multimedia Storage and Archiving Systems, Vol. IV, Boston, Massachusetts, USA, September 1999, pp. 267–271.

[29] J. Shanbehzadeh, F. Mahmoudi, A. Sarafzadeh, A.-M. Eftekhari-Moghadam, Z. Asarzadeh, Image indexing using edge orientation correlogram, Proceedings of the SPIE: Internet Imaging, Vol. 3964, January 2000, pp. 102–108.

[30] F. Mahmoudi, J. Shanbehzadeh, A.-M. Eftekhari-Moghadam, A shape-based method for content-based image retrieval, Proceedings of the Fifth Annual International CSI Computer Conference (CSICC'2000), Tehran, Iran, March, 2000, pp. 11–16.

[31] G.J.G. Upton, B. Fingleton, Spatial Data Analysis by Example, Vol. I, Wiley, New York, 1985.

[32] R.C. Gonzalez, P. Wints, Digital Image Processing, Addison-Wesley, Reading, MA, 1992.

[33] G. Salton, M. McGill, Introduction to Modern Information Retrieval, McGraw-Hill, New York, 1983.

[34] J.R. Smith, Image retrieval evaluation, Proceedings of the IEEE Workshop on Content-Based Access of Image and Video Libraries, June 1998, pp. 112–113.

[35] M. Vissac, J.-L. Dugelay, K. Rose, A novel indexing approach for multimedia image database, Proceedings of the IEEE Third Workshop on Multimedia Signal Processing, Copenhagen, Denmark, September 1999, pp. 97–102.

[36] H. Mueller, W. Mueller, D.M. Squire, M. Marchand-Maillet, P. Pun, Performance evaluation in content-based image retrieval: overview and proposals, Pattern Recognition Lett. 22 (5) (2001) 593–601.

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