CBIR with dual tree complex wavelet transform using maximally flat all-pass filter

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In the following paper linear-phase filters for Dual-Tree Complex Wavelet Transform implementation based on all-pass filter synthesis with maximally flat characteristics is proposed. This transform is a part of already presented content-based image retrieval algorithm with local features, using Hausdorff distance. It is based on the image division (8x8) from which local features are extracted through the Dual-Tree Complex Wavelet Transform, respectively feature vectors built. Then, we compare its experiment results with the ones of other three algorithms based on both local or global features and the Dual-Tree Complex Wavelet Transform. The used distance measures are Hausdorff distance and Euclidean distance. From the four discussed algorithms the proposed one has the best Precision results because of the vectors formed on the base of the local position of the details and the use of Hausdorff distance. The accomplished experiments show that this algorithm successfully detects details, shape and texture between objects with sharp jumps in the intensity of the two dimensional signal.

Извличане на изображения по съдържание чрез Комплексно уейвлетно преобразуване с дуални дървета с използването на всепропускащи филтри с максимално гладки характеристики (С. М. Ветова, И. Р. Драганов, И. Д. Иванов). *В настоящия доклад са предложени линейно-фазови филтри за внедряване на Комплексно уейвлетно преобразуване с дуални дървета, базирано на всепропускащи филтри с максимално гладки характеристики. Тази трансформация е част от вече представен алгоритъм за съдържателно извличане на характеристики с използването на локални такива и разстояние на Хаусдорф. Той е проектиран на базата на разделянето на подизображения (8x8), от които се извличат локални характеристики чрез Комплексното уейвлетно преобразуване с дуални дървета и съответно се формират векторите от характеристики. Получените резултати са сравнени и анализирани с тези на други алгоритми, базирани на локални или глобални характеристики и същото преобразуване. Използваните метрики за подобие са разстояние на Хаусдорф и Евклидово разстояние. От четирите алгоритъма предложеният се отличава с най-добри резултати по отношение на ефективност, тъй като векторите от характеристики са генерирани на базата на локалното разположение на детайлите. Проведените изследвания показват, че разработеният алгоритъм успешно разпознава детайли, форма и текстура между обекти с остри скокове в интензитета.*

Introduction

The Wavelet Transform is a technique for image representation through spatial and frequency features. The transform analyses the image through multiscale constructions in low computational cost and high speed.

Taking account of these advantages, a great number of researchers design and propose wavelet transform based algorithms.

The usage of the wavelet transform technique may be classified into three groups: for primitives feature extraction, for statistics data computation and for reducing the size of the feature vector.

Thus, for a primitive feature extraction Bhat and Sundaraguru [1] propose a CBIR algorithm for texture features combining wavelet transform and Local Binary Pattern (LBP) to achieve a rotation normalization method using the circular shift of the feature.

Krishna, Sirisha and Mdhavi [2] propose another algorithm for texture extraction, dividing an image into “blocks” and obtaining their features apply the Discrete Wavelet Transform.

To extract shape features, Vijendran and Kumar [3] design an algorithm, combining the Discrete Wavelet Transform and the Histogram Oriented Gradient. Their purpose is to describe a 16x16 pixel region of a preliminarily calculated interest point.

For combined primitives features extraction, most often authors propose methods for texture and color feature extraction.

In [4] Hossain and Islam design a CBIR method using the Discrete Wavelet Transform and Gabor wavelet transform. They calculate mean and standard coefficient on the base of the previously calculated wavelet ones, using the first transform. Then, they apply the second one to generate feature vector under each scale and orientation and combine the result features of the two transforms. In addition, they add the color feature vector generated, using HSV histogram, autocorrelogram and color moment and achieve a 1x190 feature vector. As a result, the algorithm reaches retrieval speed of 1,385586 sec.

Although the wide usage of Gabor wavelet transform, the orientation and scales on the precision rate of the CBIR are not included in the CBIR algorithms design [5]. That’s why, Said and Khurshid [5] apply Gabor wavelet transform, color correlogram, HSV histogram, the effect of varying the number of scales and orientations in Gabor texture for color and texture features vectors generation.

In [6] the authors propose a new algorithm for texture and color features. They catch the primitives using respectively the wavelet transform and the color histogram. For each R, G and B component of a RGB image the color histogram is generated and then the transform executed.

Similarly, in [7] the authors use RGB images and they transform the RGB color space into three subsets and apply segmentation. For each segment they obtain color features through dominant color descriptor (DCD), histogram and statistic components. To extract texture features, the authors propose wavelet transform for wavelet coefficient computation for the entire image. The final feature vector includes the features from the segmentation and the ones obtained on the base of the entire image.

To build algorithms for feature extraction for the three basic primitives (color, texture and shape), Pandey and Kushwah [8] combine color coding (CC) for color, Hu moments for shape and both Gray Level Difference Method (GLDM) and the Discrete Wavelet Transform for texture features extraction. Thus, they achieve a rotation, scaling and translation resistant feature vectors.

In [9] Gupta and his research team propose another CBIR algorithm. They use the Discrete Wavelet Transform for texture analysis, the Dominant Color Descriptor (DCD) for color and Hough Transform for shape feature extraction.

Using the wavelet transform for statistics data computation, Giveki and colleagues [10] design an algorithm for color features extraction. To this end, they convert the RGB images into Lab color space and then they extract the features of each of the color channels, using wavelet transform. As a result, they generate a feature vector on the base of the first and second order moments of the wavelet coefficients.

Similarly, in [11] the authors design another CBIR algorithm for color features extraction where Red, Green and Blue components are extracted from RGB images and then 2D Haar wavelet transform is executed on each of the color matrices.

In order to generate feature vectors with small size, other authors apply the wavelet transform to reduce the size. Thus, Patel and Jerpude [12] convert the RGB image into YCbCr color space since Y component contains grey scale information and the other two the color one. They use Canny edge detection on the Y component for edge detection and build the color histogram on the R, G and B components. To reduce the size of the achieved feature vector, Haar wavelet transform is used.

According to another classification for the wavelet transform usage, the transform may be applied on the entire image [1], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12] or on its segments [2], [7].

In the presented report, we propose a CBIR, using 8x8 division of the image. Local features are extracted from the subimages and the feature vectors are built. We estimate and compare the work of four different algorithms, using local or global features and Hausdorff distance and Euclidean distance as a distance measure.

Method

The Dual-Tree Complex Wavelet Transform (DT CWT) is designed in 1998 by Nick Kingsbury. Its construction uses one binary wavelet tree for the real part and another one for the imaginary part of the Complex Transform, both consisting of highpass and lowpass filters. The Discrete Wavelet Transform is performed on each of the trees. Thus, DT CWT produces an analytic signal with the following properties: smooth non-oscillating magnitude; nearly shift-invariant magnitude; significantly reduced aliasing effect; directional wavelets in higher dimensions.

Using the transform each finite-energy analog signal *x(t)* [13] is decomposed on the base of wavelets and scaling functions via:

$$x(t)=\sum_{n=-\infty}^{\infty}c(n)\phi(t-n)+\sum_{j=0}^{\infty}\sum_{n=-\infty}^{\infty}d(j,n)2^{j/2}\psi(2^{j}t-n) \qquad (1)$$

where *c(n)* – scaling coefficients; *d(j,n)* – wavelet coefficients. Both are computed via the inner products (2) and (3) as follows:

$$c(n)=\int_{-\infty}^{\infty}x(t)\phi(t-n)dt \qquad (2)$$

$$d(j,n)=2^{j/2}\int_{-\infty}^{\infty}x(t)\psi(2^{j}t-n)dt \qquad (3)$$

Both types of coefficients provide a time-frequency analysis of the signal by measuring its frequency content at different times [13].

The wavelet coefficients consist of samples of the step response of the wavelet

$$d(j,n)\approx 2^{-3j/2}\Delta\int_{-\infty}^{2^{j}t_0-n}\psi(t)dt \qquad (4)$$

where Δ - height of the jump; $\psi(t)$ - bandpass function that oscillates around zero; *d(j,n)* – function of *n*; the factor 2^j in the upper limit ($j\geq 0$) amplifies the sensitivity of *d(j,n)* to the time shift t_0.

DT CWT is a biorthogonal transform, which uses linear-phase filters, satisfying the Perfect Reconstruction (PR) condition [8] and which produces approximately analytic signal:

$$\Psi(t):=\Psi_R(t)+j\Psi_J(t) \qquad (5)$$

where $\Psi_R(t)$ and $\Psi_J(t)$ are the wavelets generated by the two Discrete Wavelet Transforms (DWTs).

In order to reach a nearly shift-invariant wavelet transform, one of the two lowpass filters has to be nearly half-sample shift to the other:

$$J_0(k)\approx R_0(k-0.5)\Rightarrow\Psi_J(t)\approx H\{\Psi_R(t)\} \qquad (6)$$

DT CWT has 2D DT CWT extension for two-dimensional signal analysis. This version produces oriented wavelets and approximately analytic signal. To this end, it uses the following six real and six imaginary wavelets:

For -45° oriented wavelets:

$$RealPart\{\psi(x,y)\}=\psi_h(x)\psi_h(y)-\psi_g(x)\psi_g(y) \qquad (7)$$

$$ImagPart\{\psi(x,y)\}=\psi_g(x)\psi_h(y)+\psi_h(x)\psi_g(y) \qquad (8)$$

For +45° oriented wavelets:

$$RealPart\{\psi(x,y)\}=\psi_h(x)\psi_h(y)+\psi_g(x)\psi_g(y) \qquad (9)$$

$$ImagPart\{\psi(x,y)\}=\psi_g(x)\psi_h(y)-\psi_h(x)\psi_g(y) \qquad (10)$$

For -15° oriented wavelets:

$$RealPart\{\psi(x,y)\}=\phi_h(x)\psi_h(y)-\phi_g(x)\psi_g(y)$$
(11)

$$ImagPart\{\psi(x,y)\}=\phi_h(x)\psi_g(y)+\phi_g(x)\psi_h(y) \qquad (12)$$

For +15° oriented wavelets:

$$RealPart\{\psi(x,y)\}=\phi_h(x)\psi_h(y)+\phi_g(x)\psi_g(y) \qquad (13)$$

$$ImagPart\{\psi(x,y)\}=\phi_h(x)\psi_g(y)-\phi_g(x)\psi_h(y) \qquad (14)$$

For -75° oriented wavelets:

$$RealPart\{\psi(x,y)\}=\psi_h(x)\phi_h(y)-\psi_g(x)\phi_g(y) \qquad (15)$$

$$ImagPart\{\psi(x,y)\}=\psi_g(x)\phi_h(y)+\psi_h(x)\phi_g(y)\ldots(16)$$

For +75° oriented wavelets:

$$RealPart\{\psi(x,y)\}=\psi_h(x)\phi_h(y)+\psi_g(x)\phi_g(y) \qquad (17)$$

$$ImagPart\{\psi(x,y)\}=\psi_g(x)\phi_h(y)-\psi_h(x)\phi_g(y) \qquad (18)$$

In order to implement all the oriented wavelet (7) - (18) we consider the use of linear-phase filters as essential part of DT CWT. They need to be based on the all-pass filters with maximally flat characteristics. Their design is presented on Fig. 1 through block diagram, illustrating the process of the coefficient computation by steps.

Algorithm

Several parameters take part in the design of the all-pass filters as follows: *K, L* - flatness parameters; *d*-delay; *A1(z), A2(z)* – transfer functions of the all-pass filters returned by the algorithm represented by denominators $\vec{a}_1,\vec{a}_2$; *K+L* – filter degree; $\vec{p},\vec{q}$ - parameters which represent the total low-pass response. The frequency response magnitude has a flat characteristic at $w=0$ and $w=\pi$ [14].

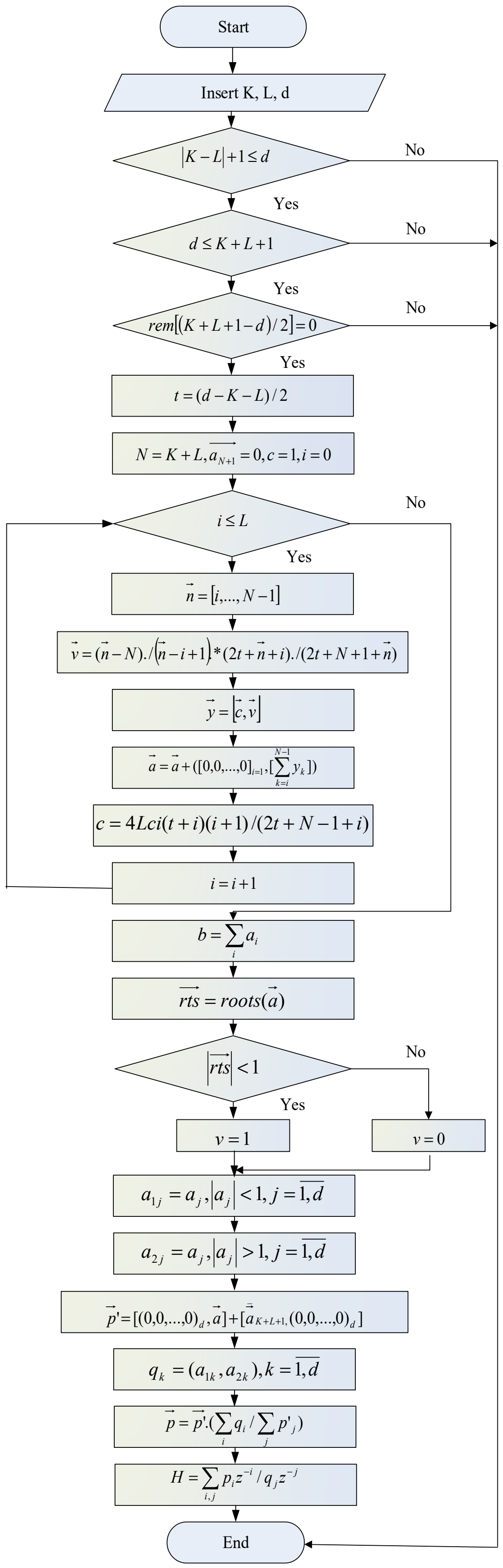

Fig. 1. Block diagram of the all-pass filters with maximally flat characteristics.

Used Data

For the purpose of the accomplished experiments, Wang image test database [15], containing 1000 RGB images, was used. The images are classified into 10 groups: “Nature”, “Architecture”, “Vehicles”, “Dinosaurs”, “Elephants”, “Flowers”, “Horses”, “Food”, “Africa” and “Social life”. They are distinguished for size of 256 x 384 px and 384 x 256 px in JPEG format.

Results

The purpose of the following experiments is to estimate the efficiency of four algorithms [16] and accomplish comparative analysis between them. The first two of them, the Algorithm with Local Features, using Hausdorff distance (ALFH) and the Algorithm with Local Features, using Euclidean distance (ALFE) are built on the base of local features extracted from 64 subimages (8x8). The other two, the Algorithm with Global Features, using Hausdorff distance and the Algorithm with Global Features, using Euclidean distance, use global features of the images.

The presented four algorithms have close Precision values (Precision and Recall are used as efficiency measures as defined in [16]) in different number of the submitted query-images. ALFH presents the best results. ALFE demonstrates close to the ALFH ones in the area of thirty query-images where ALFH Precision has a slight decrease caused by the accumulation of results with lower values. From the group of the global features, AGFE retrieves results with higher Precision and in the list of the four algorithms it takes the third place. Fig. 2 shows the advantage of the algorithms, using local features which is caused by the fact that their vectors are based on the local position of the details.

The four algorithms alter their Recall results increasing the query-image number (Fig. 3). As they increase, the ALFE Recall results gradually decrease and for the AGFE ones, it is the smallest with a tendency towards increasing. The AGFH Recall values sharply decrease and then demonstrate values close to the ones of the rest three algorithms. Reaching the maximum number of tested query-images (50), it has the highest Recall result. On the other hand, ALFH is notable for its tendency to increase and in fifty query-images it takes the second place. AGFH retrieves the greatest number of relevant and irrelevant images and ALFH retrieves less than it. The least number of images from these two groups in fifty query-images are retrieved by AGFE.

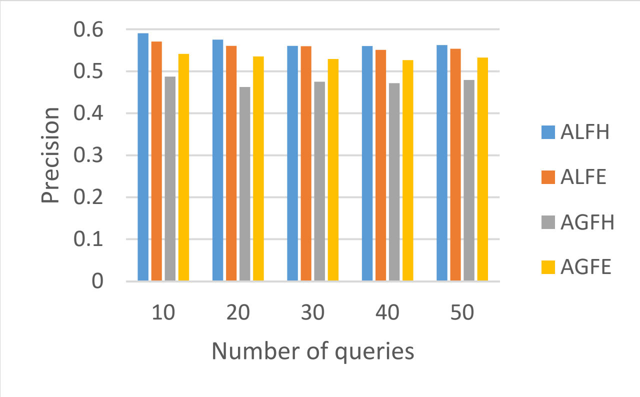

Fig. 2. Precision against number of queries for ALFH, ALFE, AGFH, AGFE.

Fig. 3. Recall against number of queries for ALFH, ALFE, AGFH, AGFE.

The Averaged Normalized Modified Retrieval Rank (ANMRR) [16] comparison on Fig. 4 shows that AGFH retrieves the greatest number of irrelevant images followed by ALFE. ALFH and AGFE have close and the lowest ANMRRvalues. This highlights their ability to retrieve less irrelevant images and leads to greater efficiency than the other two algorithms.

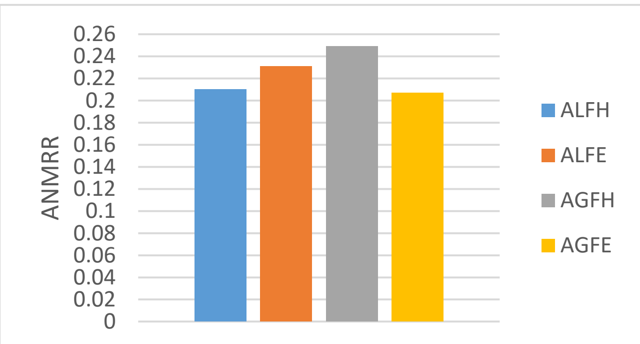

Fig. 4. Efficiency bar chart according to ANMRR.

A result retrieved by ALFH is presented on Fig. 5. For the purpose, a query-image from the group “Africa” which is listed in the first position in the sequence of images and outlined in black border is submitted. The result indicates that ALFH has the ability to detect details, shape and texture. It takes account of the homogeneous areas and the transitions between areas with sharp jumps in the intensity of the two dimensional signal. As a result, images similar to the query in respect to smooth and sharp jumps are retrieved. The images with ranks 1, 2, 3, 4, 6, 7 and 8 have sharp transitions from lower to higher intensity values. Thus, ALFH detects the shape, texture and details retrieving relevant images by these primitives. The slight semantic relevance of the images to the query-image and the differences on color are the shortcomings of the retrieved result to work upon in future.

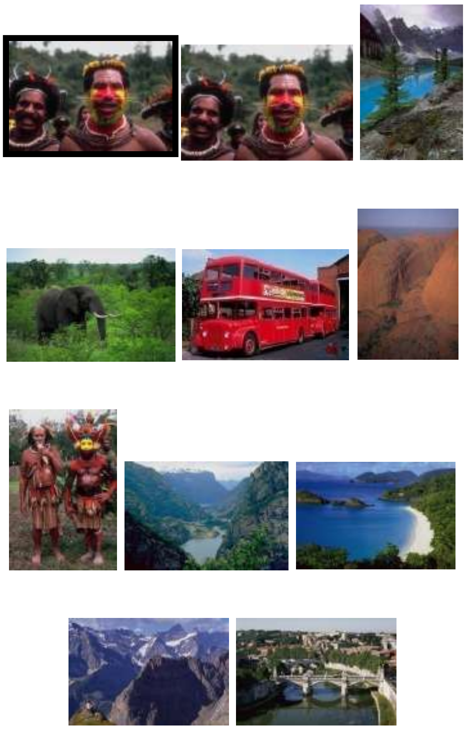

Fig. 5. Images in order of retrieval for the query in black frame from category “Africa” for ALFH.

Fig. 6 presents a sequence of images retrieved for the submitted query-image from the category “Social life”. It concerns the image detection on the base of the location of the objects relative to one another by intensity. The alternation of the homogeneous areas with close intensity values figuring borders and shapes out for the similarity computation is highlighted. The retrieved result has better semantic relevance (50%) than the result presented on Fig. 5.

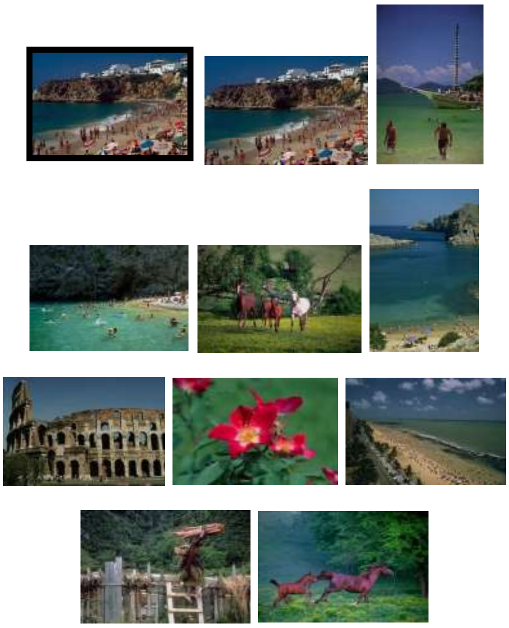

Fig. 6. Images in order of retrieval for the query in black frame from category "Social life" for ALFH.

For the submitted query-image from the category "Food" (Fig. 7) ALFH retrieves images, detected as similar on the base of the spatial location of the objects and their shape.

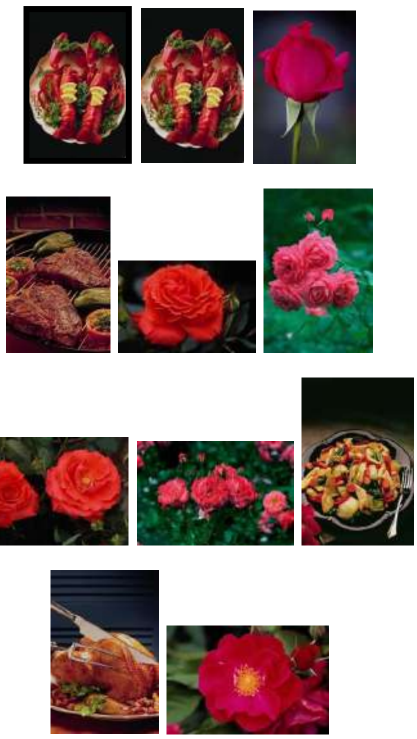

Fig. 7. Images in order of retrieval for the query in black frame from category "Food" for ALFH.

The small by size and regularly repeated by structure shapes with equal directionality, complexion and contrast define the primitive texture. Thus, ALFH demonstrates the ability to retrieve similar images by texture. The result for the discussed category reaches detection on semantics for 40%.

Conclusion

From the four discussed algorithms ALFH has the best Precision results because of the vectors formed on the base of the local position of the details and the use of Hausdorff distance which takes account of the details of the shape.

On the other hand, ALFH takes the second position in the list of the number of retrieved images. Nevertheless, it has the best ratio of number of relevant retrieved images to the total number of retrieved images which causes the highest Precision values for this algorithm.

The accomplished experiments show that the designed ALFH successfully detects details, shape and texture between objects with sharp jumps in the intensity of the two dimensional signal. Besides, ALFH has the ability to detect homogeneous areas with close intensity which figures borders and shapes out.

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