



Content-based Image Retrieval Speedup Based on Optimized Combination of Wavelet and Zernike Features Using Particle Swarm Optimization Algorithm

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ABSTRACT

This paper presents a novel method to speedup content-based image retrieval (CBIR) systems. The proposed method can be very useful for retrieving images from a large database. For this task, Zernike and Wavelet features are first extracted from the query image, then an interval of potential matching images is computed from the database images using the extracted feature. Therefore, the query image is compared with images in the interval rather than the whole database which to speedup the retrieval process. Particle swarm optimization is employed to select relevant features among Zernike and Wavelet features, which leads to decrease feature extraction time. Three types of experiments are conducted to evaluate effectiveness the proposed method in terms of database reduction, retrieval accuracy and retrieval time. In the best case, the Corel-1k database is averagely reduced up to 33.98% from its original size, and preserving 71.92% of relevant images. Retrieval accuracy in reduced database is increased by 1% in comparison with retrieving from the original database. Meanwhile, the retrieval time is reduced up to 58.57% in comparison with retrieval time from the original database.

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1. INTRODUCTION

There are many applications for image processing algorithms including medical diagnosis, art collections, crime prevention and geographical information [1–6]. Image retrieval is among the most important applications for handling large image databases. Images can be retrieved based on text and content, which are referred as text-based and content-based image retrieval (CBIR), respectively [7]. Text-based image retrieval was proposed in 1970 for searching and indexing images in which manual annotation is done for images in database by assigning one or more words to each image. These words are used by database management system for image retrieval. In CBIR, each image is represented by a feature vector and this vector is used for image indexing and computing similarity with query image. Based on image similarity measures, the most relevant images are retrieved [8].

Researchers have proposed many CBIR systems, some of which are reviewed here in this research. In [9],

images are first resized to 128x128 and then wavelet transform is applied in fourlevels. Component in the lowest level (LL) and standard deviations in levels 3 and 4 are used as texture features. In [10], the image is first resized to 256x256 and then transformed to Hue-Min-Max-Difference (HMMD) color space [11]. In the next step, wavelet transform is applied in this color space and the LL component is used as a feature vector. In [12], a method was developed based on convolutional neural network (CNN) to increase CBIR precision. This method extracted deep and high-level features from images. Radon transformation as well as a deep network were proposed in [13] to retrieve medical images from a highly imbalanced benchmark. Keyword spotting and relevance feedback were used to present a document image retrieval in [14].

In [15], images are first indexed and retrieved to make a CBIR system. Indexing phase was first proposed based on MapReduce method for accelerating and speeding up the process. Then, parallel implementation of the k-Nearest Neighbors was used for retrieval phase.

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In [16], local derivative radial patterns (LDRP) was proposed as texture features computed from higher derivation orders in different directions. In [17], a CBIR system based on combination of dominant color domains, wavelet and curvelet features using particle swarm optimization (PSO) is presented.

To speed up the retrieval process, features with light computational cost are extracted from query image and a lot of images are ignored from database by a fast comparison. This procedure eliminates the need for extracting features with high computational cost and helps speed up image retrieval. Following this idea, many speedup methods have been proposed in literature.

In [18], a parallel method in graphics processing unit was presented for image indexing referred as plane semantic ball. In [19], a speedup procedure for image retrieval systems was proposed on RDISK machine. In [20], an efficient CBIR system based on speeded up robust features referred as SURF is presented followed by an optimization method. In [21], speedup scheme was proposed for CBIR using shape information of images to facilitate the retrieval process. In [22], a fast solution for Manifold-Ranking (MR); a ranking method for CBIR systems; was introduced which exploited two important properties shared by many real graphs, including linear correlations and block-wise community-like structure. In [23], a fast calculation method of cosine similarity with L2 norm indexed in advance on Elasticsearch was presented for CBIR systems constructed using CNNs. In [24], a fast and efficient image retrieval scheme was proposed for searching images among JPEG2000 compressed image databases. In [25], a CBIR approach was presented to solve high computational time, handling high dimension data, and comparing images consistent with human perception. In [26], an efficient and effective CBIR technique was applied directly to the compressed domain and thus did not need full decompression for feature extraction. In [27], a fast retrieval scheme was designed for big data applications such as images to be retrieved from large image databases. It used reasonable elements ranking, and appropriate distance metric to decrease retrieval time. In [28], a fast image retrieval procedure was presented by classifying image features into different levels. Levels are considered as features and retrieval is done by similarity comparison between query image and database images. In [29], a fast and simple content access method and retrieving JPEG images with DCT coefficients of coded blocks was presented without needing for complete decompression of coded images. In [30], a fast medical image retrieval system based on wavelet features and image signature calculated using Kurtosis and standard deviation was proposed to help physicians in medical images analysis and identification. In [31], indexing method for color images was proposed with Error Diffusion Block Truncation Coding (EDBTC) feature extraction followed

by an unsupervised clustering to decrease required time for comparing the target and query image. In [32], a fast CBIR system was introduced with a Bayesian logistic regression model. This model was used to compute pseudo-metric weights and led to increase discriminatory capacity and retrieval accuracy. In [33], a novel and fast CBIR model was proposed based on Dual-Cross Patterns (DCP). These patterns encoded second order information of local surrounding region of every center pixel in the vertical, horizontal and diagonal directions.

The Particle Swarm Optimization (PSO) method was introduced in 1995, inspired by the behavior of social groups such as birds, ants and fishes. In this algorithm, information is shared between members by interaction to find a common solution. PSO has been applied to solve numerous areas of optimization problems [19].

This work extends our previously proposed CBIR systems in [17, 34–36] with different features and retrieval schemes. Our main motivation is to find a solution to make a CBIR system almost independent to database size. For this task, for each query image, the Zernike and Wavelet features are extracted as shape and texture features, respectively, and then an interval is computed based on extracted features for the query image. For each image in the database, it is determined whether the image is within the computed interval of the query image. Images within the interval are kept and the rest are ignored, which leads to the search space reduction. Among the extracted Zernike and Wavelet features, most relevant ones are selected by the PSO which leads to the optimum search space reduction and subsequently the higher accuracy. Therefore, query images are not compared with the whole database. This paper is presented in the following sections. The proposed method is described in Section 2. Experimental setup and experimental results are provided in Section 3 and 4, respectively. Finally, the conclusion is drawn in Section 5.

2. PROPOSED METHOD

CBIR consists of two steps: feature extraction and retrieval. Since in many CBIR applications, feature extraction is done in offline phase, CBIR speed depends on retrieval phase in which query image should be compared with the whole database images. Therefore, retrieval time depends on the number of images in database, hence high number of images leads to increase retrieval time significantly. In this paper, database (search space) reduction method is proposed for CBIR speedup. Reduction is done by removing irrelevant images from database. In the proposed method, for each image query, first irrelevant images with query images are removed before image retrieval phase. The flowchart of the proposed method is shown in Figure 1.

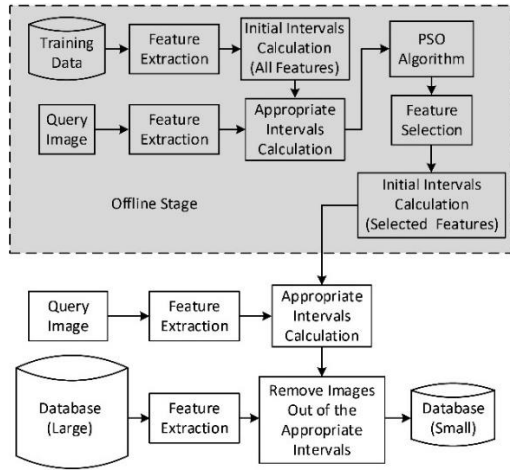


Figure 1. The flowchart of the proposed CBIR system

As it is depicted in Figure 1, database reduction is considered as preprocessing phase in CBIR systems and should be very fast with low computational cost. Generally, image features are divided into three categories: shape, texture and color; the texture and shape categories have more image information and stronger image discriminability.

In this research, Zernike moments and Wavelet coefficients are used as shape and texture features, respectively, duo to their low cost and high speed for extraction. Furthermore, to make the feature extraction faster, number of features should be limited. Therefore, a limited number of Zernike and Wavelet features should be selected. This problem can be formulated by feature selection algorithms. For this task, the PSO feature selection is proposed to select most significant Zernike and Wavelet features among the whole feature set. In the subsequent sections, Zernike and Wavelet features are presented and then feature selection and database reduction using these features are explained.

2. 1. Zernike Moments

Zernike moments extract shape features from images. In these features orthogonal Zernike polynomials are used to extract a set of complex orthogonal polynomials inside unit circle. Another derivation of Zernike moments are Pseudo moments. These moments have been used in many image processing applications as a good shape descriptor of images since they are robust against noise and rotation and can be extracted very fast and efficiently. These properties make Pseudo Zernike moments suitable for database reduction. Orthogonal polynomials are represented by $V_{mn}(x, y)$ as follows [37], [38]:

$$V_{mn}(x, y) = V_{mn}(\rho, \theta) = R_{mn}(\rho) \cdot e^{in\theta} \quad (1)$$

where $\rho = \sqrt{x^2 + y^2}$, $\theta = \tan^{-1}(y/x)$ and n is polynomial degree. Radius orthogonal Zernike polynomials are defined in Equation (2) [3].

$$R_{mn}(\rho) = \sum_{s=0}^{m-|n|} \frac{(-1)^s (2m+1-s)! \rho^{m-s}}{s!(m+|n|+1-s)!(m-|n|-s)!} \quad (2)$$

Since polynomials are orthogonal, $g(x, y)$ can be decomposed in orthogonal space as follows:

$$g(x, y) = \sum_{m=0}^{\infty} \sum_{\{|n| \leq m\}} A_{mn} V_{mn}(x, y) \quad (3)$$

where A_{mn} and n are Pseudo Zernike descriptors and repetition, respectively, computed as follows:

$$A_{mn} = \frac{m+1}{\pi} \iint_{x^2+y^2 \leq 1} g(x, y) V_{mn}^*(x, y) dx dy \quad (4)$$

Size of this coefficient is used as image descriptors. Zernike features of order m and repetition n for j th image from i th class are represented by z_{ij}^{mn} .

$$z_{ij}^{mn} = \left| \frac{m+1}{\pi} \iint_{x^2+y^2 \leq 1} g_{ij}(x, y) V_{mn}^*(x, y) dx dy \right| \quad (5)$$

where g_{ij} is j th image from i th class. Finally, Zernike feature set for image g_{ij} in order P is defined as follows:

$$z_{ij} = \{z_{ij}^{pq} | p = 0, 1, 2, \dots, P, |q| \leq p\} \quad (6)$$

2. 2. Wavelet Features

Wavelet transform is performed by decomposing image into four sub-images LL, LH, HL and HH. L and H mean low pass and high pass filters, respectively. Texture Wavelet features are extracted by applying different functions to these sub-images [9]. Here, Frobenius norm of LL, LH, HL and HH components are used as Wavelet features. Consider j th image from i th class as g_{ij} with dimension $M \times N$ and its corresponding decomposed components as $Comp$. As it is depicted in Figure 2, Wavelet features are computed as follows:

$$w_{ij}^{L, Comp} = \sqrt{\sum_{n=1}^N \sum_{m=1}^M Comp_{ij}^2(m, n)} \quad (7)$$

$$L = 1, 2, 3, \dots$$

$$Comp = LL, LH, HL, HH$$

In this equation, indices $Comp$ and L above w indicate decomposition component types (LL, LH, HL and HH) and decomposition level, respectively. Also, indices i, j, m and n represent i th class, j th image, m th row and n th column, respectively. Figure 2 shows that features are computed for all decomposition levels by this way that the first image is decomposed into four components LL, LH, HL and HH to extract four features. Then LL is further decomposed into its components LL, LH, HL and HH. This procedure continues to reach the last level of decomposition. Therefore, Wavelet feature set for image g_{ij} is defined by Equation (8).

$$w_{ij} = \{w_{ij}^{L, Comp} | Comp = LL, \dots, HH, L = 1, 2, \dots\} \quad (8)$$

The final feature set for image g_{ij} is a concatenation of Zernike and Wavelet feature vectors as follows:

$$f_{ij} = \{z_{ij}, w_{ij}\} \quad (9)$$

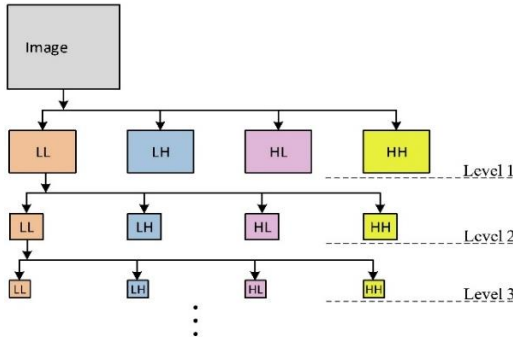


Figure 2. Wavelet feature extraction

2. 3. Proposed Interval Calculation In the proposed model, it is supposed that there are I classes and J images in each class and K features are extracted from each image. For j th image of i th class, g_{ij} , k th feature is represented by f_{ij}^k . For this feature, a_i^k and b_i^k are computed by Equations (10)-(11).

$$a_i^k = \min\{f_{i1}^k, f_{i2}^k, \dots, f_{ij}^k\}, i = 1, 2, \dots, I \quad (10)$$

$$b_i^k = \max\{f_{i1}^k, f_{i2}^k, \dots, f_{ij}^k\}, i = 1, 2, \dots, I \quad (11)$$

As it is demonstrated in Figure 3, lower and upper bounds for k th feature in i th class are depicted with blue lines.

In the next step, the center and radius are calculated for the k th feature of the i th class using Equation (12):

$$\text{Class } i: R_i^k = \frac{b_i^k - a_i^k}{2}, C_i^k = \frac{b_i^k + a_i^k}{2} \quad (12)$$

Then, R_{max}^k is computed using Equation (13).

$$R_{max}^k = \max\{R_{i1}^k, R_{i2}^k, \dots, R_{iI}^k\} \quad (13)$$

Finally, $C_1^k, C_2^k, \dots, C_I^k, R_{max}^k$ are computed for all features.

For a query image presented for CBIR system, all features are extracted and the k th feature is denoted by f_q^k . Based on Equations (14)-(15), appropriate intervals for all features are computed.

$$S_1^k = [f_q^k - R_{max}^k, f_q^k] \quad (14)$$

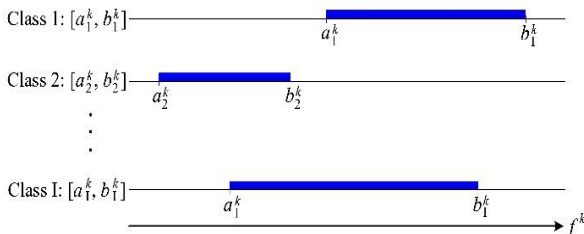


Figure 3. Lower and upper bounds for k th feature in different classes

$$S_2^k = [a_m^k, b_m^k], m = \underset{i}{\operatorname{argmin}}(|f_q^k - C_i^k|), k = 1, 2, \dots, K \quad (15)$$

The final interval for all features is computed using Equation (16).

$$S^k = S_1^k \cup S_2^k, k = 1, 2, \dots, K \quad (16)$$

After computing the final interval, all images with features out of this interval are ignored and are not forwarded for the CBIR system.

2. 4. Feature Selection

The main challenge is to choose appropriate features from the feature vector for database reduction. This challenge has been addressed by the PSO feature selection. Each member in swarm is a particle and has position vector, x_i , and velocity vector, v_i . In subsequent iterations, particles move randomly towards new positions based on their current position, best position in current iteration and best position in all iterations. Velocity and position of particle i is updated using Equations (17) and (18), respectively [19].

$$v_i(t + 1) = kv_i(t) + \alpha_1 r_1 (\hat{x}_i - x_i(t)) + \alpha_2 r_2 (\hat{x} - x_i(t)) \quad (17)$$

$$x_i(t + 1) = x_i(t) + v_i(t + 1) \quad (18)$$

where v_i is the speed of i th particle, k is the speed importance of previous iteration, α_1 and α_2 are weights for considering velocity in previous iteration, r_1 and r_2 are the random variables, \hat{x}_i is the position of the best local particle and \hat{x} is the position of the best global particle. In this application, a weight is assigned to each feature and considered as a particle. In fact, the importance of each feature is encoded to its weights. Combination of weights creates all particles. PSO is configured to find the best weight for each feature to lead to the best performance in term of cost function minimization. Here, cost function is proposed by the way that follows two criteria. The first one is that new database is as small as possible, and the second one is that number of relevant images in the new database be as high as possible. These two conditions reduce database and keep relevant images, both as much as possible simultaneously. The first criterion is formulated in Equation (19) which is the number of images in new database (N_{new}) over the number of images in the original database ($N_{original}$).

$$N_A = \frac{N_{new}}{N_{original}} \times 100\% \quad (19)$$

By the same way, the second criterion is expressed as the number of relevant images in new database ($N_{R,new}$) divided by the number of relevant images in the original database ($N_{R,original}$) using Equation (20).

$$N_R = \frac{N_{R,new}}{N_{R,original}} \times 100\% \quad (20)$$

It is clear that higher values for N_R and lower values for N_A are desired. Therefore, the proposed cost function is defined in Equation (21).

$$C(t) = N_R - N_A \quad (21)$$

PSO selects features yielding a better $C(t)$. These features are used in online phase of the CBIR system.

To sum up, in offline phase, intervals are computed for all features based on training data. Then, PSO feature selection is used to select the most relevant features. Finally, in online phase, selected features are extracted from the query image and intervals are computed; all images out of the intervals are ignored and won't further be used in retrieval. This procedure results in retrieval speedup.

3. EXPERIMENTAL SETUP

The proposed method has been evaluated on four databases Corel-1k, Corel-10k, Caltech-256 and ZuBuD reported in Table 1.

In each database, 50% of data is used for training and remained 50% for test. For Zernike features, parameters p and q are configured with values 2 and 4, respectively, which leads to 27 features. Also, for Wavelet features images are resized to 256×256 and then Frobenius norm is computed for each component. By this computation, 28 Wavelet features are extracted. The most relevant features are first selected using the PSO with parameters in Table 2.

TABLE 1. Databases for proposed method evaluation

Database	Categories	Total Images	Images per category		
			Min	Mean	Max
Corel-1k	10	1000	100	100	100
Corel-10k	100	10000	100	100	100
Caltech-256	257	30607	80	119	827
ZuBuD	201	1005	5	5	5

TABLE 2. PSO parameters

Parameter	Value
The number of generations:	100
The number of particles	20
The dimension of a particle	55
The maximum velocity	0.2
The weight	1.0
The acceleration coefficients	1.5
r_1 and r_2 are random variables in:	[0,1]

4. EXPERIMENTAL RESULTS

To evaluate the proposed method, three experiments are applied on the databases. These experiments have been done to show the effectiveness of the proposed method in database reduction, retrieval accuracy and retrieval time.

4. 1. Database Reduction In the first experiment, the effectiveness of the proposed method is evaluated for database reduction. For this task, an image is selected as query image, then its interval is calculated and all images out of this interval are removed from database to create new database. There are two important parameters associated with this reduction. The first one is the number of images remained in new database, which is better to be as low as possible. The second parameter is the number of images in new database belong to the same class with query class, which is better to be as high as possible.

Figures 4-6 show the results of the proposed reduction method applied in Corel-1k database with Zernike, Wavelet and both Zernike and Wavelet features, respectively. In each plot, blue line represents the percentage of remained relevant images and the red line is the percentage of the remained images. In each experiment, 50% of images are used for training and 50% of the rest for test. Therefore, among all 1000 images in Corel-1k with 10 classes, 500 images; 50 images in each class; are used for training and 500 images; 50 images in each class; are used for test. Each point in these plots is an average of 50 images in each class.

For example, in category 1 in Figure 4 with Zernike features, 35% of database is reduced before retrieval phase. This 35% is an average reduction for all 50 test images in category 1. Among the remained 65%, almost 90% are relevant with the query image. 10% of relevant images are removed from the database which. Figures 4-6 demonstrates that the proposed reduction method shrinks database and preserves relevant images with query image simultaneously.

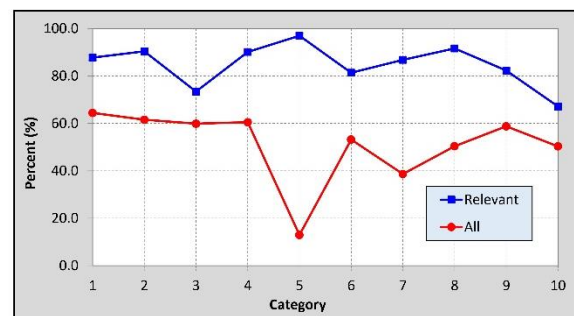


Figure 4. Percentage of remained relevant images with query image and the remained images with Zernike features in Corel-1k database

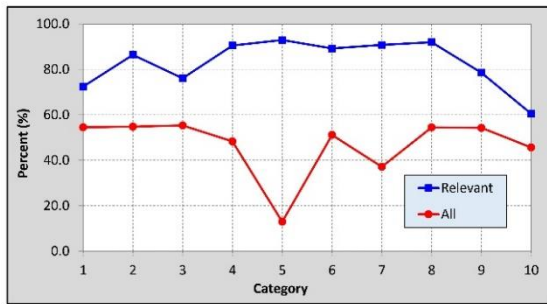


Figure 5. Percentage of remained relevant images with query image and the remained images with Wavelet features in Corel-1k database

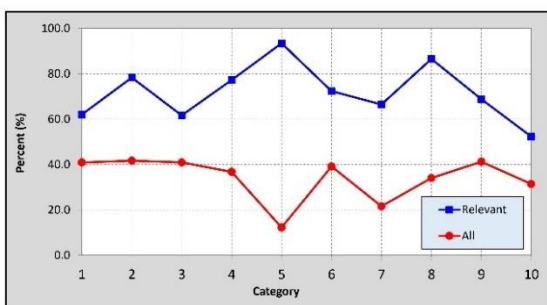


Figure 6. Percentage of remained relevant images with query image and the remained images with both Zernike and Wavelet features in Corel-1k database

Average reduction in all image categories in Corel-1k database is reported in Figure 7 for Zernike, Wavelet and both Zernike and Wavelet features. For Zernike feature, 51.05% of images is remained and forwarded for further processing in CBIR, and 84.79% of all relevant images is preserved in the reduced database. It means that database is reduced by half. Using Wavelet features, database is reduced to 46.84% while keeping 82.93% of relevant images which is a reduction more than half. Finally, by combination of Zernike and Wavelet features, database is resized to the 33.98% of original database preserving 71.92% of relevant images. It can be concluded that the combined feature set leads to the highest level of irrelevant image reduction in comparison with using each feature set separately.

A same database reduction with Zernike and Wavelet features has been done for other databases Corel-10k and Caltech-256 in Figure 8 which are reduced to 62.1% and 52.47%, respectively. Average percentage of relevant images in Corel-10k and Caltech-256 are 84.56% and 72.86%, respectively. This experiment shows a low percentage of remained images and a high percentage of relevant images.

4. 2. Retrieval Accuracy

The previous section showed that the proposed method reduces databases significantly and preserves relevant images

simultaneously. In this section image retrieval is done in original database and reduced database, then their accuracy is compared.

This experiment reveals the effect of database reduction on retrieval accuracy. It is expected that the accuracy of the retrieval in the reduced database is as close as the accuracy in the original database. Table 3 reports retrieval accuracy of CBIR systems in [39], [17] and [40] on original and reduced Corel-1k database. The average retrieval accuracy achieved by CBIR system in [39] for the original and reduced Corel-10k database are 67.50% and 66.72%, respectively. These accuracies in [17] are 69.20% and 69.09%. Finally in [40], retrieval accuracies in original and reduced databases are 51.12% and 51.18%. In [39] and [17], database reduction by the proposed method decreases the retrieval accuracy less than a percent while in [40], retrieval accuracy is increased after database reduction. From these experiments, it can be concluded that the proposed database reduction preserves retrieval accuracy (see Figure 9).

As it is clear from Figure 10, database reduction in Corel-10k improves retrieval accuracy by 0.77% (from 36.37% to 37.14%) in [17] and by 0.38% (from 21.98% to 22.36%) in [40], while decreases it by 0.70% (from 33.72 to 33.02%) in [39]. Finally, effect of database reduction in retrieval accuracy for Caltech-256 database

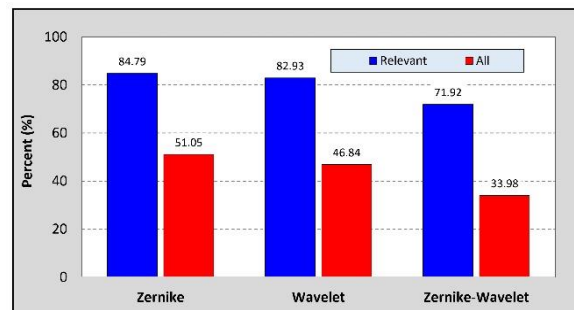


Figure 7. Average reduction in all image categories in Corel-1k

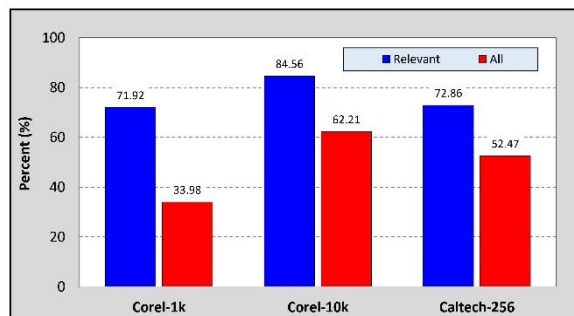


Figure 8. Average database reduction percentage and relevant preserving percentage on Corel-1k, Corel-10k and Caltech-256 databases

TABLE 3. Retrieval accuracy of all categories by CBIR systems in [39], [17] and [40] in original and reduced Corel-1k database

Category	Precision					
	[39]		[17]		[40]	
	Without database reduction	With database reduction	Without database reduction	With database reduction	Without database reduction	With database reduction
1	56.80	55.20	69.40	70.00	47.10	46.40
2	54.80	56.80	49.00	48.10	35.90	36.20
3	52.80	50.80	55.40	55.00	24.20	23.40
4	61.20	63.80	74.40	75.30	54.10	56.60
5	98.80	98.80	98.60	98.80	96.10	96.00
6	57.40	54.60	61.40	60.20	48.40	47.20
7	88.00	85.80	69.20	68.40	79.30	78.60
8	91.40	92.40	96.20	95.20	60.20	60.20
9	45.00	45.20	43.40	45.70	30.90	32.40
10	68.80	63.80	75.00	74.20	35.00	34.80
Average	67.50	66.72	69.20	69.09	51.12	51.18

is reported in Figure 11. In this database, retrieval accuracy in CBIR systems in [39] and [17] are decreased by 0.79% (from 11.87% to 11.08%) and 0.60% (from 12.21% to 11.61%), respectively.

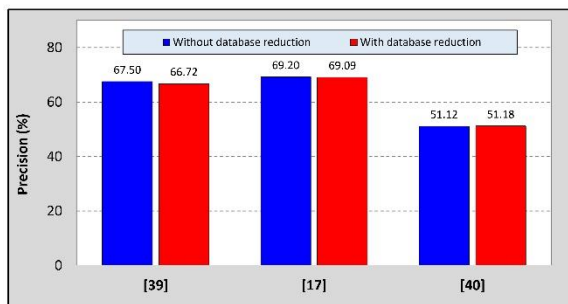


Figure 9. Retrieval accuracy of CBIR systems from the methods in [39], [17] and [40] on the original and reduced Corel-1k database

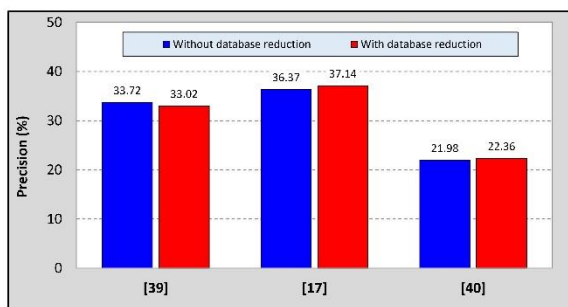


Figure 10. Retrieval accuracy of CBIR systems from the methods in [39], [17] and [40] on original and reduced Corel-10k databases

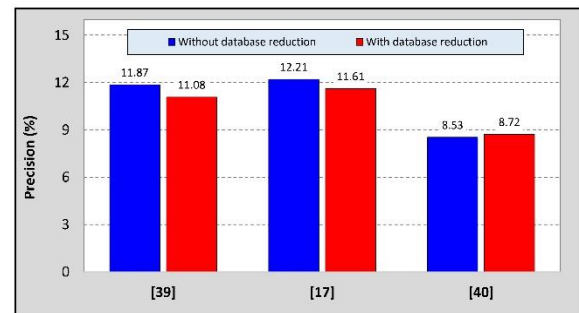


Figure 11. Retrieval accuracy of CBIR systems from the methods in [39], [17] and [40] on the original and reduced Caltech-256 databases

It can be concluded that the proposed database reduction not only preserves retrieval accuracy but also improves it slightly in some cases. It means the relevant images are preserved in reduced database. The proposed method is also compared with two speedup methods in [32] and [33]. Three human subjects were used in [32] to evaluate retrieval accuracy. Subjects are asked to rank retrieval results with scores 0, 1 and 2 for worst, fair and best performances, respectively. The precision is computed as the sum of goodness scores for retrieved images over the number of images returned to the user. In our experiments, retrieval score is computed from the label of images in dataset.

Retrieval results applied to Corel-1k and ZuBuD databases are shown in Figures 12 and 13, respectively. It is clear that the method in [32] on Corel-1k database has higher precision for low number of retrieved images while for high retrieved images it is vice versa. The

higher number of retrieved images the larger difference of precision is achieved. It means that by increasing the number of retrieved images, precision of the proposed method is preserved constant with a slight decrement while in [32] it is decreased significantly with a negative slope.

In ZuBuD database, the proposed method almost achieves the better precision in all cases except the case 5 retrieved images.

In the last experiment of accuracy assessment, the proposed method is compared with the method in [33] on Corel-1k dataset shown in Figure 14. In 5 out of 10 categories, the proposed method outperforms the method in [33], in one category they are almost same and in the remained four categories, method in [33] achieves higher precision than the proposed method. Retrieval times of the proposed method and [33] are 10.61s and 34.75s, respectively, means that the proposed method is very quicker than the method in [33].

4.3. Retrieval Time The smaller database size, the higher retrieval speed is achieved since retrieving relevant images from smaller database needs less time than a larger database. To show the effectiveness of the proposed method in retrieval speedup, the retrieval time of CBIR methods in [39], [17] and [40] are reported in two cases of the original and reduced databases in Table 4.

Reported time complexities show that retrieval time for reduced database is less than the original database. The best speedup is appeared in CBIR system in [17] from 18.37, 1046.25 and 5037 in original databases to 7.61, 228.30 and 502.7 in the reduced databases on Corel-1k, Corel-10k and Caltech-256, respectively. The main reason is that in [17], similarity measure computation is strongly depends on the number of images in database and by linear increment of the number of images in database, retrieval time is increased exponentially. Therefore, in this case, database reduction has more effect on retrieval time.

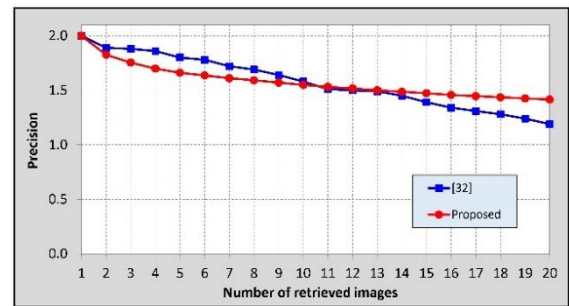


Figure 12. Retrieval precisions of the proposed CBIR system and the method in [32] on Corel-1k database

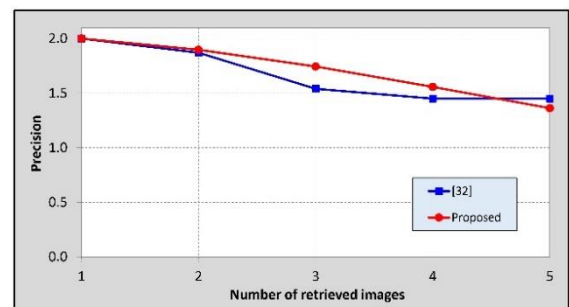


Figure 13. Retrieval precisions of the proposed CBIR system and the method in [32] on ZuBuD database

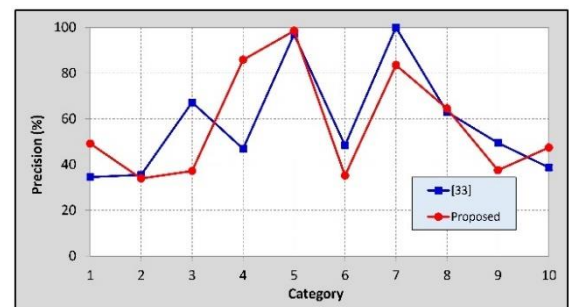


Figure 14. Retrieval precisions of the proposed CBIR system and the method in [33] on Corel-1k database

TABLE 4. Retrieval time of CBIR systems in [39], [17] and [40] on the original and reduced databases

Method	Retrieval Time (ms)					
	Corel-1k		Corel-10k		Coltech256	
	Without database reduction	With database reduction	Without database reduction	With database reduction	Without database reduction	With database reduction
[39]	4.79	3.60	105.38	63.40	139.21	86.50
[17]	18.37	7.61	1046.25	228.30	5037.11	502.37
[40]	6.40	4.18	102.70	61.10	128.22	82.39

5. CONCLUSION

Acceleration and speedup scheme was proposed in this paper based on an interval computed from efficient

combination of Zernike and Wavelet features. This interval was computed for each query image to remove all irrelevant images from database. Most appropriate features among Zernike and Wavelet features were

selected using PSO to have the highest reduced database. Three cases of experiments including database reduction evaluation, retrieval accuracy and retrieval time were performed to show the effectiveness of the proposed method. Experiments revealed that the proposed database reduction method decreases database size significantly, keeps relevant images and preserves retrieval accuracy simultaneously. Future works can be proposed towards acceleration methods based on color features in different color domains as well as appropriate features for images with irregular objects. Finally, efficient combination of intervals achieved from different features can be proposed as another future effort.

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Persian Abstract

چکیده

این مقاله یک روش جدید برای افزایش سرعت سیستم های بازیابی تصویر مبتنی بر محتوا (CBIR) ارائه می دهد. روش پیشنهادی می تواند برای بازیابی تصاویر از یک پایگاه داده بزرگ بسیار مفید باشد. برای این کار، ابتدا ویژگی های Zernike و Wavelet از تصویر پرس و جو (query) استخراج شده سپس یک بازه از تصاویری که پتانسیل تطبیق با تصویر پرس و جو را دارند، از ویژگی های استخراج شده محاسبه می شود. بنابراین، تصویر پرس و جو بجای مقایسه با کل پایگاه داده با تصاویر بازه مقایسه می شود که منجر به افزایش سرعت بازیابی می شود. برای انتخاب ویژگی های مرتبط از میان ویژگی های Zernike و Wavelet، از الگوریتم بهینه سازی ذرات استفاده می شود که منجر به کاهش زمان استخراج ویژگی ها می شود. به منظور ارزیابی روش پیشنهادی، سه روش ارزیابی از جنبه های کاهش پایگاه داده، دقت بازیابی و زمان بازیابی انجام می شود. در بهترین حالت، پایگاه داده Corel-1k به طور متوسط ۳۳.۹۸٪ نسبت به اندازه اصلی خود کوچک شده در حالی که ۷۱.۹۲٪ از تصاویر مرتبط در پایگاه داده باقی مانده اند. دقت بازیابی در پایگاه داده کوچک شده در مقایسه با پایگاه داده اولیه ۱٪ افزایش یافته است. در همین حال زمان بازیابی در پایگاه داده کوچک شده در مقایسه با پایگاه داده اولیه ۵۸.۵۷٪ کاهش یافته است.
