

Content-Based Images Retrieval with Discrete Wavelet Transform

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Abstract – The Wavelet transform is described as a tool for creating an image pseudo-hash in order to enable content-based image retrieval. The images are decomposed in few levels and the most important wavelet detail coefficients are selected to compose the pseudo-hash. When searching for digital images in large database, the pseudo-hashes of the images are considered instead of the images themselves.

Keywords – Wavelets, images database, pseudo-hash, query.

I. INTRODUCTION

Content-based image retrieval (CBIR) deals with the retrieval of most similar images corresponding to a query image from an image database by using visual contents of the image itself. It requires feature extraction and computation of similarity. The CBIR technology has been used in several applications such as fingerprint identification, digital libraries or medicine.

In this paper, we propose a CBIR method that uses wavelet transformation. The property of wavelets to localize both time and frequency makes them very suitable for analysis of non-stationary signals [1]. They are an excellent tool for feature extraction, signal and image compression, edge detection and compression. The reason of using the wavelet transform is that the basis functions used in wavelet transforms are locally supported; they are nonzero only over part of the domain represented. Hence, adequately chosen wavelet basis groups the coefficients in two groups – one with a few coefficients with high SNR, and other with a lot of coefficients with low SNR. Using the wavelet coefficients of images we compute a pseudo-hash information that is later used for fast querying the database. This approach for searching an image database in which a query is expressed as a low-resolution image is known as query by content [2]-[5].

The paper is organized as follows. After the introduction, the basic definitions of wavelet transform are given in Section 2. Section 3 describes the organization of database and Section 4 presents our experimental results. Section 5 concludes the paper.

II. DISCRETE WAVELET TRANSFORMATION

Discrete wavelet transform (DWT) decomposes a signal into a set of orthogonal components describing the signal variation across the scale [6]. The orthogonal components are

generated by dilations and translations of a prototype function ψ , called mother wavelet:

$$\psi_{jk}(t) = 2^{-j/2} \psi(t/2^j - k), \quad k, j \in \mathbb{Z}. \quad (1)$$

The above equation means that the mother function is dilated by integer j and translated by integer k . A signal f for each discrete coordinate t can be presented as a sum of an approximation plus J details at the J^{th} decomposed level:

$$f(t) = \sum_k a_{Jk} \phi_{Jk}(t) + \sum_{j=1}^J \sum_k d_{jk} \psi_{jk}(t) \quad (2)$$

where $\phi_{Jk}(t)$ is scaling function. The residual term corresponds to a coarse approximation of $f(t)$ at resolution J .

The estimate of d_{jk} and a_{Jk} can be achieved via iterative algorithm for decomposition using two complementary filters h_0 (low-pass) and h_1 (high-pass) [7]. This is illustrated in Fig. 1 for 1D DWT and 2D DWT.

DWT has a tendency to concentrate the energy of a signal into a small number of coefficients, while a large number of coefficients have small energy, therefore the most popular form of conventional wavelet-based signal filtering, can be expressed by:

$$\hat{d}_{jk} = d_{jk} \cdot h_{jk} \quad (3)$$

where filter h_{jk} describes “hard” or “soft” threshold filtering with a threshold τ_j , known also as wavelet shrinkage [8]:

$$h_{jk}^{(\text{hard})} = \begin{cases} 1, & \text{if } |d_{jk}| \geq \tau_j, \\ 0, & \text{if } |d_{jk}| < \tau_j, \end{cases} \quad \text{or} \quad (4)$$

$$h_{jk}^{(\text{soft})} = \begin{cases} 1 - \frac{\tau_j \operatorname{sgn}(d_{jk})}{d_{jk}}, & \text{if } |d_{jk}| \geq \tau_j \\ 0, & \text{if } |d_{jk}| < \tau_j \end{cases}. \quad (5)$$

III. QUERYING ALGORITHM

This section proposes an algorithm for image querying within images database. The image that is searched for is called query image. DWT is used and pseudo-hash information is created on the basis of small piece of information extracted from the images (wavelet coefficients from a high-resolution level). By comparing similarity (calculating distances) between pseudo-hashes of the images stored in the database and the pseudo-hash of the query image, few images (candidates) from the database are selected to be

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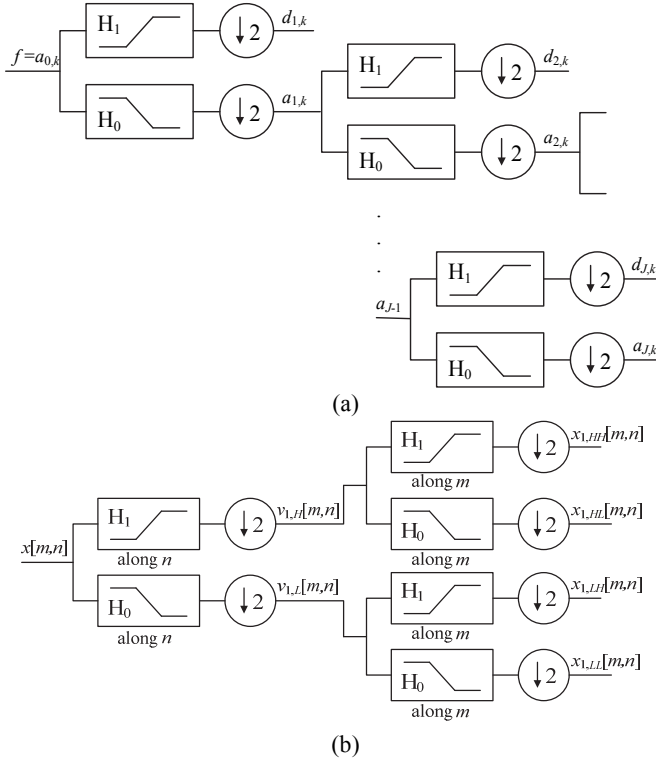


Fig. 1. Discrete wavelet transform tree for (a) 1D DWT, (b) 2D DWT

considered visually if some of them correspond to the image-query.

In order to calculate the pseudo-hash information for an RGB image, the following procedure is applied.

1) RGB image A is converted to A_1 in YCbCr colour space, where Y is the luminance (intensity) component and Cb (blue chrominance) and Cr (red chrominance) are the blue-difference and red-difference chroma components, respectively;

2) The wavelet transform at level (j) is applied over the Y component of the image A_1 and three subimages with same resolution are obtained from the horizontal, vertical and diagonal detail coefficients, $D^{(j,h)}$, $D^{(j,v)}$, $D^{(j,d)}$, respectively;

3) The three subimages $D^{(j,h)}$, $D^{(j,v)}$, $D^{(j,d)}$ are summed up in one super-subimage $D^{(k)}$, that contains all the horizontal, vertical and diagonal detail coefficients;

4) The super-subimage $D^{(k)}$ is filtered by using hard-threshold filtering given by (4) in order to keep only the most important coefficients $D_1^{(j)}$;

5) Positions (x_i, y_i) of the coefficients $D_1^{(j)}$ make up the pseudo-hash information for an image (the values of the coefficients are not important).

A database that keeps pseudohash information for the images contains three relations according to their schemas given in Fig. 2.

In the relation tbl_image , the attribute id_image is the primary key. This relation contains description of the images: $name$, $description$ and $location$ (if the images are picture files in the file system).

The relation tbl_hash contains pseudohash information for each image in the database. The primary key is the attribute id , while the attribute id_image is foreign key that takes its

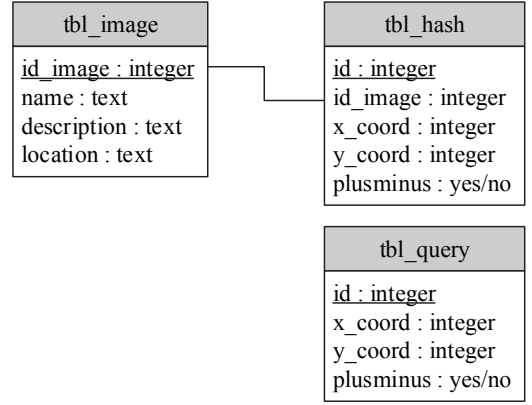


Fig. 2. Relation schemas in the images database

values from the primarykey of the relation tbl_image . The $plusminus$ attribute contains information for the sign of the wavelet coefficients.

The relation tbl_query contains the pseudo-hash calculated from the query image by applying the same algorithm as for the other images.

A list of candidate images can be obtained by measuring the similarity between pseudohashes of the images in the database and the pseudo-hash of the query-image expressed as following

$$M = \sum_{i,j} \frac{1}{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + \alpha}} \quad (5)$$

where (x_i, y_i) are coordinates of wavelet coefficient of images stored in the database, while (x_j, y_j) are coordinates of wavelet coefficient of the query image. It is not necessary the wavelet coefficients of candidate images to overlap the wavelet coefficients of query image. The influence of overlapping over non-overlapping coefficients can be controlled through the parameter α . Choosing α to be close to zero, the influence of overlapping coefficients over non-overlapping coefficients is bigger, and vice versa. Images with bigger value for the similarity M are likely to correspond to the query image.

The proposed algorithm is given in Fig. 3.

IV. EXPERIMENTAL RESULTS

This Section presents the results obtained by experiments performed. Pseudo-hash information obtained from 1000 images by using the proposed algorithm from Section 3 are stored in a Microsoft Access database with schema given in Fig. 2. Some of these images are shown in Fig. 4. The database contains data for a lot of similar images with people, animals, landscapes, objects, etc. The database does not contain the images themselves; the images are picture files in the file system.

The haar wavelet transform in three levels is applied over the Y components of the YCbCr converted images. The horizontal, vertical and diagonal detail coefficients from the

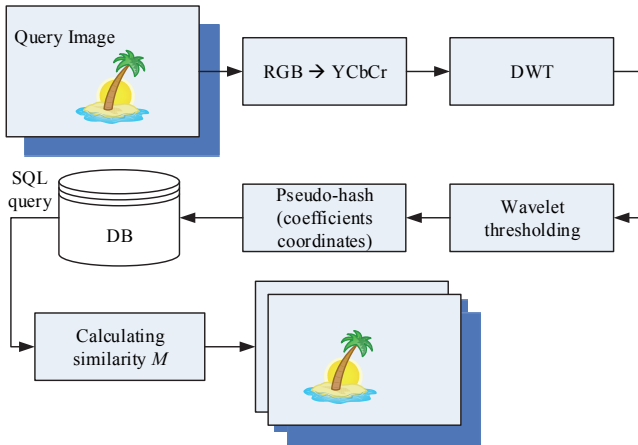


Fig. 3. Block diagram of the proposed algorithm



Fig. 4. Part of images database with 1000 images

third level are summed up and the most important 5% pixels are kept – the pseudohash.

Next, the images shown in Figs. 5a, 5b, 5c and 6a, 6b, 6c are used as query-images. They are image id 87 and its versions id 1088, id 1089, and image id 501 and its versions id 1501, id 1503. The resolutions of all the query images are 256x384. The most important third level wavelet coefficients of the three images are shown in Figs. 5d, 5e, 5f, and 6d, 6e, 6f, respectively. Their resolutions are 48x32, which means that only a few coefficients were taken into consideration for the calculation of the pseudo-hash.

The database already contains pseudo-hash information for the images with id 87 and id 501 in the table *tbl hash*. Next step is estimating the similarity between pseudo-hashes of the images in the database and the pseudo-hash of the query-image by using (5). The parameter α has value 0.1. A simple SQL SELECT statement used to process pseudohashes is:

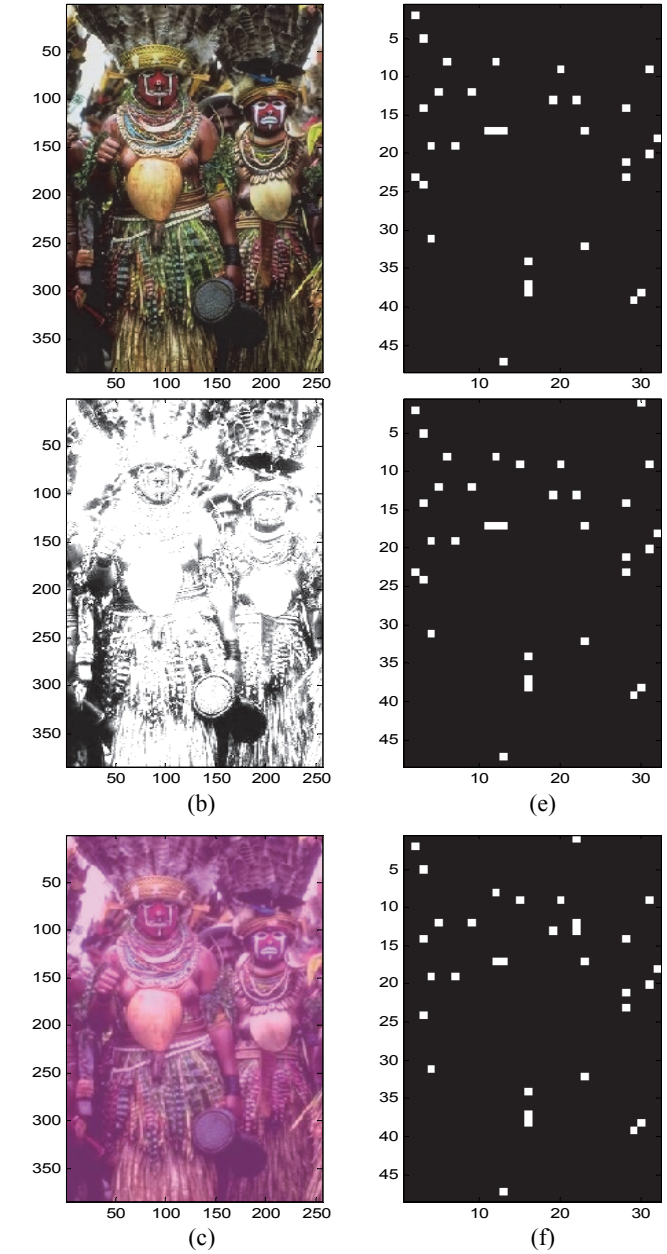


Fig. 5. (a) Query image id 87; (b) Query image id 1088; (c) Query image id 1089; (d-e-f) The most important wavelet coefficients at level 3 of images with id 87, 1088, 1089

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SELECT Sum(1/(Sqr((tblQuery].[xcoord]-
[tblHash].[xcoord])^2+([tblQuery].[ycoord]-
[tblHash].[ycoord])^2)+0.1)) AS M, tblHash.idimage
FROM tblQuery, tblHash
GROUP BY tblHash.idimage
ORDER BY Sum(1/(Sqr((tblQuery).[xcoord]-
[tblHash].[xcoord])^2+([tblQuery].[ycoord]-
[tblHash].[ycoord])^2)+0.1)) DESC;
```

The results of calculated similarities between the query images and the images in the database are shown in the Tables I and II. It can be seen that the images with id 87 and id 501 have the highest similarity.

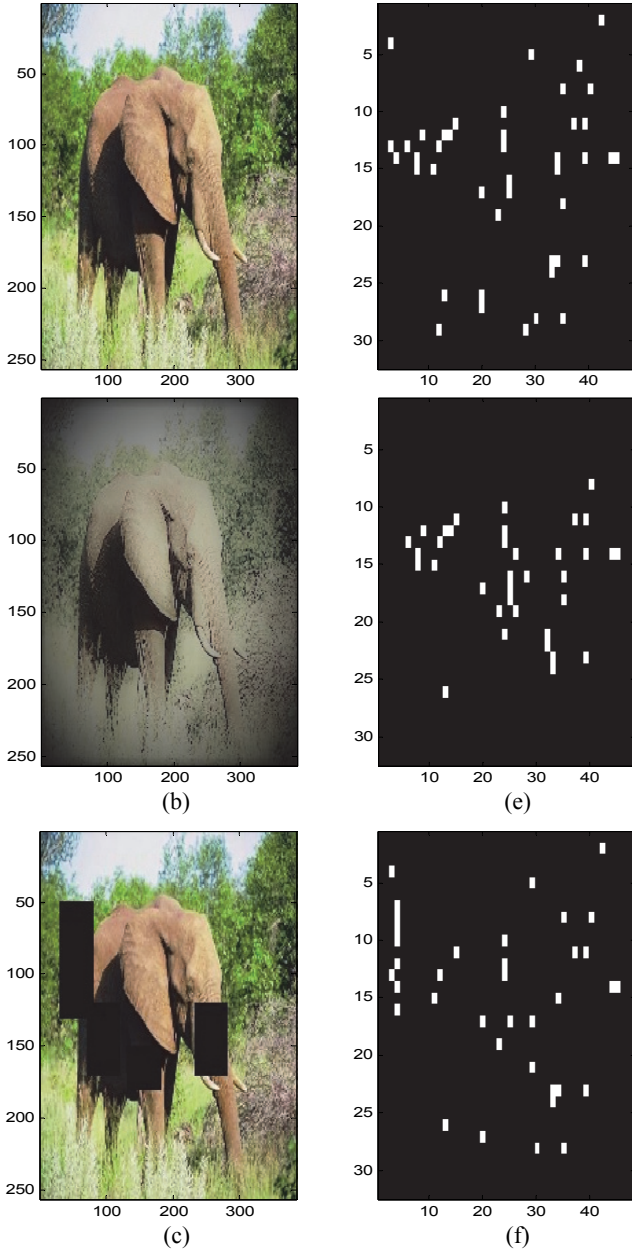


Fig. 6. (a) Query image id 501; (b) Query image id 1501; (c) Query image id 1503; (d-e-f) The most important wavelet coefficients at level 3 of images with id 501, 1501, 1503

V. CONCLUSION

In this paper an algorithm for content-based image retrieval is presented. The querying in database is based on the pseudo-hash information obtained with wavelet transform. The experiments are performed by using the presented algorithm. The experiment results validate this algorithm, showing that it works properly and delivers the expected results.

TABLE I
RESULT OF SEARCHING IMAGES IN THE DATABASE

Image id=87		Image id=1088		Image id=1089	
Image id	M	Image id	M	Image id	M
87	971,207	87	950,3951	87	908,4499
808	309,1956	808	308,8647	808	297,3539
103	308,3496	103	297,7562	13	290,356
13	303,6106	13	293,6757	271	286,6985
271	291,7238	271	291,2993	943	275,2746
943	290,1049	943	288,7366	103	274,2945
842	283,5513	842	284,0562	850	273,3468
722	269,8397	86	278,3045	842	271,9997
130	269,2978	722	270,1922	722	268,5459
86	268,2889	130	268,1649	86	268,0319
916	267,8494	916	267,8601	938	266,4457
810	265,637	810	265,8416	916	265,963
938	263,7323	850	263,3936	847	263,5181

TABLE II
RESULT OF SEARCHING IMAGES IN THE DATABASE

Image id=501		Image id=1501		Image id=1503	
Image id	M	Image id	M	Image id	M
501	980,4405	501	740,0276	501	774,1331
415	372,4684	415	446,2996	565	396,2749
491	339,702	472	408,8988	719	385,9561
423	337,9365	565	389,1053	490	375,9287
523	336,5647	445	387,8903	497	360,9072
472	335,7105	423	387,1307	415	359,0868
565	333,2177	434	386,9017	405	354,2778
435	333,1247	791	383,9149	523	350,8746
766	329,8053	407	383,6355	732	349,0866
445	329,4135	789	379,6944	143	348,9
429	328,9102	421	379,2123	79	348,4964

REFERENCES

- [1] M. Vetterli, and J. Kovacevic, *Wavelets and Subband Coding*, Prentice-Hall, 1995.
- [2] Y. Liu, D. Zhang, G. Lu, and W. Y. Ma, "A Survey of Content-Based Image Retrieval with High-Level Semantics", *Pattern Recognition*, vol. 40, no. 1, pp. 262-82, Jan. 2007.
- [3] R. Barber, W. Equitz, W. Flickner, W. Niblack, D. Petkovic, and P. Yanker, "Efficient Query by Image Content for Very Large Image Databases", *Comcon Spring'93, Digest of Papers*, pp. 17-19, IEEE, 1993.
- [4] C.E. Jacobs, A. Finkelstein, and D. H. Salesin, "Fast Multiresolution Image Querying", *SIGGRAPH '95 Proceedings of the 22nd Annual Conference on Computer Graphics and Interactive Techniques*.
- [5] J.Z. Wang, G. Wiederhold, O. Firschein, and S.X. Wei, "Content-based Image Indexing and Searching Using Daubechies' Wavelets", *International Journal on Digital Libraries*, vol. 1, no. 4, pp. 311-328, 1998.
- [6] G. Strang, and T. Nguyen, *Wavelets and Filter Banks*. Wellesley-Cambridge Press, 1996.
- [7] P.P. Vaidyanathan, *Multirate Systems and Filter Banks*, Prentice - Hall, 1992.
- [8] D.L. Donoho, "Wavelet Thresholding and W.V.D.: A 10-minute Tour", *Int. Conf. on Wavelets and Applications*, Toulouse, France, June 1992.