INDEXING OF MEDICAL IMAGES BASED UPON THE JPEG-2000 WAVELET COMPRESSION SCHEME.

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Abstract: This paper investigates the possibilities of efficient content-based image retrieval, based on the JPEG-2000 compression scheme. The proposed indexing technique takes advantage of this compression scheme for characterizing images without extracting significant features. We use histograms obtained from the compressed images in JPEG-2000 wavelet scheme to build signatures. Image retrieval is carried out by calculating weighted signature distances between the query and database images. Retrieval efficiency is studied for different wavelets used in JPEG-2000. Influence of histogram weights is evaluated. The application field is diagnosis aid in diabetic retinopathy. A classified diabetic retinopathy image database is on building, and its actual state allows already relevant algorithms tests. On the present image database, results are promising: retrieval effciency is higher than 70% for some lesion types.

Introduction

In this work, we try to find methods for diagnosis aid, in diabetic retinopathy early detection, using eye retina angiographic images. For the moment, we address only a subset of the problem in this work - the creation of an index that allows retrieval of images similar to a given image, with no semantic meaning of similarity. This work adress the general problem of .Content-Based Image Retrieval (CBIR) in medical image databases. Medical imaging systems produce now more and more digitized images in all medical fields: visible, ultrasound, X-ray tomography, MRI, nuclear imaging, etc... which are stored in data bases after having been used for diagnosis. They may be very interesting for new diagnosis purposes, using them for comparisons with images under study: they are directly related to patients pathology and medical history. But the amount of images we can access nowadays is so huge that database systems require efficient indexing to enable fast access to images in databases. Possible and promising solutions to effectively manage image databases lie in automatic or semi-automatic image indexing using image digital content retrieval (Content-Based Image Retrieval) [1]. The idea is to give an expert the possibility of carrying out a research "like a blind man" in the base, without formulating a semantic description of the image he is examining. In the ophthalmology field, fluorescein angiography produces various types of retinal images which often require time-consuming interpretations and classifications in order to adequately guide medical therapy. In our work, we are interested in building signatures from compressed [2][3] photographic and angiographic images of diabetic retinopathy. We propose in this work a signature derived from coefficients histograms of wavelet transform used in JPEG-2000 compession standard scheme.

1 MATERIAL and METHOD

One of the problems of content-based image retrieval is to dispose of relevant image databases. These databases should be as complete as possible in order to cover all the situations encountered in images of diabetic retinopathy. We used two different databases for testing our algorithms : a well-known faces database and a retinal images database. Notice that an initial standardized classification of all images in this last database is needed in order to validate our algorithm. This classification is performed by practicians.

1.1 Database

1.1.1 Faces database [4]

We included ten different images for each of the 40 distinct subjects of the database. For some subjects, the images were taken at different times, with different lightings, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position. All the database can be reviewed by consulting the site *http://www.uk.research.att.com/facesataglance.html*. Fig. 1 shows the 10 face images of the same subject. Even though it is not our main purpose, this database can be easily classified. Images belong to the same class if and (epresent the same subject. The 400 database images are then classified in 40 classes.

figure

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(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 1: Ten images sequence of the same person's face

1.1.2 Retinal images database

This database has been conceived only for research purposes. It deals with retinal images of diabetic patients. Diabetes is a metabolic disorder characterized by sustained inappropriate high blood sugar level. This will progressively affect the conditions of the blood vessels of many organs; which in turn will lead to renal, retinal, cardiovascular and cerebral serious complications. The retina contains the sensory elements of the eye (photoreceptors). Like any other organ in the body, retina receives nutrition through blood vessels. In diabetes, these blood vessels will be damaged causing lesions that will lead to a sick retina and ultimately to blindness. Fluorescein angiography is a technique consisting of injecting a fluorescent dye into the patient's blood circulation. This dye will progressively reach the retina. Under the presence of the dye, retinal blood circulation as well as retinal pathological changes are highlighted. In fact, fluorescein dye having a peak of absorption in the 470 nm wavelength will be detected by a fundus camera equipped with both exciter and barrier interference filters. The latter will allow only green light (520-530 nm) from the fluorescent dye passing through the vessels to be recorded on a sensor, this exclusively outlining the vascular pattern and pathologic structures containing the dye.

The retinal images of 60 diabetic patients recruited in Brest University Hospital since June 2003 were acquired by experts using a Topcon Retinal Digital Camera (TRC-50IA) connected to a computer. No initial image processing is done and images are saved in a lossless compression form (TIFF file). Four types of images are obtained: color, red free, blue-light images and the angiographic sequence. 995 images are then analysed and classified by ophthalmologists using the criteria of the *International Clinical Diabetic Retinopathy Disease Severity Scale* [5] thus allowing the creation of a computerized database. Nine types of lesions are described: microaneurisms, hemorrhages, soft exsudates, hard exsudates, diffusions, ischemias, IRMA, neovessels, venous anomalies. More than 2500 lesions are described.

1.2 CBIR Method

1.2.1 JPEG-2000 wavelet compression scheme

Wavelets in image processing have been widely used since the publication of the JPEG-2000 standard of compression [6]. Some publications use this norm in the CBIR field; for more details, please refer to Xiong et al. [7]. This method offers many advantages : it follows the arrival of the new compressed image algorithms, and the compressed domain for JPEG-2000 images offers interesting characteristics. Recursive image decomposition in sub-bands allows a space and frequency description.

1.2.2 Practical considerations

A query image is compared to all database images. The content base image retrieval algorithm ranks all the images according to their distance (see below) to the query image. It proposes the nearest images to the user. This process uses two concepts. First, a signature is created for each image. It should take in consideration the requested characteristics of the images (contours, forms, textures...) and should be small compared to the original image size. Second, a distance between two images is created, it corresponds to the distance between the two image signatures. For operational reasons, the computing

l be short enough to allow many comparisons to take place.

figure

1.2.3 Signature

The use of wavelet coefficients histograms allows to characterize each image [8]. Our signature is composed of $3N_\ell+1$ histograms, N_ℓ being the number of levels of decomposition. A 32 bins histogram is computed for each sub-band (see Fig. 2). Maximal and minimal values are statistically calculated on the hole database for each N_ℓ value. Table 1 provides an example of maximal and minimal values for $(N_\ell) = 3$.

Each histogram is normalized in term of coefficient numbers. Consequently $\sum_{j=1}^{32} H_i^n(j) = a$ with $H_i^n(j)$ the j^{th} bin of histogram i in image n and a a fixed constant. The comparison of images with different dimensions is then possible.

1.2.4 Distance

The distance used is : $d(Im_1, Im_2) = \sum_{i=1}^{3N_\ell+1} \lambda_i (H_i^1 - H_i^2)$

with H_i^n the i^{th} histogram of image Im_n and λ_i the weight for the i^{th} histogram.

and $H_i^1 - H_i^2 = \sum_{j=1}^{32} \left(H_i^1(j) - H_i^2(j)\right)$

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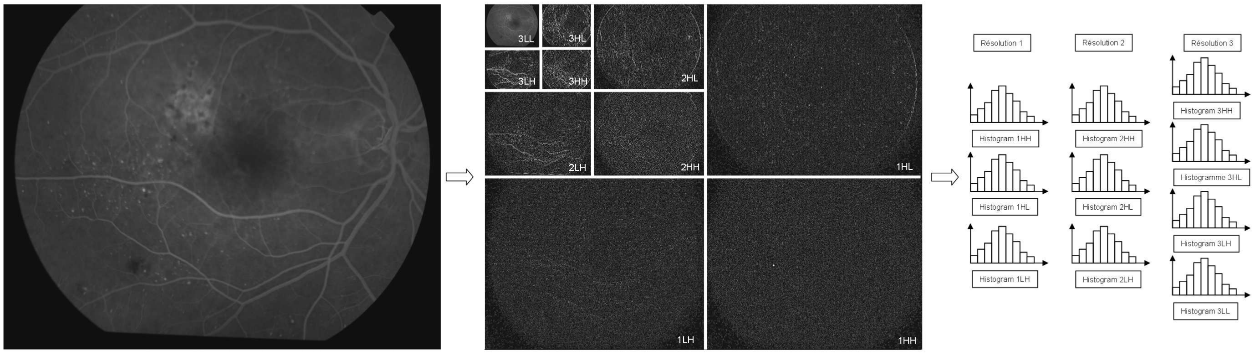

Figure 2: Example of wavelet decomposition and signature creation. The original image (left) is decomposed using Daubechies 9-7 [12] or 5-3 [13] wavelets with 3 levels of decomposition (center). Signature is made of one histogram by block.

Table 1: min and max for $N_\ell = 3$

	9/7 wavelet		5/3 wavelet	
Sub-band	Min	Max	Min	Max
1HH	-323.778	322.402	-242	230
1HL	-234.429	234.536	-266	246
1LH	-169.41	147.08	-248	254
2HH	-221.304	206.685	-281	319
2HL	-158.543	185.794	-327	324
2LH	-158.993	115.008	-314	320
3HH	-215.918	185.413	-360	347
3HL	-125.911	157.84	-371	464
3LH	-139.524	139.429	-416	426
3LL	-104.706	220.459	-336	594

with $H_i^n(j)$ the value of j^{th} bin of the i^{th} histogram of image n.

1.2.5 Performance evaluation [9] [10]

To evaluate our algorithm performance on the faces database, we use the retrieval efficiency as criterion [11]. This is defined as follows: for each image i, in a database of size K, similar images contained in the database are initially identified, being N_i, $1 \leq i \leq K$, the number of such images. We then apply an indexing technique for a query image-q, and retrieve the first $(N_q + \tau)$ images, where τ is a positive integer, understood as the retrieval tolerance. If n_q is the number of successfully retrieved images, the retrieval efficiency can be defined as:

$$\eta_r = \frac{\sum_{q=1}^{K} n_q}{\sum_{q=1}^{K} N_q}$$

Note : Having N_q images in the class q, we take in general $\tau = 0$.
This general method is used on the faces database. The use of this criterion is not adapted for helping ophthalmologists in daily practice. In fact physicians search only for few similar images for establishing a diagnosis; that is why the efficiency test proposed is performed on the 4 images closest to the query image.

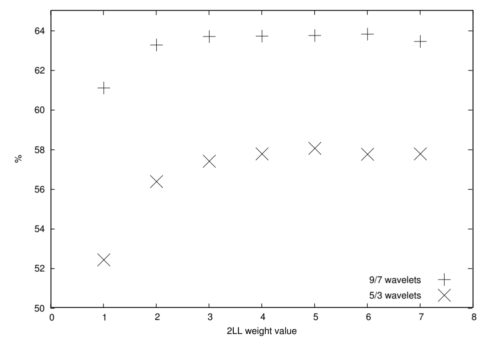

Figure 3: Efficiency variation function of the histogram weight 2LL. The level of the wavelet decomposition for the faces database is two. Two type wavelets have been used: 5/3 see [13] or 9/7 see [12]

2 RESULTS

The previous algorithms are independently tested on the two databases. On the faces database, maximal efficiency (see section 1.2.5 and Fig. 3) is obtained by choosing : Daubechies 9/7 wavelets [12], $N_\ell = 2$, $\lambda_i = 1$ for each i except for the $2LL$ block: $\lambda_{2LL} = 6$.

The weight is based on the chosen classification. For the faces database we propose that two images belong to the same class if the faces presented belong to the same person. This choice will favor the global aspect of the image on its details. As for the retinal images database, in the aid for diagnosis context, lesions are the most important for content-based image retrieval. These lesions, as well as the clinical setting will allow to make a diagnosis. Most of the images we are treating have many lesions of different types. The efficency test is performed for each lesion independently and only for the first 4 retrieved images (see section 1.2.5). The chosen weight λ_i of the distance (see section 1.2.4) are computed using genetic algorithms [14] with the following parameters:

- Population size = 25
- Generation number = 100
- Mutation probability = 0.01

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Lesion type	Number of images (proportion) in the database	Retrieval efficiency
Microaneurisms	501 (50.35%)	76.34%
Hemorrhages	434 (43.61%)	71.71%
Soft exsudates	20 (2.01%)	37.50%
Hard exsudates	47 (4.72%)	42.55%
IRMA	18 (1.80%)	30.26%
Diffusions	77 (7.73%)	51.29%
Ischemias	84 (8.44%)	42.85%
Neovessels	31 (3.11%)	54%
Venous anomalies	11 (1.10%)	31.81%

Table 2: Efficiency for lesions images

- Crossover probability = 0.9

Table 2 shows the number and the proportion of images in the database for each lesion type, and the corresponding retrieval efficiency. Algorithm performance depends on the lesion type. Rare lesions like *Venous anomalies* or *Soft exsudates* are well detected in considering their low proportion in the database. However this difference between the two proportions is less evident when dealing with frequent lesions (*Microaneurisms, Hemorrhages*). A sample of the results is proposed (see Table 3). Three series are presented. The query image is shown on the left. Retrieved images are ranked according to their distance to this reference image. Retrieved images for each of the series 1, 2 and 3 have the same lesion types. Images in series 1 & 2 belong to the same diabetic retinopathy stage. Series 1 presents normal retinas with no visible abnormalities; the five images belonging to two different patients (three eyes). Series 2 shows treated non active diabetic retinopathy. The five images belong to two different patients (three eyes). Series 3 request image shows Mild Non Proliferative Diabetic Retinopathy, and same grade for images 1 & 4. The five images belong to four patients (five eyes). Images of rank 2 & 3 have the same [illegible] types but where classified in the Moderate Non Proliferative Diabetic Retinopathy grade.

table

3 CONCLUSIONS AND PERSPECTIVES

In this paper, we have presented an image indexing method for CBIR using JPEG-2000 wavelet decomposition, applied to diabetic patients retinal images. The important number of classified images allowed us to perform a wide scale test of our algorithms. Images classification is an objective tool for the measurement of retrieval quality. The use of JPEG-2000 wavelets based decomposition is in accordance with advances in image compression algorithms and allows the method to be robust with respect to spatial resolution. Images with different resolutions may be compared. First results are promising, but, for the moment, results quality depends yet on the type of lesion. It seems to be related to the lesion type proportion or to the lesion size (few pixels for microaneurism and hemorrhages versus large image zone for ischemias and neovessels), due probably to the direct use of wavelet coefficients histograms. The work in progress include enlarging the database to increase the number of rare lesions, and improving the signature-distance couple to take into consideration small as well as large size lesions.

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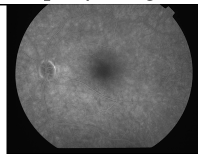
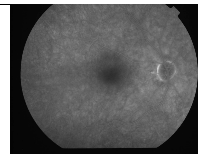
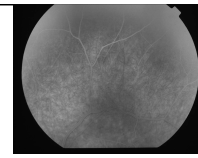
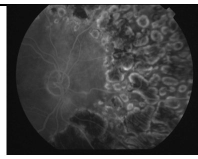
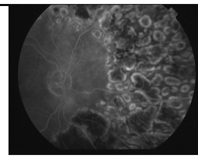
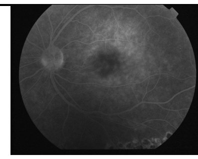
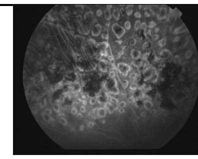
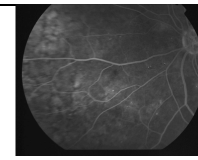
Table 3: Results for retinal images

	query image	rank 1	rank 2	rank 3	rank 4
series 1					
series 2					
series 3					

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