MultiWaveMed: A System for Medical Image Retrieval through Wavelets Transformations

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Abstract

This paper presents the MultiWaveMed system, which is a new software allowing to index and retrieve medical images through the comparison of their texture features. The features are extracted by Wavelet transforms, and are organized in feature vectors. The system extracts the image texture features, computes the distance between the query image to all images in the database, through the comparison of their features, and retrieve de n most similar images regarding this kind of feature. The proposed system has implemented both Daubechies and Gabor wavelets. The feature vectors extracted from the images are used to organize the images through access methods, which are the basis to perform the query-by-content operations over the images. The focus of this paper is to show the utility of the wavelet transforms on medical image characterization and their suitability for image indexing and retrieval.

1. Introduction

The medical field has been benefited and revolutionized by the computer and imaging technology. However, it is arduous and difficult to deal with the ever-increasing amount of digital data generated by image exams in a medical facility. The possibility of performing image retrieval by content using characteristics automatically extracted is a great help to retrieve the useful information within such enormous amount of data. Moreover, the content-based image retrieval (CBIR) techniques work on the whole information embodied into an image and are not restricted to a textual description about it. The problem with such descriptions is their inherent subjectivity, because the specialist can be, at the moment, concerned about specific aspects of the image under analysis and other important aspects may be left unreported. Therefore, we can see that the CBIR and the retrieval based on textual descriptions of the images are orthogonal, but can be integrated in a system, bringing more power to a Hospital Information System.

The selection of images in a dataset performed by a CBIR system involves comparing pairs of images and assigning a similarity coefficient to each pair. The comparison is usually executed through features extracted automatically from the images. These features are chosen aiming at getting the “essence” of the images, which should characterize each image. Therefore, an important problem in CBIR is the development of effective and efficient feature extraction methods for image representation.

The three main classes of image features are color, texture and shape [8]. Ideally, these features should be integrated to provide a better discrimination in the comparison process. The first and simpler class of features to extract is color, or brightness distribution, which is mainly given by image histograms. Extracting the image information about shape and texture is a much more complex and costly task. Therefore, a CBIR system usually first sifts the image database applying color features and afterwards employ shape and texture features on the resulting subset.

The MultiWaveMed system is presented in this paper, which is a new software allowing the indexing and retrieval of medical images through the comparison of their texture features. The features are extracted by Wavelet transforms, and are organized in *feature vectors*. The system extracts image texture features, computes the distance between the query image to the images in the database, and retrieve de *n* most similar images regarding this kind of feature. The proposed system implemented both Daubechies and Gabor wavelets. The feature vectors extracted from the images are used to organize the images through access methods, which are the basis to perform the query-by-content operations over the images. The focus of this paper is to show the utility of the wavelet transforms on medical image characterization and their suitability for indexing and retrieval.

The remainder of this paper is organized as follows. The next section summarizes the wavelets background for this work, while section 3 presents the MultiWaveMed system. Section 4 discusses the experimental results obtained with the system. Finally, section 6 gives the conclusions of this paper.

2. Wavelets background

Wavelets have been successfully used in image compression, enhancement, analysis, and classification [9]. Wavelets represent signals (in our case images) in different frequency bands, each of which with a resolution matching its scale [2]. An important characteristic of the wavelets is that they can remove statistical redundancy among pixels, providing a more compact representation of the image. Image indexing generated over the wavelet-transformed domain is believed to be more optimal than those designed over the spatial domain, because the transformed coefficients have better defined distribution than image pixels [7].

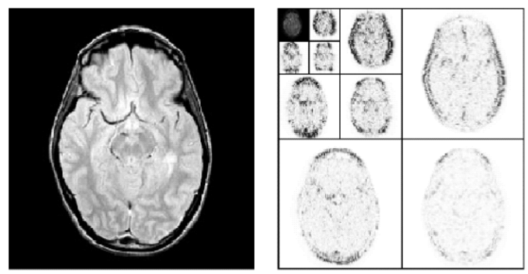

Figure 1- A three-level wavelet transform (Daubechies) over a magnetic resonance image [2].

Figure 1 gives an illustration of the multi-resolution analysis provided by wavelets using the Daubechies-4 filters. Daubechies-4 wavelet transform are usually implemented numerically by quadratic mirror filters [3] [6]. Multi-resolution analysis of the trend fluctuation of a function is implemented by convolving it with a low-pass filter (Equation 1) and a high pass filter (equation 2) that are versions of the same wavelet defined by the sequences:

$$h = \left\{ \frac{(\sqrt{3}+1)}{4\sqrt{2}}, \frac{\sqrt{3}(\sqrt{3}+1)}{4\sqrt{2}}, \frac{(\sqrt{3}-1)}{4\sqrt{2}}, \frac{\sqrt{3}(\sqrt{3}-1)}{4\sqrt{2}} \right\} \qquad (1)$$

$$g = \left\{ -\frac{\sqrt{3}(\sqrt{3}+1)}{4\sqrt{2}}, -\frac{(\sqrt{3}-1)}{4\sqrt{2}}, \frac{\sqrt{3}(\sqrt{3}+1)}{4\sqrt{2}}, -\frac{(\sqrt{3}+1)}{4\sqrt{2}} \right\} \qquad (2)$$

The Daubechies wavelets are frequently used to extract features based on the color distribution over the wavelets sub-spaces, and applying further statistical measurement. For example, we can extract features for evaluating the average brightness of the image (given by the mean), the smoothness of the image (expressed by the entropy), and the uniformity (given by theenergy).

Another class of wavelets, are the ones generated by Gabor functions, which has been used to make filter-based multi-resolution representation of images. For example, for a given image *I(x,y)* with size PxQ, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y) = \sum_s \sum_t I(x-s, y-t)\psi^*_{mn}(s,t)$$

where, s and t are the filter mask size variables, and ψ^{*}_{mn} is the complex conjugate of ψ_{mn} ,which is a class of self-similar functions generated from dilation and rotation of the following wavelet:

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)\right]\cdot\exp(j2\pi Wx)$$

where W is called the modulation frequency. The self-similar Gabor wavelets are obtained through the generating function:

$$\psi_{mn}(x,y) = a^{-m}\psi(\tilde{x},\tilde{y})$$

where m and n specify the scale and orientation of the wavelet respectively, with m=0,1,...M-1, n=0,1, ...,N-1, and

$$\tilde{x} = a^{-m}(x\cos\theta + y\sin\theta)$$
$$\tilde{y} = a^{-m}(-x\sin\theta + y\cos\theta)$$

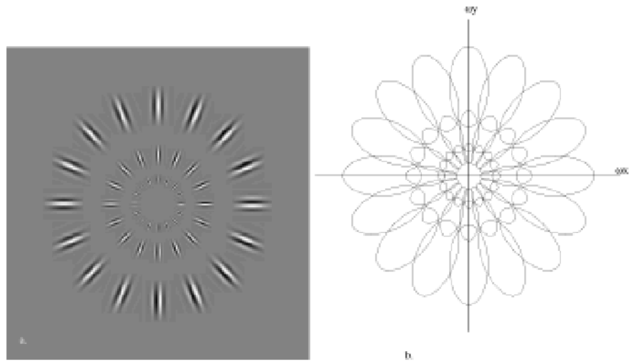

Figure 2 - (a) Spatial distribution of the Gabor Wavelets. (b) Spatial coverture [4]

where $a > 1$ and $\theta = n\pi/N$.

After applying Gabor filters on the image with different orientation at different scale (see figure 2), we obtain an array of magnitudes:

$$E(m,n) = \sum_x \sum_y |G_{mn}(x,y)|, \quad m=0,1, ..., M-1; n=0,1, ..., N-1$$

These magnitudes represent the energy content at different scale and orientation of the image. The main purpose of texture-based retrieval is to find images or regions with similar texture. It is assumed that we are interested in images or regions that have homogenous texture. Therefore the following mean μ_{mn} and standard deviation σ_{mn} of the magnitude of the transformed coefficients are used to represent the homogeneous texture feature of the region:

$$\mu_{mn} = \frac{E(m,n)}{P\cdot Q} \qquad \sigma_{mn} = \frac{\sqrt{\sum_x\sum_y \left(|G_{mn}(x,y)| - \mu_{mn}\right)^2}}{P\cdot Q}$$

A feature vector ***f*** (texture representation) is created using the means μ_{mn} and the standard deviations σ_{mn} as the feature components [5]. For example, considering four scales and six orientations, when applying the Gabor Filters will produce a feature vector with 48 elements (24 regarding μ_{mn} and 24 regarding σ_{mn}) given by:

$$f = (\mu_{00},\sigma_{00},\mu_{01},\sigma_{01},...,\mu_{05},\sigma_{05},\mu_{10},\sigma_{10},...\mu_{15},\sigma_{15},...\mu_{35},\sigma_{35})$$

This multi-resolution representation is sometimes called Gabor wavelets for short [4]. The use of Gabor wavelets for extracting textural features has increased in importance, because Gabor wavelets map the modeling of the simple cells in the visual cortex [4]. Gabor functions can be considered as both orientation (t) and scale (s) tunable edge and line (bar) detectors, and the statistics of these micro-features in a given region are often used to characterize the underlying texture information. Gabor functions form a complete, yet not orthogonal basis (there is redundant information in the filtered images). However, in [5] is proposed a technique to reduce this redundancy, which was used in this work.

3. The MultiWaveMed System

The MultiWaveMed system is based on multi-resolution wavelet techniques applied to magnetic resonance medical images. As is shown in figure 3, as each new image is stored in the image database, it is processed by having their features extracted generating its feature vector, which is stored together with the image in the database. Every time the user asks for images similar to a given one, the query image has also its features extracted, in order to be used in the comparison processing. The results will be presented to the user as is shown in figure 4. The query image (on the upper left corner in this figure) is chosen through a visual browser and the most similar images are presented initially as thumbnails. The user can select any of them and visualize it in full size.

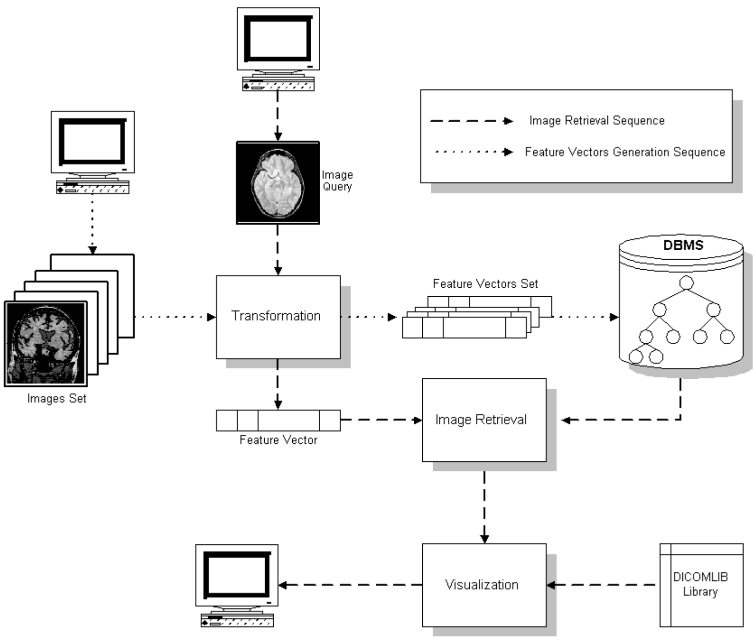

Figure 3 - Architecture of the MultiWaveMed.

The feature vectors are obtained through a convolution over each image by the wavelets filters (Daubechies, Haar or Gabor), following the user specification and considering the multi-resolution approach. Over the transformed image is then applied a set of statistical measures, aiming to identify the desired characteristics of the image. Regarding the Gabor filters, the statistic parameters are computed for each scale (*s*) and direction (*t*).

The MultiWaveMed system allows the use of brightness (mean), contrast (variance), complexity and randomness (calculated as entropy and variance) as the statistic parameters. For example, if one uses the mean μ_{st} and the standard deviation σ_{st} of the magnitude of the transform coefficients, then, μ_{st} and σ_{st} are employed as the features to represent the region for classification and retrieval purposes. For instance, considering four scales (s=4) and six orientations (t=6), the resulting feature vector of 48 values is composed by 24 mean and 24 standard-deviation values. One set of values of all these characteristics constitutes the feature vector of an image. The numbers of scales and orientations as well as the number of resolutions for the Gabor functions are parameters that can be configured by the database administrator.

The feature extraction process of the dataset is done offline, without interfering with the query processing. Therefore, besides the query execution requires massive underlying image processing, the user gets the queries answered in fractions of seconds, even when the database has thousands of images, because the bulk of the processing is made before, when each image is stored.

The two most used types of similarity queries, the *k*-nearest-neighbor and range queries, are provided by this system. The MultiWaveMed system was developed in C++Builder over MSWindows platform. It uses a Dicom library (DicomLib), to open, store and display the images received from the modalities devices.

4. Experimental Results

We have conducted retrieval experiments both on color and texture-based features for image retrieval. The set of images corresponds to groups of tomographics exams, where consecutive images present little changes. In order to generate the precision/recall[1] graph (figure 4) was used a dataset composed by seven groups (classes) of 30 images and a group of 290 images without pertaining to any class to act as noisy data.

In the experiments, it was applied five extractors on each image, generating five feature vectors per image (*Mean*, *Energy*, *Entropy*, *Gabor* and *GaborManju*) in order to get distinct properties from the medical images. To compare the images, were used

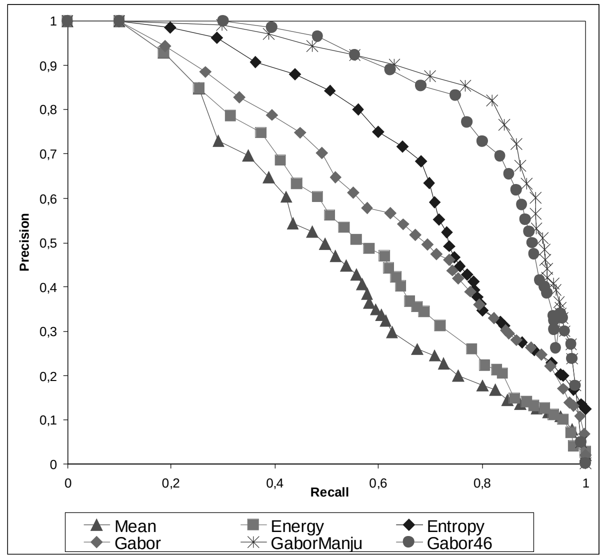

Figure 4 - Precision and Recall plots obtained from average of 10 nearest neighbor queries using the 5 types of features extracted by wavelets.

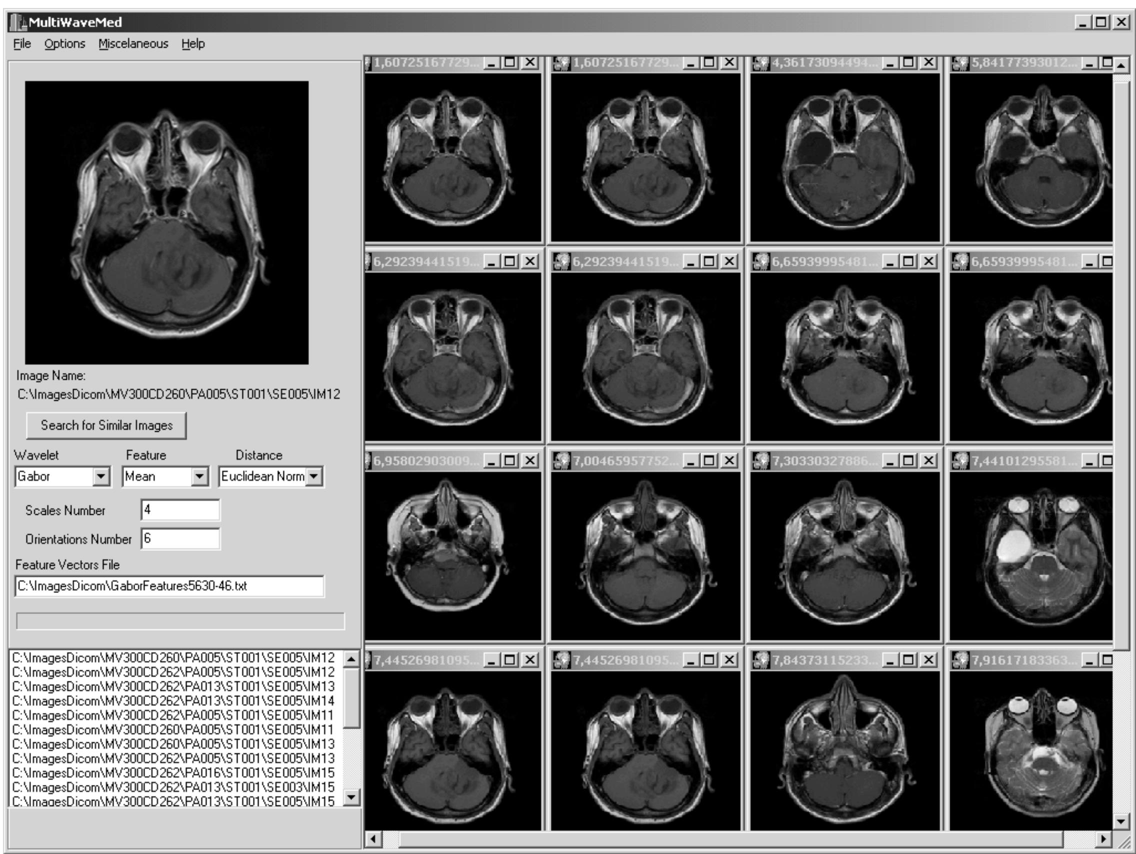

Figure 5 - Results of the 16-nearest neighbor query performed on the features extracted by Gabor wavelets returned by the MultiWaveMed.

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[1] *Recall* is given by the fraction of the relevant images which has been retrieved, whereas *Precision* is the fraction of the retrieved images which is relevant for the query [1].

two distance f unctions. That is, for the *Mean*, *Energy*, *Entropy* extracted from Dabeuchies and *Gabor* we have used the usual Euclidean metric function, and for the *GaborManju* feature we have used a normalized Euclidean function, which gave better results than the pure Euclidean Function, because the components of the feature vectors are normalized by the median and the standard deviation of the data.

We have performed sets of 10 nearest-neighbor queries computing the average of the results and computed the *precision* and *recall* plots over them. Figure 4 shows such plots, and we can see that the gabor wavelet (*GaborManju*) with the normalized Euclidean metric function is the best extractor for this set of images. We have done the same experiments on a larger database with 5631 images, and got equivalent results. An example of a query processing is shown in figure 5, where the Gabor wavelets, with four scales and 6 orientations, were used to generate the textural feature vector.

5. Conclusions

The proposed MultiWaveMed extracts the texture features from the image database and allow the user to graphically query the images by their contents. The results obtained during the query processing are very motivating, not only regarding precision but also regarding time. As the system uses an indexing structure to organize the feature vectors, the time to obtain the query answer is very short. For instance, considering a dataset of 5631 images, the processing took from 0.2 to 0.8 second in a Pentium IV 1.7 MHz machine.

The use of textural image features in content-based image retrieval has proven to be very effective. The use of such techniques is a useful tool to help the physicians to recall similar cases to the one under analysis, without having to use any textual description.

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