Wavelets Families and Similarity Metrics Analysis in VIR System Design

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Abstract: - This paper presents an analysis of some novel approaches for visual information retrieval (VIR) system design which are based on extraction of wavelet coefficients and applying specific similarity metrics. Four families of wavelets and three techniques for computing similarity between queried and retrieved images have been tested using designed Image Retrieval by Neural Network and Wavelet Coefficients (RetNew) system. The best Symlet transform and similarity metrics based on Euclidian distance have been adopted in a proposed VIR system called Image Retrieval by Wavelet Coefficients (IRWC). Additionally, in order to evaluate a proposed approach and a novel designed system the recall and precision metrics used for analysis of the performance of VIR facilities have been applied on base of the standard COIL-100 image collection. The obtained results show the increment of retrieval efficiency up to 93% without additional increasing a processing time. Therefore a proposed approach may be considered as a good alternative for designing new VIR systems. The obtained results allow facilitating the development of new methods for solving this still open problem of efficient image retrieval.

Key-Words: - Image Processing, Visual Information Retrieval, Similarity Metrics, Wavelets

1 Introduction

Actually, in well-known searching engines the seeking and retrieval of documents in Web is based on textual queries. The same approaches are used for retrieval of documents with images assuming that those images have textual annotations. In general, these approaches are not efficient for visual information because documents in Web frequently have not any textual descriptions. In order to overcome this problem the alternative techniques are used. In well-known visual information retrieval systems the extraction of image features is the principal procedure used for image indexing and interpretation instead of a textual description which may be associated with those images [1], [2].

These methods sometimes are slow and too complex for design of real-time applications. Additionally, VIR systems use only low-level feature vectors, which do not provide mechanisms to represent a meaning of images. Another significant problem of the image retrieval process is computing similarity between feature vectors of visual query and images in preprocessed collection, which are candidates to be retrieved. The comparison of the feature vectors without their adjustment and normalization frequently is not efficient and convenient way to find the matching between them. That is why, the feature vectors must be converted to another domain for simple and efficient image characteristics extraction, indexing, and classification [3], [4].

There are a lot of reports about novel approaches and methods for searching, retrieval, indexing, and classification of visual information on base of analysis of low-level image features, such as a color, texture, shape, etc. [5]. Among the commercial VIR systems that may be used as prototypes for development of novel image retrieval techniques, the

CIRES (Content Based Image REtrieval System) is the one of efficient facilities that provides features retrieval, such as a structure, color, and texture of image combining them with user specifications of importance of these features in a query [2].

Other ones are AMORE (Advanced Multimedia Oriented Retrieval Engine) and SQUID systems that provide image retrieval from the Web using queries formed by keywords specifying similar images, sketches, and SQL predicates [6], [7].

SIMPLIcity (Semantics-sensitive Integrated Matching for Picture Libraries) provides image retrieval from the Web using texture, indexing by clustering of image segments, and feature vectors are generated by wavelets transform [8].

There some approaches which do not use directly the image features mentioned before in image indexing and retrieval process. For example, Sumimoto in [9] proposes to use specific techniques in which regions of interest are indexed and authenticated on base of embedded watermark. This approach is based on DCT transform frequently used in image compression process. In the watermark embedding process a watermark sequence is extracted from a region of interest within analyzed image and it is embedded into the previously generated DCT mapping list. In the authentication and recovery process the watermark sequence is extracted from the corresponding DCT mapping list and then it is compared with the sequence extracted from the region of interest.

Another interesting approach for retrieval of documents with visual information has been proposed by Woosaeng [10] where similarity between structure and content of XML documents is the principal measure used for image indexing. There is not general criterion to measure the similarity between two XML documents. Woosaeng assumes that two documents are structurally similar when they are structurally identical or structurally contained in each other.

Another VIR facility for classification of segmented images combining neural networks and wavelet matching is known as RetNew system [11]. This system designed by authors provides a region growing using multiresolution in YIQ color domain applying Jacobs' metrics for computing similarity between retrieved images and visual query. The feature vector for image indexing is formed by 12 low-level image characteristics. Additionally, the wavelet transform and neural network are used for description of a visual query. That is why, RetNew system applies a wide range of techniques and it may be used as basic architecture for selection and test of the best approaches in image retrieval process.

After analysis of these systems some common disadvantages have been detected, such as a low percentage of relevant retrieved images, low speed of the feature vector generation, significant number of image retrieving iterations, and necessity of complex organization of the preprocessed image collections. Therefore, in this research we propose to test some VIR approaches using as base RetNew system and to improve it designing a novel VIR system.

The possible applications of proposed image retrieval approaches are systems for supporting digital image processing services, high performance exchange of multimedia data in distributed collaborative and learning environments, medical and biological researches, digital libraries, and others where information is presented in visual form.

This paper is organized in the following manner: in the section 2 the analysis of methods related with well-known VIR systems and, particularly, with RetNew system are presented. The section 3 shows conceptual considerations for analyzed and proposed approaches as well as a selection of the best wavelet transforms. The similarity metrics analysis is presented in the section 4. The experimental part and evaluation of proposed approach in improved Image Retrieval by Wavelet Coefficients IRWC system are presented in section 5.

2 Related Approaches and RetNew

Among the image features the color and shape are most important because they define the specific regions in image which may be interpreted and classified as a set of objects with certain significance in a scene. In this case the shape or region that represents objects in image has a meaning by itself and may be used as a principal feature in VIR. However, a shape matching is considered as one of the most difficult aspects of image processing due to they need a lot of parameters to be indexed, classified, and represented explicitly. The well-known methods for global color/shape/region description such as Elasticity correspondence [12], Curvature scale space approach [13], B-splines and chain case codes [5], Two-Segment Turning function and Star field approaches [1], Fourier spectral descriptors [14], etc. sometimes are too complex for fast non-sensitive to spatial variations processing and frequently they do not provide the efficient feature extraction.

After the analysis of well-known methods, some of them have been selected taking into account their performance and usefulness for improving the VIR process parameters such as processing speed, high grade of similarity with input visual query, low number of iteration in retrieved process, and simplicity in description of image semantics. One of the approaches with the mentioned characteristics is based on applying wavelet transform because it provides a high grade of relevance of retrieved images, extracts image features in noised multimedia data, and sometimes they are invariant to spatial distortions in image [15].

The selected VIR facility as used prototype, which may be improved applying a novel retrieval approaches, is RetNew system presented in Fig. 1. The system consists of two channels: one of them generates wavelets characteristics of an input querying image and another one retrieves the centroid of image from preprocessed image collection during their comparison. The centroid is the generalized image representing the class or group of images in collection with similar content providing in this way the distribution of images in collection on base of their semantic features. This process of distribution of images and organization of collection is made by using the Resonance Adaptive Theory ART2 neural network.

According to results obtained by neural network, the processed image obtains corresponding parameters that define to which group this image belongs, for example, to group of buildings, maps, animals, landscapes, etc. In general the image preprocessing implies image segmentation, wavelet coefficient extraction, computing a corresponding centroid, and calculation of similarity measure as it shown in Fig. 2.

The image segmentation process is based on YIQ decomposition and region growing [16]. As result, twelve image features presented in Table 1 are extracted and they form the feature vector that is used as input of the ART2 neural network.

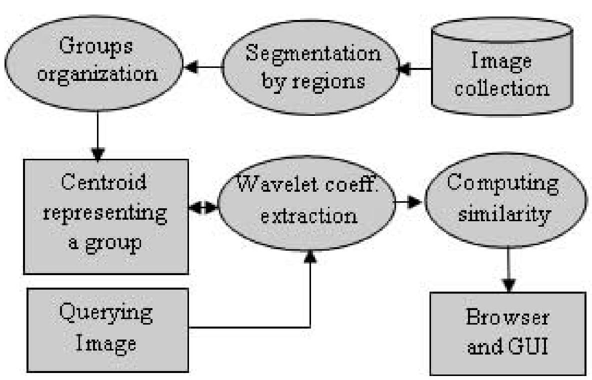


Fig. 1. Block diagram of RetNew VIR system.

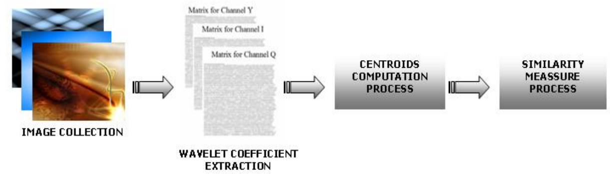


Fig. 2. Image retrieval process in RetNew system

Table 1. Extracted features in preprocessing step

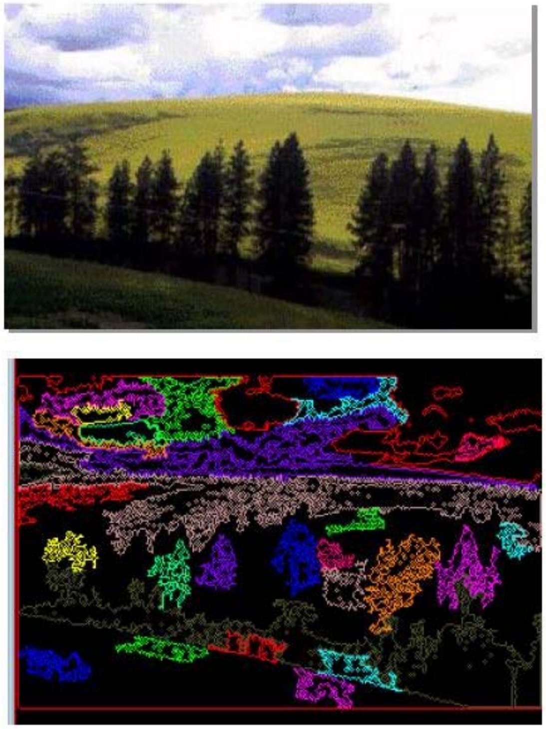
	Feature Name	Computing operation
1	Area	In pixels
2	Average R	For channel
3	Average G	For channel
4	Average B	For channel
5	Isometrics	*ra/rb*
6	Structure Factor	Isometric · Bulkiness
7	Bulkiness	($4\pi \cdot ra \cdot rb$)/Area
8	Deviation R	*average R + absolute R*
9	Deviation G	*average G + absolute G*
10	Internal Circle	lowest area
11	Convexity	*area/circle convex area*
12	Circularity	$area / \pi \cdot r^2$

In the table the variables *ra* and *rb* are the largest and the smallest radiuses of segmented region, the variable *r* is the radius of circular region. The structure of the neural network consists of three layers with 12 input and 20 output nodes. The result of input image segmentation is shown in Fig. 3 where selected regions are used as base for generation of image feature vector.

When the collection of images is classified in semantic groups the retrieval process may be started. For each classified image in the group wavelet coefficients are computed, and then the feature vector (centroid) for each particular group is defined

The centroid for a group of images is generated by calculation average value in matrix composed by wavelet coefficients for particular group. Then these values are normalized to a range from *0* to *1*. This process is applied to all images in collection and, using Euclidian distance metrics as square root of difference between the squares of computed for each image average values, the classification of images is provided.

A matrix with the lowest Euclidian distances is taken as a final matrix or signature and it labeled as Tridimensional Centroid Signal (TCS) or centroid of this group. Centroid computing process is illustrated in Fig.4. A pseudo code for this process is shown as it follows.



a)

b)

Fig. 3. YIQ decomposition and segmentation: (a) original image, (b) preprocessed image

When the collection of images is classified in semantic groups the retrieval process may be started. For each classified image in the group wavelet coefficients are computed, and then the feature vector (centroid) for each particular group is defined

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However, these centroids do not express general meaning of an images in group, they show how similar is one image to other in collection taking into account only low-level image characteristics defined in feature vector. That is why, the user feedback is needed to interpret semantics of each image with user-oriented indexing vocabulary for description of the scenes in these images.

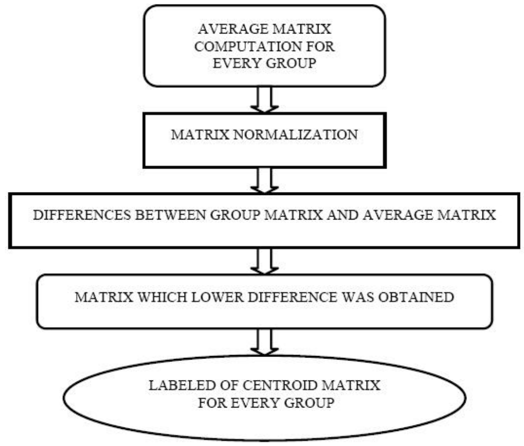


Fig. 4. Centroid computing process

Pseudocode for centroid computing process

```
/* Given a group k with n images Average matrix equal
to accumulative sum of matrix in group k */
for n_i from 1 to n
  Avg_Matrix k [i][j]+ = WC_Matrixni[i][j];
end
/*Matrix normalization */
For each average matrix
  for k from 1 to 4
    if (Avg_Matrixk[i][j]>1) then
    Avg_Matrixk[i][j] = 1 ;
    else
    Avg_Matrixk[i][j] = 0 ;
  end
end
/*Difference between group k and average matrix*/
For all wavelet coefficient in group k for n_i from 1 to n
Diff_Matrixni[i][j]=Euclidian Distance
{WC_Matrixn_i[i][j]-Avg_Matrixk[i][j]};
/*accumulative sum of Difference matrix columns*/
for rows from 1 to i
  for columns from 1 to j
    cumsum_columnsn_i[rows]+ =
    Diff_Matrixni[rows][columns];
  end
end
/*accumulative sum of Difference matrix for rows*/
for rows from 1 to i
  cumsum_rowsni+=
  cumsum_columnsn_i[rows];
end
/* keep each difference value in differences_vector k */
for n_i from 1 to n
  differences_vector k[n_i]=cumsum_rowsn_i;
end
/* get lower value inside differences_vector*/
[index,value] = min(differences_vectork);
/*Identification of Centroid in group k*/
n_i=index;
tridimensional_centroid_signal = WC_Matrixni[i][j]
```

The users' feedback in the image retrieval process may be implemented by a following interface shown in Fig. 5. It has been designed for textual description of an object or whole content of image. It is necessary because some users may interpret the same object in a different way. For example, the closed up selected by proposed CORPAI (Convex regions preprocessing algorithm in images) algorithm object in Fig. 5 may be interpreted as a mobile robot [1]. But another user may describe the same object as vehicle, toy, car, machine, mobile engine, etc.

Thus, the textual descriptions of a retrieval object will be quite different. That is why, user must be a part of the image retrieval process through specific feedback. The proposed feedback mechanism is flexible enough to associate as many meanings to an object as it is necessary for generation of centroid and then for efficient image interpretation and retrieval.

The image analysis and retrieval processes in RetNew system include four steps: visual query preprocessing, the corresponding centroid generation, computing the matching between centroids, and retrieval of images with high grade of similarity to a query. The input querying image is divided in regions applying YIQ multiresolution decomposition and then 12 features that compose the vector of image characteristics, such as, color, region area, its maximum radius, moments, luminosity, RGB average, elliptical envelope, convex shape description, etc. are computed for each region (object).

The input visual query that may be thumbnail image, sketch, or shape is converted to its feature vector and then the computing similarity is provided by matching of this vector with all centroids in collection.

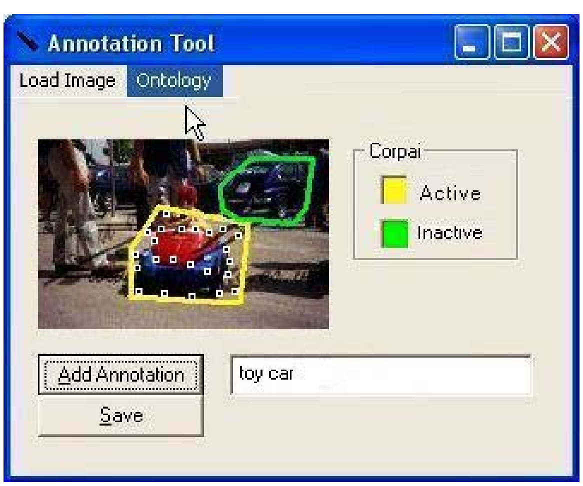


Fig. 5. GUI for textual description of object.

The highest grade of similarity between feature vectors defines the group of images that may be candidates for retrieval. This grade is computed according the procedure proposed by Jacobs [15].

$$\|Q,T\| = w_{(0.0)}\left|Q[0,0]-T[0,0]\right| + \sum_{j,j} w_{(i.j)}\left|\tilde{Q}[i,j]-\tilde{T}[i,j]\right| \qquad (1)$$

where Q represents the feature vector of a querying image and T is the centroid corresponding to compared particular class of image collection, $w_{(i,j)}$ is a semantic weight associated with a class of images to which centroid belongs in T.

When the best correspondence with one or more centroids is found a comparison of the wavelet characteristics of images within the selected class is applied to find those that have the highest grade of similarity to low-level features of querying image. Thus, RetNew system has two steps of matching: first one consists in selection of a class after analysis of similar content of compared images, and second one includes a selection of the most similar images within the class on base low-level features using neural network.

Therefore, in the indirect manner RetNew system retrieves images using not only low-level image features but meaning of a visual query due to organization of image collection in groups of centroids.

The disadvantage of the proposed approach implemented in RetNew system is a significant time that it takes for feature vector generation and for organization of collection with preprocessed reference images, which additionally requires the user feedback for textual description of image semantics.

Using personal Intel-based computer of 2GHz and RAM of 2GB we determined empirically that this time is about some seconds for image retrieval from on-line collection which has 7200 images [17].

Additionally, if a new querying image that has not corresponding similar preprocessed images (centroid) in collection, the approach is failed retrieving usually nonsense information. In this case, the collection must be updated with a new image generating a new semantic class and training of the neural network has to be applied for definition of a centroid corresponding to this class.

It is important to mention that a set of relevant retrieved images frequently depends on the quality of image collection organization in classes or centroids and may be improved using other approaches of Web semantic techniques, for example, applying ontological indexing and description of images in collection.

The performance of the RetNew may be improved by a novel approach implemented in proposed IRWC system.

3 Proposed IRWC System

The proposed approach may be described as a set of procedures applied to input querying image with the principal purpose to find a set of similar images in the previously organized collection. The block diagram of the designed IRWC system is shown in Fig. 6. It adopts the principal concepts of RetNew system but a sequence of visual information processing is different that reduces the complexity of the used in RetNew algorithms without increment of computational cost.

The modifications of implemented IRWC system include simplification of the preprocessing steps where only YIQ color decomposition of image is applied. It is important feature because a color reduces significantly a set of images to be processed. The neural network is substituted by wavelet transform for generation of characteristics to be compared. Therefore, computing similarity does not use centroids of images reducing two-steps image matching process adopted in RetNew to one-step feature vector comparison.

As it shown in the Fig. 6 the input query is an image to be converted to color and luminance features of used YIQ model because they are more informational characteristics.

Than the wavelet transform is applied to color regions extracted by YIQ decomposition module with the principal purpose to generate a feature vector that consists of wavelet coefficients representing the regions.

Computing similarity of querying image vector with preprocessed images in collection is provided by using one of some similarity metrics well adopted in VIR systems. The decision about used appropriate similarity metrics is taken on base of analysis of their efficiency in retrieval process. Finally, the retrieved images are presented in user interface with the corresponding degree of similarity.

In order to select the best type of approaches for generation of feature vectors, four families of wavelet transforms have been implemented. Particularly, Haar, Daubechines, Biorthogonal wavelet, and Symlet transforms that provides satisfactory results in some VIR systems are analyzed and tested.

The first simplest way for multiresolution analysis of regions is Haar wavelet transform that may be defined by the following equations [18]:

$$\begin{aligned} \psi(x) &= 1, \quad if \quad 0 \le x \le 0.5 \\ \psi(x) &= -1, \quad if \quad 0.5 < x \le 1.0 \end{aligned} \tag{2}$$

where $\psi(x)$ is Haar transform and x is an input querying image.

The other one is Daubechines transform that belongs to family of discrete orthogonal wavelets computed as it shown in (3)

$$Daubechies_{(y)} = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k \tag{3}$$

where C_k^{N-1+k} denotes binomial coefficients, N is a size of processed set and y is the input pixel.

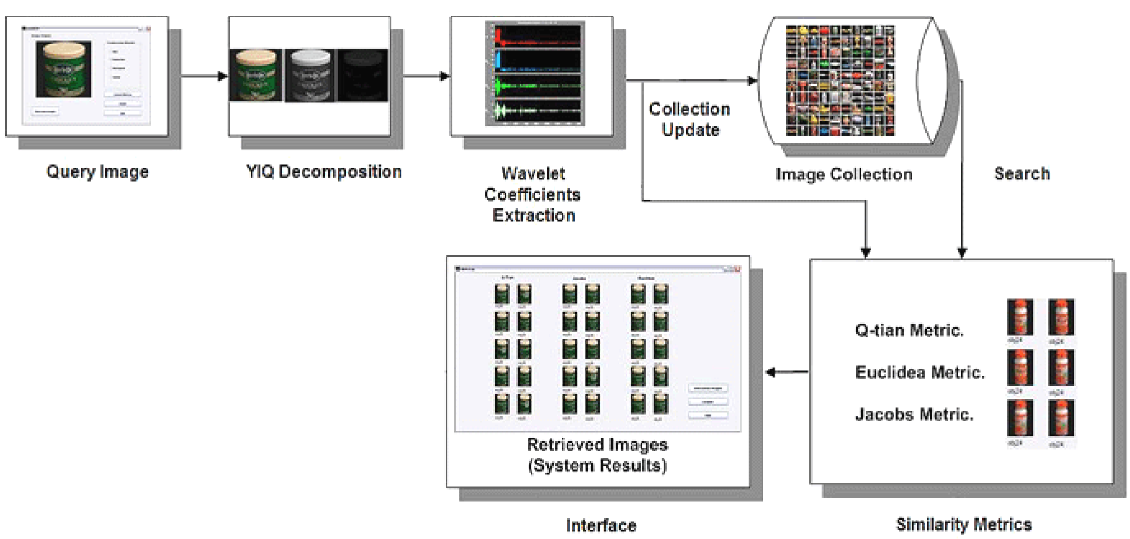


Fig. 6. IRWC system for image retrieval using wavelet characteristics.

The third wavelet family which has been evaluated is Biorthogonal transform. It is efficient for image reconstruction applying the equation

$$Biort_{j,k} = \int s(x)\tilde{\psi}_{j,k}(x)dx \qquad (4)$$

where j and k are coordinates of pixels in the input image, $\tilde{\psi}_{j,k}(x)$ is Haar wavelet transform obtained from (2), and $s(x)$ is defined as first derivative of image x.

The last one is the Symlet transform. It is similar to Daubechines wavelet but it provides the best symmetry and may be obtained by the following equation

$$Symlet_{(X)} = e^{\varphi(i)\omega} \qquad (5)$$

where x is input image, $\varphi(i)$ is Daubechines transform for each pixel i, and ω is the moment of an image.

The feature vector generated by wavelet transform may be considered as identifier of a visual query (image signature). This signature represents wavelet coefficients, which has been digitalized (quantized) and normalized in range of the values from 0 to 1. It is used then for comparison with wavelet coefficients of preprocessed images in collection.

The simple algorithm for wavelet coefficient extraction and generation of the feature vector is presented as it follows.

```
Start
  Image selection from collection COIL_100
  Select wavelet transform
  Select decomposition level
    For 1 to max number of images in COIL-100
      YIQ decomposition of image
      Wavelet coefficient extraction
      Quantization of wavelet coefficients
      Normalization of coefficients in range
      Generation of feature vector
    End For
End
```

The GUI for analysis of efficiency of wavelet transforms is shown in Fig. 7, where user may submit a visual query and select one form four wavelet transforms on the right of the interface. The system returns the feature vector of query with its complete description.

Fig. 7. Graphical user interface for analysis of wavelet families

The visual representation of extracted by wavelet characteristics for mentioned four families are shown in Fig. 8 where the x-axis shows the number of wavelet coefficients obtained for each processed image and y-axis corresponds to value of each coefficient without normalization.

The normalization process consists in adjustment of all wavelet coefficients in the range from 0 to 1. The non-normalized coefficients in the Fig. 8 include the noise of image and distortions due to specifics of used method.

The length of feature vector and the level of decomposition for each transform are presented in the Table 2. All vectors have a similar decomposition ability limited by noise that they generate, and significant length of feature vector provides more precise comparison during similarity computing process.

Table 2. Characteristics of feature vector for four wavelet transforms.

Wavelet type	Decomposition	Feature vector size
Haar	5.0	1x4096
Daubechines	4.0	1x4489
Biorthogonal	6.8	1x5184
Symlet	4.0	1x4489

The advantages of wavelet-based approaches comparing them with other image feature extraction methods consist in better convergence of results, symmetry, and regularity useful for image processing with presense of noise [11].

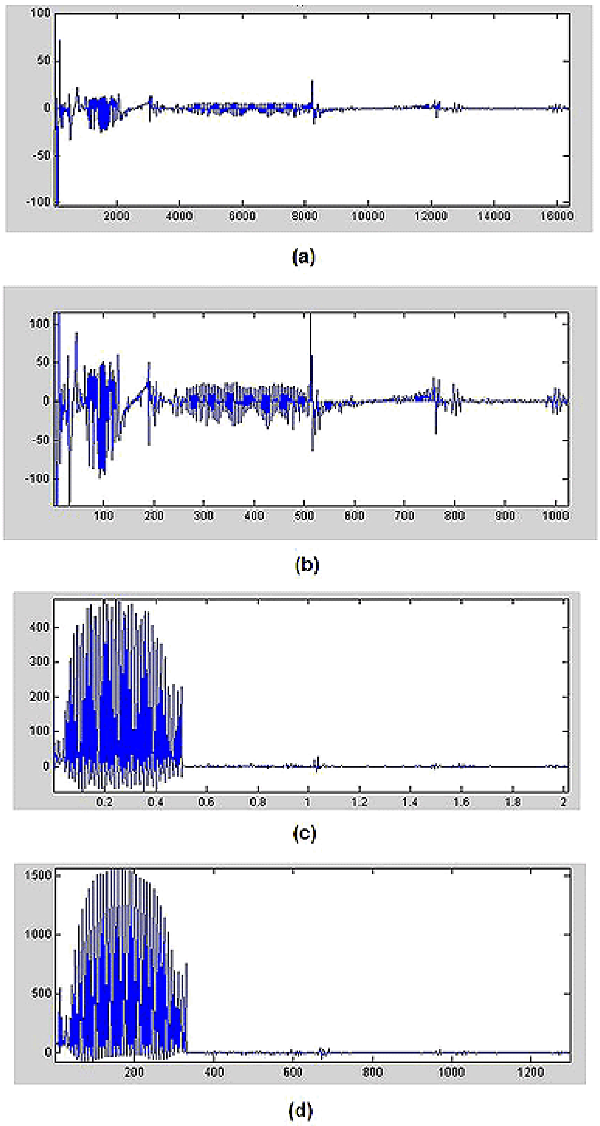


Fig. 8. Wavelet coefficients extraction by
a) Haar, b) Daubechines, c) Biorthogonal wavelets, and d) Symlet transforms

4 Similarity Metrics Analysis and Test

One of more important and quite complex step of image retrieval process is computing similarity between a feature vector of input image obtained after applying the wavelet transforms and the vectors of previously preprocessed images in collection. In this research the evaluation of some techniques for computing similarity metrics is done in order to define which one provides more reliable and relevant results.

The first tested similarity metrics is based on Jacobs' equation (1) we used in RetNew system.

This equation has been modified in the following manner to use it with wavelet coefficients of IRWC system, such as

$$\|Q,T\| = |Q[0,0] - T[0,0]| + \sum_{i,j} |\tilde{Q}[i,j] - \tilde{T}[i,j]| \qquad (6)$$

where Q and T represent the features of a querying image and images in collection respectively.

The comparison is made in the following way: if the coefficients for particular feature are similar that means $Q(i,j)=T(i,j)$, the accumulative similarity metrics for these vector is incremented, otherwise it is not modified. The maximum accumulative value of metrics for each pair of compared vector elements is considered as the basic measure for retrieval.

The second metrics is based on Euclidian distance between feature vectors, particularly, between wavelet coefficients computed by applying the following equation:

$$\|P,Q\| = \sqrt{(p_x - q_x)^2 + (p_y - q_y)^2} \qquad (7)$$

where P and Q represent the wavelet characteristics of preprocessed image from collection and input querying image respectively.

The Q.Tian metrics frequently used for computing similarity $S_j(f_i)$ may be obtained applying next equation [19]

$$S_j(f_i) = (x_i - q_i)^T (x_i - q_i) \qquad (8)$$

where x_i is the $\boldsymbol{i}$-th vector of the $\boldsymbol{j}$-th image within a collection and q_i is the $\boldsymbol{i}$-th vector of querying image, $(x_i - q_i)^T$ is the transposed response of the difference $(x_i - q_i)$.

These three metrics have been tested on designed RetNew and IRWC systems. Table 3 shows the performance comparison of designed RetNew and IRWC with and other VIR systems which use the wavelet transforms and similar matching techniques.

Particularly, the table shows a set of well-known systems with relation to used wavelet transform, similarity metrics, size of the corpus of reference images (collection), and reported percentage of relevant to query retrieved images.

Table 3. Well-known approaches versus IRWC

Related Work	Wavelet type	Metrics type	Corpus Size	Retriev. %
[17]	Daubech.	PCA/LDA	1,500	85.38
[13]	Haar	Jacobs	20,558	75.7
[18]	Haar Daubech.	Neural Network	800	90.21
[15] RetNew	Haar	Jacobs	221	78.3
[19]	Haar Daubech.	Jacobs Euclidian Q. Tian	1,400	90.65
IRWC	Haar, Daubech. Biorthogon. Symlet	Jacobs Euclidian Q. Tian	7,200	92.55

5 Experiments and Discussion

For analysis of wavelet transform performance and estimation of similarity metrics efficiency the experiments have been divided into two groups. The first one is *Candidate Images Selected by Different Similarity Metrics* experiment, which consists in applying Jacobs', Euclidian, and Q.Tian metrics over a sets of previously classified images in collections (Columbia Object Image Library collection COIL_100) [17]. The purpose of this experiment is to observe how well the used techniques for computing similarity are able to choose the relevant images from collection.

In the Table 4 the results of experiments for selected four wavelet transforms using three different matching techniques in RetNew system are presented.

Each experiment consisted of random selection of 100 querying images form 72 different classes in COIL-100 collection of 7200 images. Table 5 shows the results obtained for the same experiment of wavelet family analysis using IRWC system.

Table 4. Average values of relevant retrieved images for used wavelets and similarity metrics in RetNew system

Wavelets	Jacobs	**Euclidian**	Q.Tian	Average for transform,%
Haar	89	**88**	88	88.3
Daubechines	92	**95**	92	93
Biorthogonal	92	**95**	88	91.6
Symlet	**95**	**95**	**92**	**94.0**
Average for metrics,%	92.0	**93.25**	90	

Table 5. Average values of relevant retrieved images for used wavelets and similarity metrics in IRWC system

Wavelets	Jacobs	**Euclidian**	Q.Tian	Average for transform,%
Haar	90	**92**	90	90.6
Daubechines	95	**96**	89	93.3
Biorthogonal	93	**96**	89	92.6
Symlet	**96**	**97**	**93**	**95.3**
Average for metrics,%	93.5	**95.25**	90.25	

From four different wavelet approaches tested in these systems the best one is selected for final version of IRWC, particularly, the best performance, presented in bold digits in Table 5, has Symlet transform due to its property of symmetry. The best similarity metrics was Euclidian distance due to more precise comparison of each characteristic in feature vectors.

That is why, the Symlet transform and Euclidian similarity metrics have been adopted in proposed IRWC system. The same result has been obtained in experiment with RetNew system detecting that Symlet transform and Euclidian distance approach are the best ones as it is shown in table 4.

In Fig. 9 and Fig. 10 the corresponding user interfaces of RetNew and IRWC systems are presented where the relevant retrieved from collection images are shown. It is possible to note that there are some images which do not correspond to querying image reducing in this way the performance of used approach.

The input visual query is the first image on the left in each group of two columns for each similarity metrics.

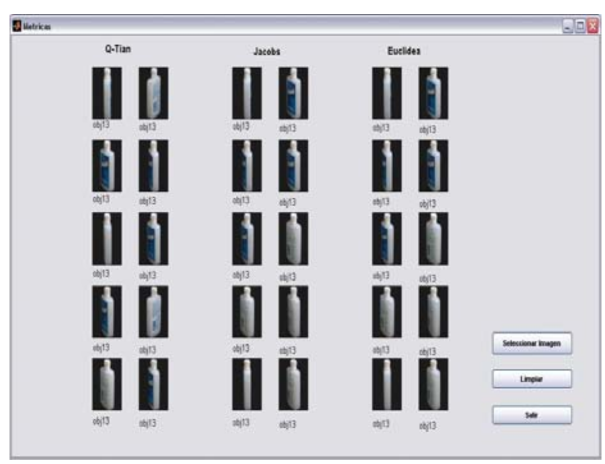


Fig. 9 GUI of RetNew system with retrieved images

Fig. 10 GUI of IRWC system with retrieved images

For simplification of analysis of used approaches, user may obtain the retrieving process statistical data as a graph where relationship between relevant and non-relevant retrieved images is presented. This graph is obtained by computing a grade of relevance of retrieved image (matching feature vectors).

The threshold value for relevant images has been selected empirically after visual check-up of similarity of querying and retrieved images. This threshold permits to consider that image is relevant if more than 70% of the wavelet coefficients in compared feature vector are similar.

One example of the statistical graph for experiments on IRWC system is presented in Fig. 11 where the distribution of grade of similarity may be appreciated in the range from 0 to 10.

The second *Candidate Relevant Images* experiment consists in evaluation of the retrieval process in proposed system. The evaluation of VIR system is non-trivial task. This is because there is an amount of subjectivity involved into query interpretation by user.

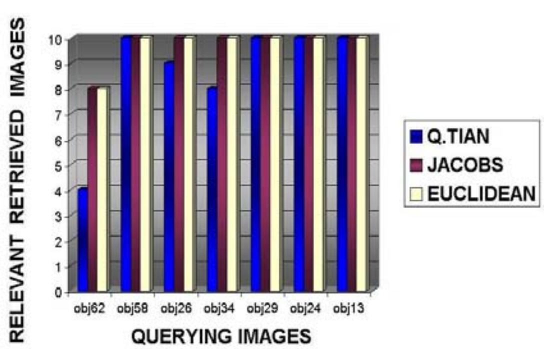


Fig. 11 Statistical graph with percentage of relevant retrieved images for different similarity metrics

The similarity between a query and a set of retrieved image depends on individual perception of user. Nevertheless, there is a standard way of judging the obtained results. This technique consists in calculation of two metrics, such as recall and precision. The recall measures ability of a system to retrieve relevant information from all collection.

The precision is the ratio between a number of relevant retrieved images and total number of relevant images in collection. These metrics may be computed according the following equation [20].

$$PRECISION = {}^{A}\!/_{B}, \quad RECALL = {}^{A}\!/_{C} \tag{9}$$

where A is a set of relevant images retrieved by system, B is a set of relevant and irrelevant images retrieved by system for particular query, and C is a set of all relevant images in collection for particular query.

Fig. 12 a) and b) show the average recall and precision in the experiments on RetNew system. The x-axis represents the number of tests with 100 images in 20 classes of COIL-100; y-axis shows the average recall and precision computed according to (9).

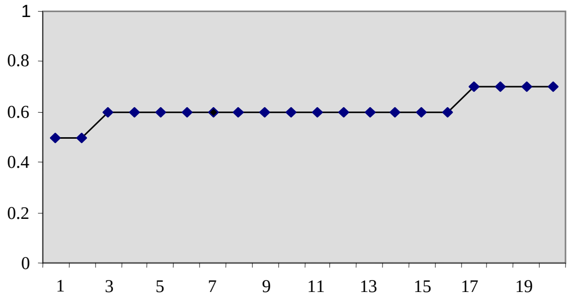
When proposed approach is applied over a small set of images, recall and precision values are low. When the number of images increases the recall/precision also grows because there are more possibilities for applying the similarity metrics over a greater number of feature vectors that belong to the class of visual query.

In the experiments on IRWC system, where the best wavelet transform and similarity metrics have been adopted, the average recall/precision values are higher as it is shown in Fig. 13 a) and b).

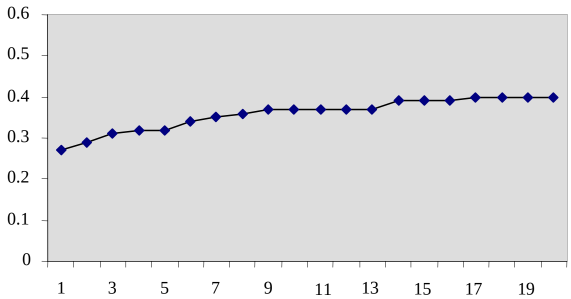
Resuming the results presented in Fig. 12 and Fig. 13 the improved IRWC systems provides better retrieval results to querying image. In RetNew system for different sets of images the recall/precision values lie in the range about of (0.5÷0.75)/(0.28÷0.4) respectively. In IRWC system the average recall/precision have higher values, which lie in the range of (0.7÷0.9)/(0.35÷0.55) respectively.

The increment of the recall/precision is obtained by using the Symlet transform with Euclidian distance similarity metrics (up to 93% of relevant retrieved images).

In this way RetNew system has been improved due to better application of wavelet transform incrementing efficiency of relevant image retrieval and decreasing the number of iterations for searching of necessary visual information.

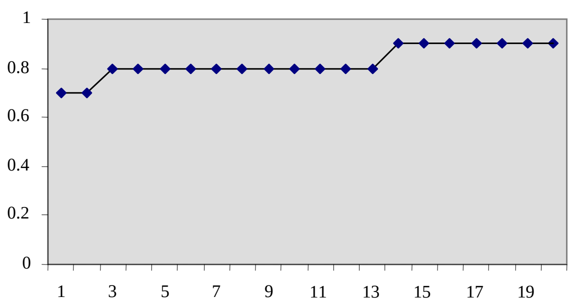


a) RetNew average recall

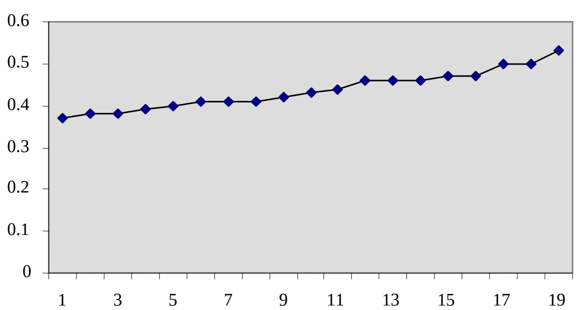


b) RetNew average precision

Fig. 12. Recall and precision metrics for RetNew



a) IRWC average recall



b) IRWC average precision

Fig. 13 Recall and precision metrics for IRWC

In Fig. 14 the user interface of IRWC system is presented where the relevant retrieves images are shown in downward order. The user may select input querying image from collection, and 10 retrieved images with higher grade of matching are visualized on GUI. User has a possibility to add a text to the results, use zooming, and save or print selected images.

The results of this research have been used for development of visual retrieval systems in different fields of science. One example is a designed VIR system for biological research, particularly, for classification of Lepidoptera (butterfly) specimens in extinction in Mexico. The user interface of on-line system is shown in Fig. 15.

The wavelet coefficients of the feature vector represent the color and shape of butterfly making the indexing and searching of images quite simple. The description of each specimen made by user feedback interface is associated with corresponding image of butterfly. Thus, the input query may be image or textual description of butterfly returning to user interface all visual and textual information corresponding to more similar images found in the preprocessed collection of the butterflies.

6 Conclusion

The evaluation of the proposed approach and testing of the designed IRWC system show that ability of system to retrieve relevant information from image collection is better than in RetNew. It is possible to achieve up to 93% of efficiency in retrieval of images. Satisfactory retrieval of expected images is provided faster due to the lower number of iterations in a searching process.

The disadvantages of a system are the presence of errors during wavelet transform and the restrictions for input visual queries, which must have small number of well-defined and separated objects.

Additionally, significant occlusions between objects, week borders or complex background in image, noised or incomplete images are not recommended in this application. The analysis of factors like tolerance to occlusion and deformation, robustness against noise, and feasibility of indexing are considered as possible extension of the proposed approach. From the obtained experimental results we conclude that the proposed approach could be considered as an alternative way for the development of visual information retrieval facilities.

Acknowledgment

This research is sponsored by Mexican National Council of Science and Technology, CONACyT, Project #52333.

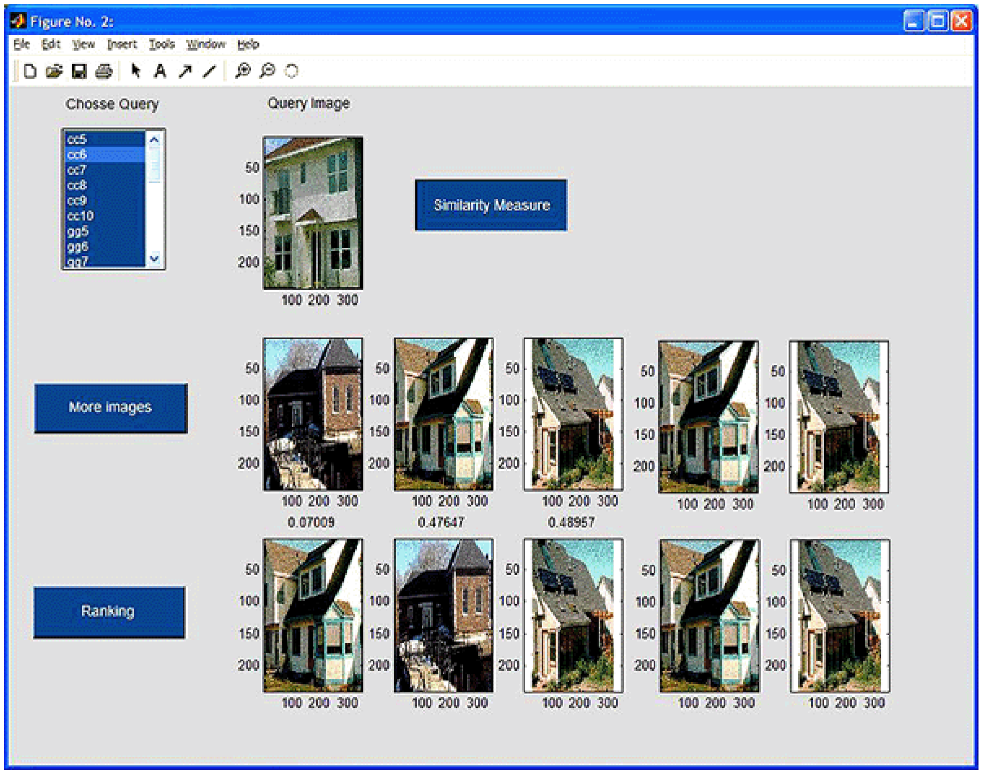


Fig. 14 The user interface of proposed IRWC system

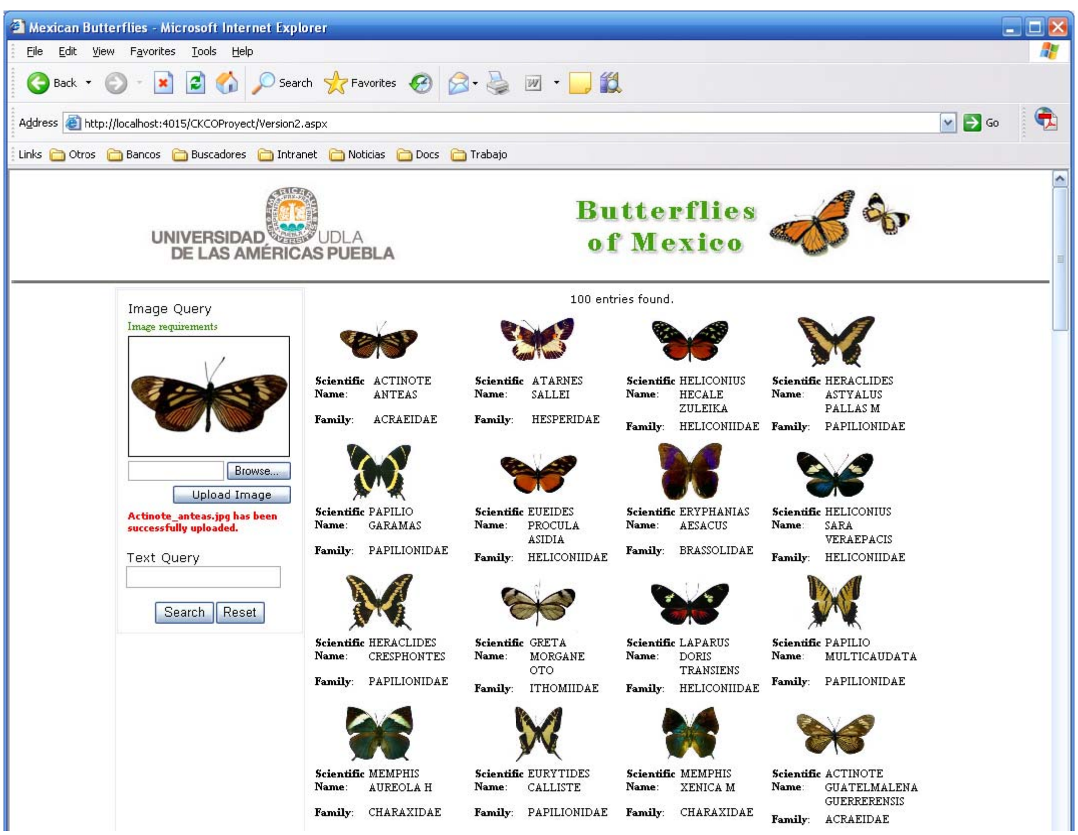


Fig. 15 GUI of a system for classification of butterflies

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