Content based Medical Image Retrieval: use of Generalized Gaussian Density to model BEMD's IMF.

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Abstract— **In this paper, we address the problem of medical diagnosis aid through content based image retrieval methods. We propose to characterize images without extracting local features, by using global information extracted from the image Bidimensional Empirical Mode Decomposition (BEMD). This method decompose image into a set of functions named Intrinsic Mode Functions (IMF) and a residue. The Generalized Gaussian Density function (GGD) is used to represent the coefficients derived from each IMF, and the Kullback–Leibler Distance (KLD) compute the similarity between GGDs. Retrieval efficiency is given for two databases : a diabetic retinopathy one, and a face database. Results are promising: retrieval efficiency is higher than 85% for some cases.**

Keywords— **Content-Based Image Retrieval, BEMD, Generalized Gaussian density, Kullback–Leibler distance.**

I. INTRODUCTION

Nowadays, medical systems produce a great amount of data images. Fast access to such huge database requires efficient indexing algorithms. CBIR system (Content-Based Image Retrieval) is one of the possible solutions to effectively manage image databases [1], [2]. The purpose is to retrieve desired images from databases using only the numerical content of images. Typical CBIR systems can be decomposed in two steps: at first, extraction of features from each medical image in the database; then, the feature vector of a query image is computed and compared to the images feature vectors of the database. For definition and extraction of visual features, many methods have been proposed, includind image segmentation and image characterization using wavelet transform and gabor filter bank [2, 3, 4, 5, 6],

Recently, a novel multiresolution decomposition method, the Empirical Mode Decomposition (EMD), was introduced by Huang and al [7]. The EMD is an adaptive decomposition which decompose any signal into a redundant set of signals denoted IMF and a residue. The original signal may be reconstruct by adding all the IMFs together and the residue, without information loss or distortion. EMD does not use any pre-determined filter or basis functions, which is quite different from Fourier analysis and wavelet analysis. In 2003, Nunes and al. [8] extend the 1D-EMD signal analysis to bidimensional signals and specifically to image processing (Bidimensional Empirical Mode Decomposition : BEMD). We propose in this work a new medical retrieval method which takes advantage of image BEMD. Wouwer and al. [9] used generalized Gaussian density functions (GGD functions) to represent texture images in the wavelet domain. In this paper we propose a new algorithm, based on Wouwer work, using BEMD decomposition instead of wavelet transform.

The setup of the paper is as follows. Section II-A describes the database we used for evaluation. Section II-B describes the BEMD method. Section II-C explains how to use GGD functions to represent the coefficients derived from BEMD. The retrieval method and Kullback–Leibler distance are described in section II-D, results are given in section III, and discussion and conclusion in section IV.

II. MATERIAL AND METHODS

A. Databases

Two databases are used to test our method.

1) Diabetic retinopathy database: the diabetic retinopathy database, developed specifically in our team, contains retinal images of diabetic patients, with associated contextual anonymized information on the pathology. The database is made up of 63 patient files, for a total of 1045 photographs, classified in 6 levels of disease severity. Image definition is 1280 pixels/line for 1008 lines/image. Patients were seen in consultation in Brest university hospital (France), within the screening or the follow-up of diabetic patient. Images were acquired by experts using a Topcon Retinal Digital Camera (TRC-50IA) connected to a computer.
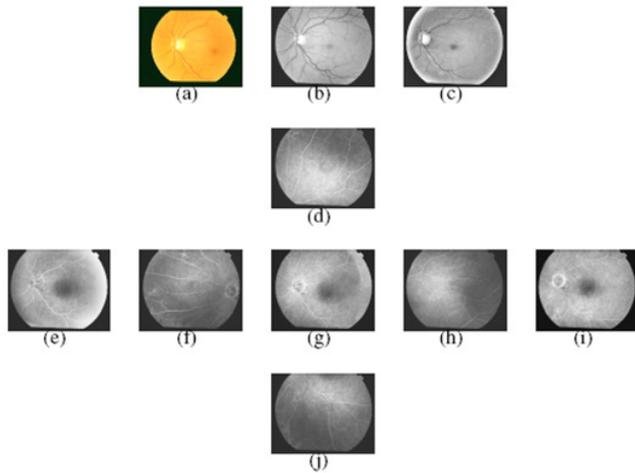
Fig. 1 Example : photograph serie of patient eye

2) FaceDataBase: This database [10] is used as a benchmark database. There are ten different images of each of 40 distinct subjects (40 classes). For some subjects, the images were taken at different times, varying the lighting, 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 (with tolerance for some side movement). Images have a resolution of 92x112 pixels; each pixel is coded on a byte.
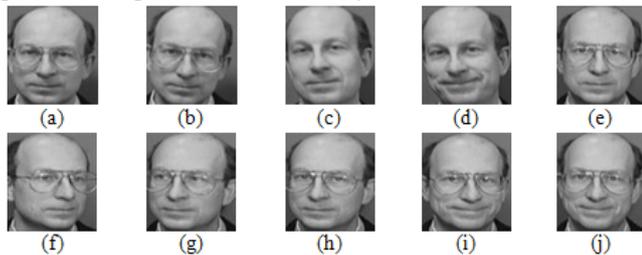

Fig. 2 Ten images sequence of the same person's face

B. BEMD

The EMD method is an adaptive decomposition which allows to decompose any signal into a redundant set of signals denoted IMF and a residue. These IMFs are obtained by means of an algorithm called sifting process.
Given a signal $s(t)$, the sifting process of EMD can be summarized as follows.

1. Initialise: $r_0 = s$ (the residual) and $j=1$ (index number of IMF),
2. Extract the jth IMF:
3. (a) Initialise $h_0 = r_{j-1}$; $i=1$;
   (b) Extract local minima/maxima of h_{i-1};

(c) Compute upper envelope and lower envelope funtions x_{i-1} and y_{i-1} by interpolating, respectively, local minima and local maxima of h_{i-1};
(d) Compute $m_{i-1} = (x_{i-1} + y_{i-1})/2$ (mean envelope),
(e) Update $h_i = h_{i-1} - m_{i-1}$ and $i = i+1$;
(f) Calculate stopping criterion (standard deviation SD_{ji})
(g) Repeat steps (b) to (f) until $SD_{ji} \leq SDMAX$ and put then $s_j = h_i$ (jth IMF)
4. Update residual $r_j = r_{j-1} - s_j$;
5. Repeat steps 2–4 with $j = j+1$ until the number of extrema in r_j is less than 2.

After IMFs are extracted through the sifting process, the original signal $s(t)$ can be represented like this:

$$s(t) = \sum_{j=1}^{n} \text{Imf}_j(t) + r(t) \qquad (1)$$

The Standard Deviation (SD) is the criteria to stop sifting process, computed from two consecutive sifting.

$$SD_{ij}^2 = \sum_{k=1}^{K} \left[\frac{|(h_{j(i-1)}(k) - h_{ji}(k))|^2}{h_{j(i-1)}^2(k)} \right] \qquad (2)$$
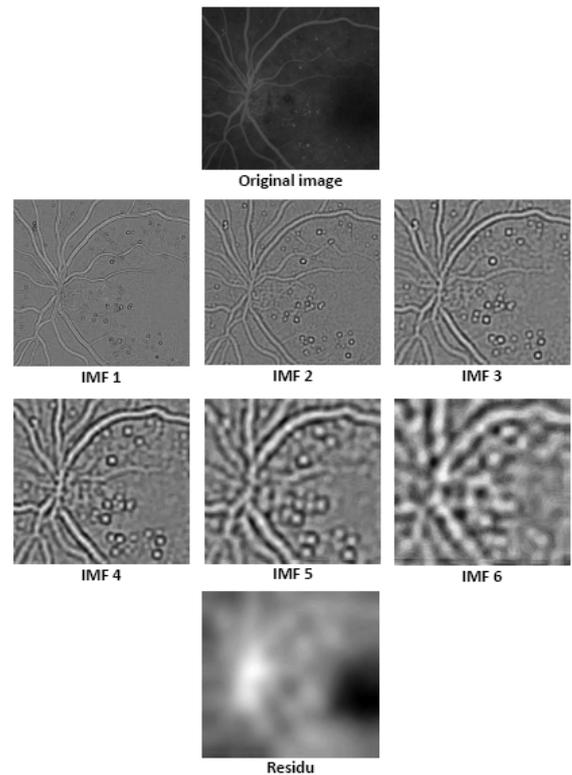

Fig. 3 Example BEMD applied to a part of a retina image

Following Nunes *and al.* [8], the bidimensional sifting process is defined as follows :

- Identify the extrema (maxima and minima) of the image I.
- Generate the 2D 'envelope' by connecting maxima points (respectively, minima points) with 2D interploation methods.
- Averaging the two envelopes to compute the local mean m_1.
- Since IMF should have zero local mean, subtract out the mean from the image: $I - m_1 = h_1$.
- repeat as h_1 is an IMF.

In this paper we use the fast and adaptive BEMD presented in [11]. We give in Fig 3 an example of the BEMD for a retinal image.

C. Numerical image characterization : signatures

In this paper we suggest to characterize globally images by generating a numerical signature of image, based on IMFs contents. Wouwer and al. [9] show that, for textured images, the distribution of coefficients in the subbands of the wavelet transform may be modeled by a generalized gaussian law. Empirically, we noticed that the distribution of coefficients derived from IMFs seems also to follow a generalized gaussian law as illustrated below.
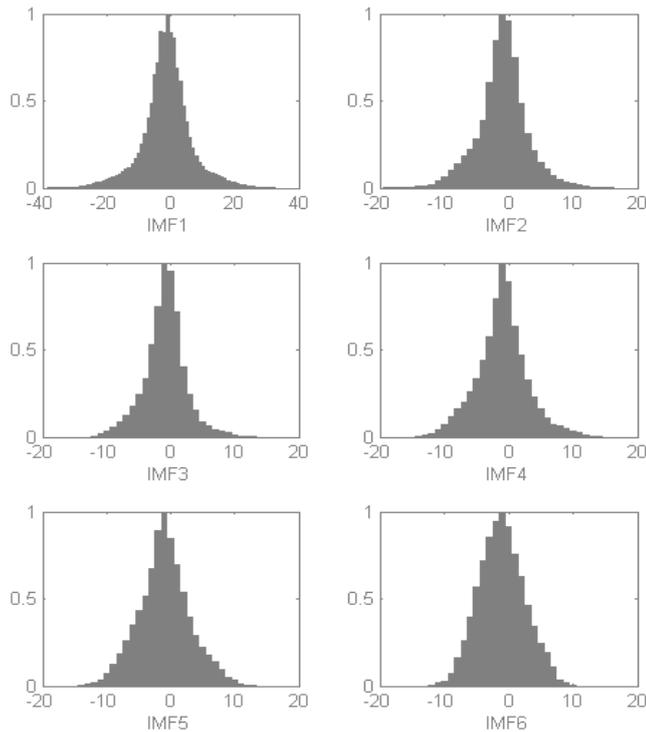

Fig. 4 IMFs coefficients distribution for image of Fig 3

The gaussian generalized law is derived from the normal law and parameterized by:

- α: a scale factor, it corresponds to the standard deviation of the classical Gaussian law.
- β: a shape parameter.

Then, law density is: $P(x;\alpha,\beta) = \dfrac{\beta}{2\alpha\,\Gamma\left(\frac{1}{\beta}\right)}\, e^{-\left(\frac{|x|}{\alpha}\right)^{\beta}}$ (3)

Where $\Gamma(.)$ is the gamma function, $\Gamma(z) = \int\limits_0^\infty e^{-t}t^{z-t}dt,\ z>0$

We propose to characterize images by using a maximum likelihood estimator $(\hat{\alpha},\hat{\beta})$ of the distribution law for coefficients of each IMF of the BEMD decomposition [4]. These estimators are defined like this: given x= $(x_1, ..., x_L)$ the BEMD coefficients for one IMF. As x having independent component, Varanasi and Aazhang [12] demonstrated that $(\hat{\alpha},\hat{\beta})$ is the unique solution of equation (3).

$$\hat{\alpha} = \left(\frac{\hat{\beta}}{L}\sum_{i=1}^{L}|x_i|^{\hat{\beta}}\right)^{\frac{1}{\hat{\beta}}}$$

(4)

$$1 + \frac{\psi\left(\frac{1}{\hat{\beta}}\right)}{\hat{\beta}} - \frac{\sum_{i=1}^{L}|x_i|^{\hat{\beta}}\log|x_i|}{\sum_{i=1}^{L}|x_i|^{\hat{\beta}}} + \frac{\log\left(\frac{\hat{\beta}}{L}\sum_{i=1}^{L}|x_i|^{\hat{\beta}}\right)}{\hat{\beta}} = 0$$

where $\psi(.)$ is the function $\psi(z) = \dfrac{\Gamma'(z)}{\Gamma(z)}$.

$\hat{\beta}$ value should be find first by a Newton-Raphson algorithm. If the Newton-Raphson iterative algorithm is well initialized, it converges with few iterations. We defined the image vector signature by the couple $(\hat{\alpha},\hat{\beta})$ derived from each IMF.

A. Distance

To compute the similarity distance between to IMFs (Generalized Gaussian) and, according to [13] Kullback-Leibler distance is used (see equation (5)).

$$KL\left(p\left(X;\theta_q\right)\| p\left(X;\theta_i\right)\right) = \int p\left(X;\theta_q\right)\log\frac{p\left(X;\theta_q\right)}{p\left(X;\theta_i\right)}dx$$

(5)

In the case of generalized gaussian distributions, we inject equation (3) in equation (5), to obtain the following distance (equation (6)):

$$KL\left(p\left(X;\alpha_1,\beta_1\right)\| p\left(X;\alpha_2,\beta_2\right)\right) = \log\left(\frac{\beta_1\alpha_2\Gamma\left(\frac{1}{\beta_2}\right)}{\beta_2\alpha_1\Gamma\left(\frac{1}{\beta_1}\right)}\right) + \left(\frac{\alpha_1}{\alpha_2}\right)^{\beta_2}\frac{\Gamma\left(\frac{\beta_2+1}{\beta_1}\right)}{\Gamma\left(\frac{1}{\beta_1}\right)} - \frac{1}{\beta_1}$$

(6)

The distance between two images I_1 and I_2 is the sum of the balanced distance between IMFs.

$$D(I_1, I_2) = \sum_{k=1}^{K} \lambda_k \, KLD\left(p(X, \alpha_1^K, \beta_1^K), p(X, \alpha_2^K, \beta_2^K) \right)$$

where λ_k are the adjustment weights.

III. RESULT

The method is tested on the two databases (see II-A), and is compared with previous methods detailed in [4, 5]. The evaluation criteria is the mean precision at 5, which is the ratio between the number of pertinent images recalled (same class than the query) and the total images recalled (here 5).

1) Each image in the database is used as a query image.
2) The algorithm find the five first images of the database closest to the query image.
3) Precision is computed for this query.
4) Finally, we compute the mean precision.

Database	Number of IMFs extracted for each image	BEMD-GG	BEMD-Gabor
Faces	4	85.55%	89.75%
Retinas	6	43.75%	52.40%

Database	Decomposition level number	Adapted wavelets-GG
Faces	2	95.50%
Retinas	3	46.10%

Table 1 Mean precision at 5.

From Table 1 we can see that a method based on adapted wavelets [14] achieved the highest mean precision 95.5% for face database, when 52.40% for retinas database is achieved with BEMD-Gabor method.

Extracting all IMFs of retinas database takes 1 day, and few minutes for face database. Then query is very fast. For this experiment we used C++ language on a AMD Athlon 64 X2 dual Core processor working on 2 GHz with 2 Gb DRAM.

IV. CONCLUSION

In this paper, we proposed a new method to characterize the numerical content of medical images, where BEMD coefficients in each IMF are independently modeled by a generalized Gaussian density law. To compute the measure of similarity between GGDs, we used the Kullback–Leibler Distance. BEMD-GGD functions proposed in this paper achieved encouraging experimental results.

So, our future work is to try to enhance retrieval results, by, first, optimizing adjustment weights (genetic algorithms). And second, by fusing semantic data (clinical data) and image content numerical informations.

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