An approach based on lifting wavelet salient points for content-based image description

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A new image description approach based on Lifting Wavelet Salient Points (*LWSP*) is developed. It integrates data representation and content description in a unified framework. Low-level image features, including color and texture, are extracted from the developed approach, which combines lifting wavelet coefficients from lowest-frequency subbands with salient points extracted from other highest-frequency subbands. By using salient points to represent local information, more discriminative features can be computed and sharp parts or edges of the image are reserved in features description. Extensive experiments are performed to demonstrate the performance of the new approach in terms of retrieval accuracy.

فى هذا البحث تطوير طريقة لتوصيف الصور بناءا على محتواها بإستخدام معاملات رفع المويجات للنقاط البارزة. فى هذه الطريقة يتم تمثيل البيانات مع وصف المحتويات للصورة داخل إطار واحد. الملامح المنخفضة المستوى للصورة مثل اللون والقوام يتم استخراجها من هذه الطريقة بدمج معاملات رفع المويجات من حيز الترددات المنخفضة مع النقاط المستخرجة من حيز الترددات العالية لتحولات المويجة. عن طريق استخدام النقاط البارزة لتمثيل المعلومات الداخلية يتم الحصول على ملامح مميزة للصورة والأجزاء الحاده أو الحافات داخل الصورة يتم حجزها فى واصف الملامح. مجموعة من التجارب الشاملة أجريت لتوضيح مدى كفاءة هذه الطريقة لوصف الصور من حيث دقه استرجاع الصور.

Keywords: Wavelet-based salient points, Image description, Low-level descriptors

1. Introduction

Digital imaging has been acquiring a soaring interest over the last few years, which has motivated the research of image description and retrieval. Early image description techniques proposed manually annotated images for their description. However, these text-based techniques are impractical for two reasons: large size of image databases and subjective meaning of images [1]. To circumvent manual annotation, an alternative approach is the content-based image description. This approach uses the visual contents of an image such as color, shape, and texture (low-level image features) to represent and describe the image. This requires much less effort in comparison with manual annotation because features can be automatically extracted [2]. For image description system, the selected features must be capable enough of identifying similar patterns as well as being capable of discriminating between different ones.

Previous research in image description systems has been focused on extracting global, geometrical, and topological features from the original image domain [3,4,5]. However, these global features cannot handle all parts of the image; therefore local features of image information are necessary. Local features can be computed to obtain an image index (descriptor) based on local properties of the image. Unfortunately, local features computation is time consuming specially when it is performed for each pixel of the image. Hence local features are extracted from limited subset of the image, the *salient points*, where the image information is supposed to be the most important [6]. Besides saving time in the indexing process, these points also lead to a more discriminative descriptor, due to their correspondence to the most visually important parts of the image.

Wavelet transform is characterized by excellent energy compaction and de-correlation properties, therefore it is employed to effectively generate compact representations that exploit the structure of the image [7,8]. Wavelets are also tolerant with respect to color intensity shifts, and can capture both texture and shape information efficiently [8]. Furthermore, wavelet transforms can generally be computed in linear time, thus allowing for fast algorithms [9]. Regarding these properties, several wavelet-based image description approaches have been recently developed [3, 6, 7, 9]. These approaches are adopting the fact that an image is" summarized" by a set of image pixels, such as salient points, that may be considered as the most important pictorial information.

Daubechies and Sweldens introduced the lifting scheme as an alternative implementation of classical wavelets [10]. The lifting scheme was originally developed by Sweldens [11] to adjust wavelet transforms to irregular data and to design the fast approximation of Discrete Wavelet Transform (DWT). The main feature of lifting is that it provides an entirely spatial domain interpretation of the transform, as opposed to the more traditional frequency domain-based constructions. Therefore it is ideally suited for building second-generation wavelets when Fourier techniques are no longer available [12].

This paper presents an approach based on lifting wavelet domain for detecting salient points. A joint set of image descriptors - including color and texture features associated to these points-are explored for image content description. The results show that extracting the image content using lifting-based wavelet salient points provides significantly improved retrieval accuracy as compared to the global feature approaches, and also show that the developed approach is appropriate for retrieval of images with moderate amount of deformations.

The rest of the paper is organized as follows: Section 2 points out relevant related work on wavelet salient points extraction methods. Section 3 presents the developed approach for extracting salient points from lifting-based wavelet domain. Section 4 introduces the image feature descriptors. Section 5 gives the experimental results, and section 6 contains the conclusion.

2. Wavelet salient points extraction

In the context of wavelet-based salient points extraction several approaches have been developed. Sun et al. [9] employed a simple approach for salient points extraction. This approach extracts these points from the whole wavelet-based compression domain using self-adaptable threshold *T.* The approach consists of two phases.

Phase 1: compute $|X_m|$ m=0,1…,N-1 is the magnitude of discrete wavelet transform of the original image. $T_i = 2^{\lfloor \log_2(\max_m\{|X_m|\}) \rfloor - i}$, i is the number of desired decomposition level;

Phase 2: compare each coefficient in the wavelet domain with the threshold value T.

if $|X_m| > T$, then X_m *is kept as salient point.*

Sebe et al. [6] developed a sophisticated approach for salient points extraction. This approach is based on the saliency values computed as the sum of wavelet coefficient tracked in finer resolutions. The approach constitute of four phases:

Phase 1: For each wavelet coefficient, find the maximum child coefficient.

Phase 2: Track it recursively in finer resolutions.

Phase 3: At the finer resolution, set the saliency point of the tracked pixel:
the sum of the wavelet coefficients tracked.

Phase 4: Threshold to extract the most prominent points.

In this work, another sophisticated approach is developed. This approach improves the computational efficiency over the Sebe approach [6] by using "lifting-based wavelet domain". As well, it improves the discriminative power by embossing lifting wavelet coefficients from lowest frequency subbands using salient points extracted from other highest frequency subbands. Fig. 1 gives a schematic description of the developed approach, and the next section discusses the facility of using wavelet-based lifting scheme and describes the algorithm for extraction salient points.

3. Lifting wavelet-based salient points

Wavelet transform decomposes a signal with a family of basis functions $\Psi_{mn}(x)$ obtained through translation and dilation of a mother wavelet $\Psi(x)$ [13], i.e.

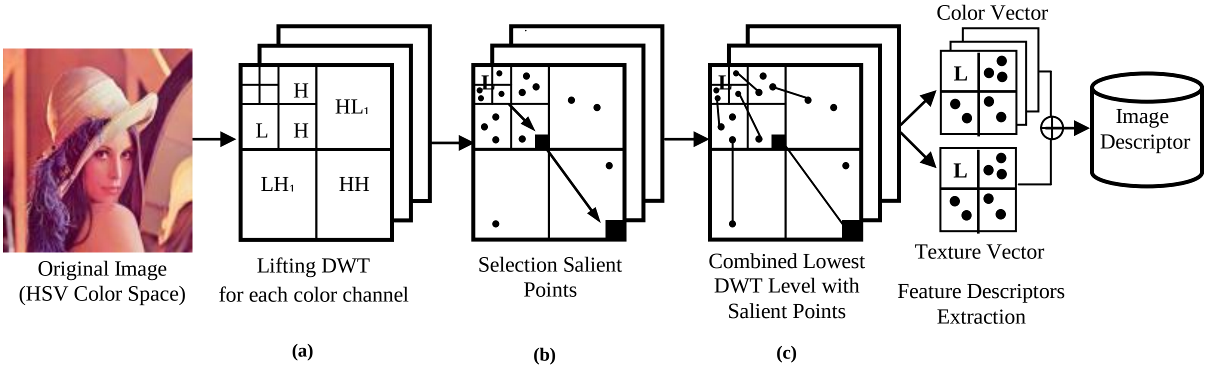

Fig. 1. Content-based image description approach using lifting wavelet-based salient points.

$$\psi_{mn}(x) = 2^{-m/2}\Psi(2^{-m}(x-n)), \quad (1)$$

where m and n are dilation and translation parameters. A signal $f(x)$ can be represented as:

$$f(x) = \sum_{m,n} c_{mn}\Psi_{mn}(x), \quad (2)$$

where c_{mn} are wavelet coefficients, which contain the information about the signal. The wavelet representation gives information about the variations in the image at different scales [14]. Wavelet decomposes the image into four subbands; one approximation subband LL and three detailed subbands LH, HL, HH whose variances are the largest, since they carry more information than the approximate ones as shown in fig. 2.

In general, various techniques to construct wavelet bases, or to factor existing wavelet filters into basic blocks are known, one of them is *lifting*. The basic idea behind the lifting scheme is very simple. It starts with a trivial wavelet, the "lazy wavelet"; a function that essentially does not do any thing, but has the formal properties of a wavelet. The lifting then gradually builds a new wavelet, with improved properties, by adding new basis functions. This is the inspiration behind the name "*lifting scheme*" [11, 12].

A typical lifting stage is comprised of three steps [10]: Split, Predict, and Update as shown in fig. 3. The split step divides the original data into two disjoint subsets, e.g. into $x_e[n] = x[2n]$, the even indexed points, and $x_o[n] = x[2n+1]$, the odd indexed points. The predict step generates the wavelet coefficients d [n] as the error in predicating $x_o[n]$ from $x_e[n]$ using predication operator P:

$$d[n] = x_o[n] - P(x_e[n]). \quad (3)$$

In update stage, $d\,[n]$ and $x_e[n]$ are combined to obtain scaling coefficients $c\,[n]$ that represents a coarse approximation to the original signal $x\,[n]$. This is accomplished by applying an update operator U to the wavelet coefficients and adding to $x_e[n]$:

$$c[n] = x_e[n] + U(d[n]). \quad (4)$$

for more details see [15]. An example of lifting scheme is the construction of the Haar wavelets from a single predicate step followed by a single update step as follows:

$$d_k^1 = c_{2k}^0 - c_{2k+1}^0, k = 0,\ldots,M_1 - 1,$$

$$c_k^1 = int\left(\frac{d_k^1}{2}\right) + c_{2k+1}^0, k = 0,\ldots..N_1 - 2,$$

$$c_{N_1-1}^1 = \begin{cases} int\left(\dfrac{d_{M_1-1}^1}{2}\right) + c_{N-1}^0, & N \to odd \\ c_{N-1}^0 & N \to odd \end{cases}, \quad (5)$$

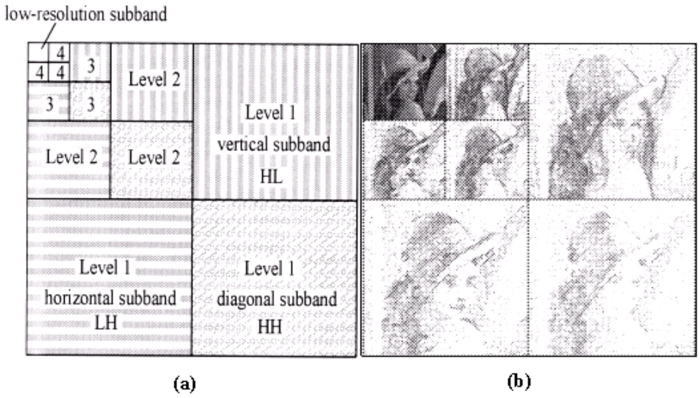

Fig. 2. Wavelet transform of 2-D image.

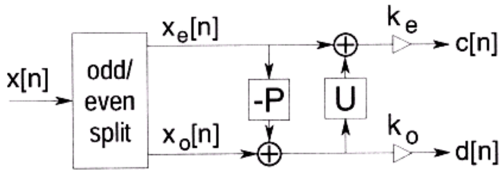

Fig. 3. Typical lifting steps: split, predict, and update.

where $\left\{c_n^0\right\}_{n=0}^{N-1}$ is the original signal where the superscript indicates decomposition level and the subscript indicates a particular point in the signal, also $\left\{c_n^1\right\}_{n=0}^{N_1-1}$ and $\left\{d_n^1\right\}_{n=0}^{M_1-1}$ are its decomposition parts at the first level, here $N_1 = \begin{cases} N/2 & N \rightarrow even \\ (N+1)/2 & N \rightarrow odd \end{cases}$, and M_1=N-N_1 [12].

The lifting-based wavelet transform allows a fully in-place calculation of the wavelet transform (i.e. no auxiliary memory is needed and the original signal can be replaced with its lifting wavelet transform). Also, all operations within one lifting step can be executed entirely in parallel, which leads to a very fast algorithm [11]. The main advantage of lifting is the reduced calculation complexity. Daubechies et al. [10] proved that, for long filters, the lifting scheme cuts computation complexity in half.

Lifting-based Wavelet decompositions allow for very good image approximation with just a few coefficients. Most information is concentrated in the low frequency subband LL, and some points with large values from high frequency subbands, called salient points correspond to edges of the image [14]. In this context, it is preferred in the developed approach to extract these salient points from the locations where significant variation happens. This is manifested by injecting the lifting wavelet coefficients, at finer decomposition levels, into the lowest frequency subbands to add more variance for the feature extraction, fig. 1-c shows the process. Fixed sized low dimensional feature vectors are computed independent of image resolution, size and dithering effects if only the lowest frequency subbands of the lifting wavelet decomposition are considered [16].

In this work, the HSV color space is chosen to do image description because of its perceptual uniformity [17]. The algorithm that depicts the developed wavelet salient points extraction using lifting scheme is as follows:

Algorithm: salient points extraction
Initialization parameter

- T is threshold value to extract the most prominent salient points,
- L is the number of desired decomposition level,
- W is the temporally place, and
- δ is the weight value to tune the contribution of each decomposition level to the lowest level.

According to the property of wavelet transformation δ = ½ , as stated in [9].

Begin

For each pixel in the image, change it from RGB color space to HSV color space;

For each color channel

Compute $|X_{i,j}|$ be the magnitude of the lifting-based wavelet transformation of the original image. The lifting wavelet representation of an image is the set of coefficients for all orientations and all scales.

For each coefficient in the lowest frequency subbands (LH, HL, HH)

W=0;

Begin

Get a Coefficients $X_{i,j}$;

Set W = $X_{i,j}$;

Repeat

Get child ($X_{i,j}$) = {$X_{2i,2j}$, $X_{2i,2j+1}$, $X_{2i+1,2j}$, $X_{2i+1,2j+1}$} at the next finer scale of similar orientation;

Set $W = W +$ Average(child ($X_{i,j}$)).δ;

Set $X_{i,j}$ = Max (child ($X_{i,j}$)); // find the maximum child coefficients.

Until (the last finer scale-1)

If | W | >T, $X_{i,j}$ is then kept as salient point;

End for each coefficient

End for each color channel

End of algorithm

The salient points extracted using this approach, are dependent on the applied lifting-based wavelet transform. The larger the spatial support of the lifting wavelet corresponds to costly computations. Only (2,2)-lifting wavelet transform by integer calculation eq. (5) is applied to offer fastest execution.

4. Image content description

This section presents the low-level image descriptors including color and texture. The connection exists between the quality of the image descriptors and the developed approach for selection salient points from lifting-based wavelet domain is stressed.

4.1. Color descriptor

Color features are among the most important and extensively used low-level features in image database retrieval. They are usually robust with noise, resolution, orientation and resizing effect [18]. The goal of color feature extraction is to obtain compact, perceptually relevant representation of the color content of an image.

Color histogram is the most widely used color descriptor; it captures global color distribution in an image. While color histograms are easy to compute, they result in large feature vectors that are difficult to index and have high search and retrieval cost. In addition, spatial information is not preserved in a color histogram [17]. Several of the recently proposed color descriptors try to incorporate spatial information. These include the compact color moments, binary color set, and color correlogram [18].

According to the moment representation theorem, infinite set of moments uniquely determines a probability distribution and vice verse [3]. This assertion justifies the use of color moments as color descriptor. Stanchev has successfully used color moments in many retrieval systems especially when the image contains just the objects [19]. Since higher order moments decay faster, the color feature vector can be reduced as well as the complexity of the feature extraction by using the first three color moments. Mathematically, the first three moments are defined as:

$$\text{Mean} = \mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} , \tag{6}$$

$$\text{Variance} = \sigma_i = \sqrt[2]{\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^2} , \tag{7}$$

$$\text{Skewness} = s_i = \sqrt[3]{\frac{1}{N}\sum_{j=1}^{N}(f_{ij}-\mu_i)^3} , \tag{8}$$

where f_{ij} is the value of the j^{th} image pixel in the color channel i, and N is the number of pixels in the image. With the fact that the statistics of the LL subband is almost the same as the statistics of the original image [9], color moments are first extracted from this subband. In order that the local feature, such as edges is taken into account for describing color features, the color moments of the lowest frequency subbands (contain salient points) are computed. For color feature generation, a 3×4- dimensional vector is used for each color channel, resulting a total of 3×3×4–dimensional vector for each image in the database.

4. 2. Texture descriptor

Textures provide important surface characteristics of the image objects and are widely chosen as feature for image classification, retrieval, and description. Obviously, color features cannot distinguish objects with identical colors from each other. But, by using a combination of color and texture properties, many common objects may be identified with a tolerable accuracy [20]. In the digital image, according to [21] texture is depicted by the spatial interrelationship between, and/or spatial arrangement of the image pixels.

Early work considered the statistics or the distribution model of texture. The difficulty with traditional methods lies in the lack of an adequate multiresolution tool [21]. The wavelet-based approach integrates the multiresolution and the space-frequency properties naturally and has demonstrated a remarkable performance for texture description and modeling [20]. The lifting wavelet domain is suitable for texture feature generation because it expresses the interrelationship among pixels with irregular frequency decomposition, similar to the human perception system [5].

Image texture features are directly extracted from the lifting wavelet decomposition domain using the local energy function for the LL subband; the goal of the local energy is to estimate the energy in a local region [9]. Local energy of LL subband in the decomposition *j* is given by the following equation:

$$E_j^{LL} = log \sum_{m,n} (C_{M,N}^{LL})^2 .$$
$$K(2^{-j}(m_0 - m), 2^{-j}(n_0 - n)) , \quad (9)$$

where $k\ (m, n)$ is the Gaussian function, and (m_o, n_o) is the center of the LL subband. Moreover co-occurrence matrices, which represent the spatial distribution and the dependence of the gray level within a local area, are applied to the lowest frequency subbands. From these matrices, sets of statistical measure are computed for building different texture descriptors. The statistical measures are:

$$\text{Entropy} = -\sum_i \sum_j N_d(i,j) \log_2 N_d(i,j) . \quad (10)$$

$$\text{Contrast} = \sum_i \sum_j (i-j)^2 N_d(i,j) . \quad (11)$$

$$\text{Homogeneity} = \sum_i \sum_j \frac{N_d(i,j)}{1+|i-j|} . \quad (12)$$

where the $N_d(i\ ,\ j)$ is the co-occurrence matrix whose elements (i,j) represent the probability of going from one pixel with gray level (i) to another with gray level (j) under a predefined distance (d) and angle θ [20]. In this work, texture descriptors are considered at three angles, namely "0°" for horizontal subband (LH), "90°" for vertical subband (HL), and "45°" for diagonal subband (HH) as well as a predefined distance of one pixel in the formation of the matrix.

For Texture feature generation, the texture descriptors described above are applied to the value (V) channel of the HSV color space. The reason to justify the use of V channel is that the Hue (H) and Saturation (S) channels represent the two color components while V channel represents the gray-scale image that can be used for texture analysis [23]. In general, a *3×3–dimensional* texture feature for co-occurrence measures in addition to LL local energy value, are used as texture descriptor for each image.

5. Experiments

The approach described in this paper has been tested using a database of 500 color images of varying content were chosen from the Corel Photo Collection. They cover a wide range of natural scenes, building, textures, flowers, persons, and objects, fig. 4 shows sample images. A java-based prototype image retrieval system is developed to study the retrieval performance of the proposed approach. The image descriptor combines color and texture to do image vector, which consists of 36-*dimensional* color vector adding 10-*dimensional* texture vector, in all, 46-dimensional vector to represent the image features content.

In the first experiment, in order to test the accuracy and robustness of various aspects of the developed approach, 10 variations of a database consisting of 200 images of color objects such as cat, bird, flower and car were used. The format and motivation behind the variations are listed in table 1.

Testing began by isolating each image variation in the dataset. Using the original image as the probe, and for each of the image variations, the database is searched. This procedure is performed to measure the approach's performance under each of the conditions produced by the image variations. The top-5, top-10, and top-15 matches from each search were analyzed. The search results were used to calculate the cumulative match characteristic (CMC) score. The CMC score is the cumulative count of the correct number of returns [22]. It is shown as a percentage of the total number of correct images expected. The CMC scores for each image variation search are summarized in table 1.

The results indicate similar relative strengths in the developed approach. Noising posed the biggest problem, requiring 15 returns before a CMC score of 63 % was achieved. The brightness, contrast and crop images had near-good results with CMC scores ranging from 68 % to 85 % in the top search return. Grayscale, resized, stretch, and auto-level images still generated good results.

For benchmarking purposes, the second experiment compares the retrieval accuracy results obtained with two different image description approaches. The three approaches considered are; the developed "Lifting-based Wavelet Salient Points" approach (*LWSP*), the Wavelet-based Salient Points (*WSP*) developed by Sebe et al. [6] as another state-of-the-art salient points approach and the Global Salient Points approach (*GSP*) implemented in [9]. The retrieval accuracy is measured by recall and precision.

$$\text{recall}\,(K) = \frac{C_K}{M} \quad , \text{ precision}\,(K) = \frac{C_K}{K} \, , \qquad (13)$$

where K is the number of retrievals, C_K is the number of relevant matches among all the K retrievals, and M is the total number of relevant matches in the database obtained through the subjective testing [24]. Each test set image is used as a query, for K=10 the average recall and precision curves are plotted in fig. 5.

It can see from the figure that the developed approach has better recall-precision performance than the other approaches. This behavior is expected because the developed approach represents the most important visual information of the image. The *LWSP*

Fig. 4. Sample images from 4 categories: building, flowers, objects, and natural scenes.

Table 1
Using every original image, each image variation was searched for in turn and its CMC score was recorded. The percentage of the variations returned within each ranking category is listed

Image variation	Purpose	% Returned in top 5	% Returned in top 10	% Returned in top 15
Grayscale	Color invariance	90 %	93 %	95 %
20% Brightness	Pixel and color invariance	81 %	83 %	85 %
20%Contrast	Pixel and color invariance	79 %	81 %	84 %
Auto-level	Color invariance	83 %	87 %	90 %
80 % Resized	Invariance to small size change	89 %	91 %	94 %
50 % Resized	Invariance to large size change	79 %	83 %	88 %
10% x & y crop	Spatial shift invariance	68 %	70 %	73 %
20 % x Stretch	Aspect change invariance	87 %	90 %	93 %
13 % Gaussian noise	Invariance to small noise	63 %	66 %	68 %
20 % Gaussian noise	Invariance to large noise	55 %	61 %	63 %

approach builds the feature vectors depend on local image features like the *WSP*. *M*oreover, it takes into account the edges of the image in features extraction. While the *GSP* approach extracts the features from partly wavelet coefficients, and adds high frequency coefficients to LL subband to present sharp features, it does not consider local features of the image.

6. Conclusions

In this work, an integrated lifting-based wavelet salient points extraction scheme is developed. It demonstrates the use of salient points set for content-based image description. All the features are based on significant lifting wavelet coefficients and their energy distribution among subbands. Since salient points are distinctive, invariant, and able to capture the local feature information, they provide a better characterization for the image content [6].

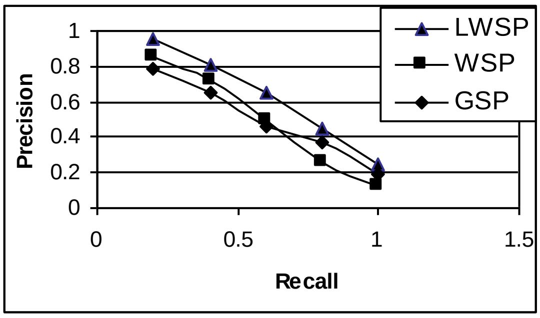

Fig. 5. Average Precision vs. Recall.

The lifting-based wavelet transform is very convenient to locate salient points, because it gives information about the variations in the image at different scales. The idea of the developed approach is to find a relevant point to represent this global variation by exploring lifting-based wavelet coefficients at finer resolutions. Color features are briefly extracted based on lowest resolution subband of wavelet coefficients using color moments. For the texture feature vectors, the extraction is directly performed in the lowest frequency subbands using energy function and statistical measures for co-occurrence matrix.

Some experiments were conducted and the results show that the developed approach achieves the best performance in the overall consideration of retrieval accuracy, computational cost, and storage space of the feature vectors. The developed approach provides good improved results in terms of storage space of the feature vectors because the feature vectors are formed mainly from the lowest subbands, and also reveals good result in computational cost because using lifting scheme reduces the calculation complexity.

In conclusions, the content-based image retrieval can be improved by using local information provided by the lifting wavelet-based salient point. These points are able to capture the local image features and therefore, they can provide a better description for images. Finally, The developed approach can be classified as" open description architecture"; other visual features representation can be easily incorporated if needed.

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