Image Features Extraction Using The Dual-Tree Complex Wavelet Transform

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Abstract: - In his/her daily round each man feels the necessity to use a database containing images. The user’s basic requirements reduce to the following. The image features extraction rate to be as much as possible, the accuracy degree to be high as well as the time for comparison between the image features to be minimum. Besides, for the needs of the modern image databases it is important the extracted features to be rotation and noise resistant. With the present paper we introduce a novel algorithm for image feature extraction using DT CWT for a CBIR system. The performed experiments show that the algorithm produces results which satisfy the conditions for feature extraction rate, feature vector length and high information concentration necessary for a CBIR system.

Key-Words: - The Dual-Tree Complex Wavelet Transform, DT CWT, wavelet transform, feature extraction, feature vector, image signature, DT CWT coefficients, wavelet coefficients, image decomposition

1 Introduction

In the recent decay the amount of digital information has been continuously increasing. This process imposes the availability of large storage spaces to store the information and large databases to manage it. There are two basic approaches for image retrieval according to the type of the query: Text-Based Image Retrieval (TBIR) and Content-Based Image Retrieval (CBIR). The first approach uses text keywords. The user is given the option to enter a keyword (or some keywords) in a text field which is (are) used to accomplish the image searching process. This approach is most widespread but it is remarkable for its three drawbacks: first, it is expensive since it requires the human participation to annotate the images in the database. Second, entering the annotations makes it time-consuming. And third, the retrieved result depends mostly on the human perception which takes part in annotating images.

These drawbacks lead to the second and more efficient Content- Based Image Retrieval approach. A CBIR system implements two basic tasks: first, image feature extraction where according to the used techniques a set of features (feature vectors, image signatures) is generated. This set brings image information and represents it in an image database occupying much less storage space. The second task is similarity measurement. It computes the distance between the image query submitted by the user and all the images in the database using their feature vectors. The most similar to the query images are displayed as a result of the searching process.

The implemented techniques for image feature extraction use low-level features like color, shape, texture and layout. They may be classified into two groups: spatial and spectral. The first one relies on computing statistical values and suffer from rotation irresistance, insufficiency of number of features and sensibility of image noise. Such methods are [1], [2]. In contrast to this, the spectral group of methods effectively measure image energy, generates rotataion resistant image feature vectors which cannot be influenced by image noise. This methods include Gabor filters [3], [4], wavelet [5], [6], DCT [7], curvelet [8], DWT [9], contourlet [10], [11], [12], [13].

This paper presents an algorithm for image features extraction using the Dual-Tree Complex Wavelet Transform. It is arranged as follows. Section 2 discusses the Dual-Tree Complex Wavelet Transform as a filter bank (FB) structure, running process, conditions for shift-invariance and applications. Section 3 is divided into two subsections. Subsection 3.1 introduces the algorithm for image features extraction using the Dual-Tree Complex Wavelet Transform. Subsection 3.2

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describes the accomplished test experiments and the experimental results.

2 The Dual-Tree Complex Wavelet Transform

In 1998 Nick Kingsbury introduced an effective Complex Wavelet Transform (CWT) method called the Dual-Tree Complex Wavelet Transform (DT CWT). It is CWT based on complex valued scaling function and complex-valued wavelet:

$$\Psi_c(t) = \Psi_r(t) + j\Psi_i(t) \qquad (1)$$

where $\Psi_r(t)$ - real and even part, $j\Psi_i(t)$ - imaginary and odd part, $\Psi_c(t)$ - analytic signal;

Kingsbury's idea was to develop a transform which produces analytic signal on the analogy of Fourier transform and which possesses the following properties:

1. smooth non-oscillating magnitude;
2. nearly shift-invariant magnitude;
3. significantly reduced aliasing effect;
4. directional wavelets in higher dimensions;

For the DT CWT realization Kingsbury uses two Discrete Wavelet Transforms (DWTs) performed on two different binary wavelet trees A and B (Fig.1) for each. Thus he designs the real and the imaginary part of DT CWT to produce the analytic signal.

Figure 1 illustrates graphically the 1-D DT CWT analysis filter bank (FB) structure.

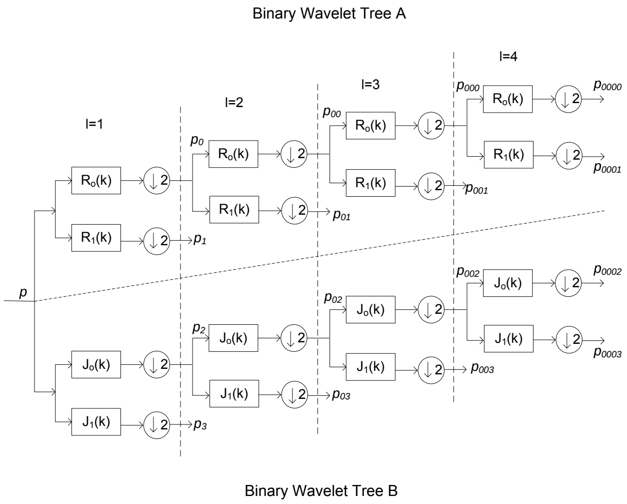

Fig.1. The 1-D DT CWT analysis filter bank (FB) structure

The input signal p is decomposed by the lowpass filters $R_0(k)$ for the real part and $J_0(k)$ for the imaginary one and decimated by 2:1 generating its lowpass components p_0 and p_2. The highpass filters $R_1(k)$ and $J_1(k)$ and decimation by 2:1 produce the highpass components p_1 and p_3 of the signal p. This process continues as far as required for levels $l=1, 2, 3, 4$. The final result of the decomposition of p is: p_1, p_{01}, p_{001}, p_{0001} for the real part and p_3, p_{03}, p_{003}, p_{0003} for the imaginary part. The filters used for DT CWT are chosen to be linear-phase satisfying the Perfect Reconstruction (PR) condition [14] and are joined so that the final result of the transform is approximately analytic:

$$\Psi(t) := \Psi_R(t) + j\Psi_J(t) \qquad (2)$$

where: $\Psi_R(t)$, $\Psi_J(t)$ - wavelets generated by the two DWTs.

In addition, both low-pass filters $R_0(k)$ and $J_0(k)$ have to be designed to possess a property so as the corresponding wavelets to form an approximate Hilbert transform pair:

$$\Psi_J(t) \approx H\{\Psi_R(t)\} \qquad (3)$$

where:

$$\Psi_R(t) = \sqrt{2}\sum_k R_1(k)\Phi_R(t) \qquad (4)$$

$$\Phi_R(t) = \sqrt{2}\sum_k R_0(k)\Phi_R(t) \qquad (5)$$

For this goal one of the two lowpass filters has to be nearly half-sample shift to the other:

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

This half-sample delay leads to nearly shift-invariant wavelet transform.

Besides one-dimensional application, DT CWT may be used for two dimensional tasks through 2-D DT CWT relying on the M-D dual-tree wavelets properties to be approximately analytic and oriented. Thus, it is suitable for edge and surface detection in image processing. The process of filtering is performed by two different groups of filters providing two 2-D separable DWTs and six subbands: two HL, two LH, and two HH subbands.

2-D DT CWT finds application in image segmentation [15], motion estimation [16], texture analysis and synthesis [17], feature extraction [18].

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3 Proposed algorithm and experimental results

3.1 Image Feature Extraction Using DT CWT

In the following section, we propose an algorithm for image features extraction using DT CWT for the goals of a CBIR system.

1. The source image (*I*), shown in Fig.2 is resized to the size of *MxN* for *M=N=256* where *M* - number of rows, *N* – number of columns through the Matlab function *imresize (A,[mrows,ncols])* which performs image resize without information loss. The obtained result (I') is shown in Fig.3.

2. The result (I') of step 1 (Fig.3) is converted from a RGB color space image (I') into a grayscale color space image (I'') with values of the pixel in the range of [0,1], as shown in Fig.4

3. The image (I'') is divided into $n \times n$ $(n = 8)$ non-overlapping subimages $(I_1'' \div I_{64}'')$.

4. DT CWT is performed on each of the subimages $(I_1'' \div I_{64}'')$ obtained in step 3 at level $l = 4$ to decompose them and generate their lowpass and bandpass components. Each subimage has 10 components (2 lowpass and 8 bandpass), imaginary and real parts.

5. The extracted wavelet features form the image feature vectors (Table 2) which are stored in a CBIR database.

Fig.2. Source image (*I*)

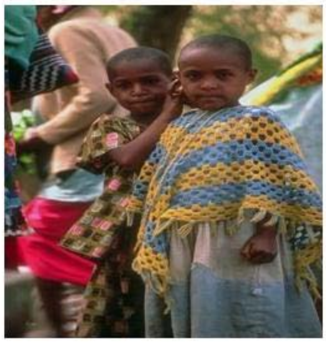

Fig.3. Resized image (I')

Fig.4. Converted grayscale image (I'')

Figure 5 depicts the flowchart of the image preprocessing and wavelet decomposition in Matlab.

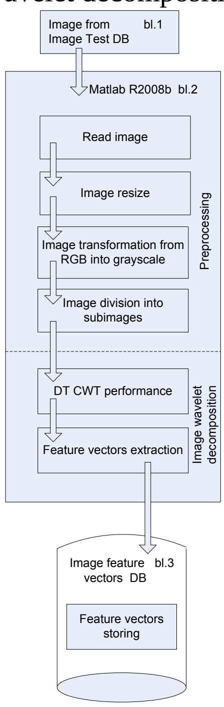

Fig.5. Flowchart of the image preprocessing and wavelet decomposition

3.2 Experimental results

For the goal of the proposed algorithm, Wang image test database containing 1000 RGB images was used. The images are classified into 10 groups: nature, architecture, vehicles, dinosaurs, elephants, flowers, horses, food and two groups of people each of 100 images. They are distinguished for size *256x384px* and *384x256px* in JPEG format.

The algorithm is tested via the software for mathematical and engineering computation Matlab R 2008b on personal computer with the following configuration: Intel (R) Core (TM) 2 Duo 2,40 GHz, 32-bit Operating System.

The proposed algorithm is designed for a CBIR system development.

The goal of the implemented experiments is to choose a decomposition level where the accuracy of the extracted information is highest, the time for comparison of the separate feature vectors in the process of searching in a CBIR system by a query is minimal and the feature extraction time is optimum.

As the algorithm shows, each image of the test database is divided into 64 subimages $(I_1^{''} \div I_{64}^{''})$ on which DT CWT is performed. To estimate the results produced by each of the DT CWT levels *l=1, 2, 3, 4* we computed and compared the feature vector length, feature extraction time and the number of the generated wavelet coefficients. The obtained result is tabulated in Table 1.

Table 1
Feature vector length, feature extraction time, and number of generated wavelet coefficients at level l=1, 2, 3, 4

DT CWT Level (l)	Feature Vector Length	Feature Extraction Time (ms)	Number of Generated Wavelet Coefficients
l=1	256	84.243×10^{-3}	65 536
l=2	384	115.137×10^{-3}	16 384
l=3	512	139.772×10^{-3}	4 112
l=4	640	168.006×10^{-3}	1 024

Figure 6 graphically illustrates the variation of the feature extraction time towards each of the DT CWT levels *l=1, 2, 3, 4*. As it shows, the time necessary for image feature extraction increases at each level. It is related to the required time for image energy computation by the highpass and lowpass filters at each level separately. Thus, with the subsequent level the feature extraction time increases.

In addition, Figure 7 depicts the curve of the number of the generated wavelet coefficients towards the four levels. According to it, as the number of levels of the wavelet decomposition increments, the number of the generated wavelet coefficients reduces. This result makes the generated at *l=4* coefficients suitable for bringing image information for a CBIR system due to its small number, heightened degree of information concentration and preserved features in diminished data size which is a recommended requirement for a CBIR database.

On the other hand, the curve of the feature vector length towards the DT CWT levels illustrated at Figure 8 shows that the feature vector length is related in direct proportion to the wavelet decomposition levels. This is due to the increasing number of highpass and lowpass filters at every following decomposition level.

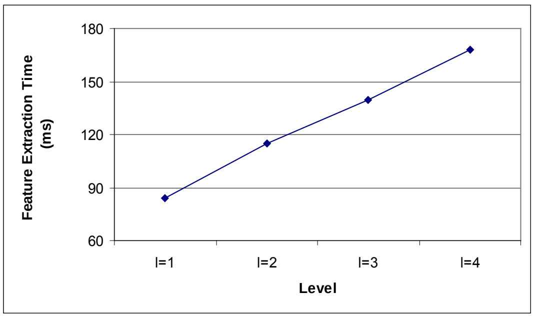

Fig.6. Feature Extraction Time

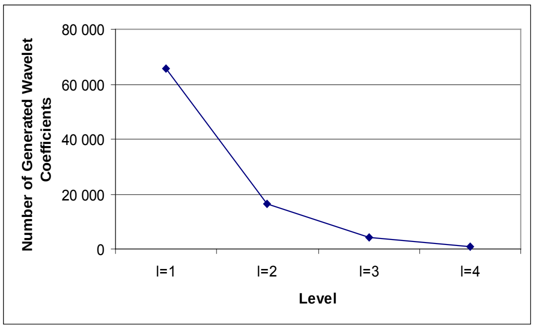

Fig.7. Number of the Generated Wavelet Coefficients

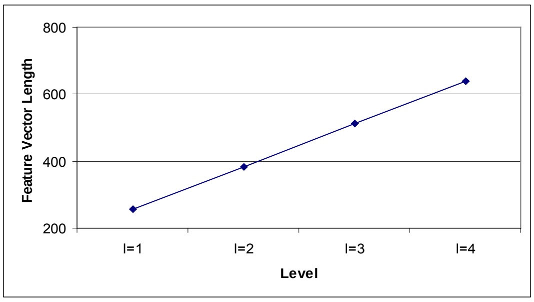

Fig.8. Feature Vector Length

On the base of the implemented experiments it is evident that the incrementation of the decomposition levels leads to reduction of the generated wavelet coefficients which increases the search rate by query and reduces the time for comparison between the separate feature vectors in a CBIR system.

In spite of the higher extraction time towards the preceding levels as well as the larger feature vector length, for the algorithm implementation the fourth decomposition level is chosen which produces significantly smaller number of generated coefficients than the other levels.

A fragment of the decomposition wavelet coefficients of the image shown in Fig. 4 is introduced through Table 2.

Table 2
DT CWT Wavelet Coefficients at level l=4

$n-1$	$I_0^{''}(n-1)$	$I_1^{''}(n-1)$	$I_2^{''}(n-1)$	$I_3^{''}(n-1)$
0	3.066568	3.386725	3.106316	2.368321
1	4.282288	4.392587	4.391616	4.27694
2	0.931068	0.96555	2.260443	4.012131
3	4.03369	4.090285	4.824982	5.762218
4	2.835722	3.166951	2.992187	2.398773
5	5.231376	5.63129	5.464097	4.816027
6	0.998505	1.648798	3.107206	4.439908
7	3.877163	4.145173	4.698016	5.174538
8	2.493329	2.844083	2.848315	2.489418
9	5.09853	5.615036	5.729543	5.34775
10	1.122385	2.670797	4.08559	4.438445
11	3.362603	3.957018	4.577253	4.828389
12	2.264777	2.646075	2.778882	2.567673
13	4.000135	4.372544	5.030196	5.548205
14	1.230736	3.383911	4.559256	3.976466
15	2.833159	3.667376	4.570423	4.981925

4 Conclusion

This paper introduces an algorithm for image feature extraction using DT CWT. It satisfies all modern requirements for optimum feature extraction rate, shortened data size and high accuracy in comparison between feature vectors in a CBIR system.

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