Retrieval by Content of Medical Images Using Texture for Tissue Identification

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Abstract

This work aims at supporting the retrieval and indexing of medical images by extracting and organizing intrinsic features of them, more specifically texture attributes from images. A tool for obtaining the relevant textures was implemented. This tool retrieves and classifies images using the extracted values, and allows the user to issue similarity queries. The application of the proposed method on images has given encouraging results that motivate to apply the method as a basis to more experiments, at diversified contexts. The accuracy degree obtained from the precision and recall plots was always over 90% for queries asking for similar images for up to 20% of the database.

1. Introduction

Recently, with the emergence of **PACS** (*Picture Archiving and Communication Systems*) [1] [2], there has been a crescent interest to integrate all the information related to patients (texts, images, charts, temporal data, etc.) in unique systems.

The huge amount of digital images generated in hospitals and health care centers leads to the need of automatic storage and retrieval of them. Therefore, a PACS should incorporate properties allowing to retrieve these images in a timely manner. Moreover, in order to effectively aid the physicians in their analysis and diagnosis, the retrieval should bring images that match the criteria given by the specialists [3]. As it is imprecise to retrieve images based on textual annotations, lately there has been a great interest on content-based image retrieval (**CBIR**). CBIR techniques use the intrinsic visual features of images, such as color, shape and texture, to organize and retrieve them [4]. Adding CBIR capabilities to PACS makes it more powerful to assist diagnosis, allowing easier and more efficient manipulation and organization of stored images.

Among the visual features, for medical images**, texture** acquires distinguished importance, because it constitutes the core in identifying tissues, and this process of identification is normally the first step required by all other processes.

This work focuses on the study of medical images representation and comparison, based on image texture features. Regions of images that represent different human body tissues are used. The goal is to characterize an image by numeric values (signature) acquired through calculations on the brightness (gray) levels of the image. The inter-relationship between these brightness levels defines the image texture. Besides this, rules to establish the similarity between images based on the respective signatures, are proposed and used in order to classify them. A tool was implemented, which retrieves and classifies images using extracted values and allows the user to issue similarity queries for obtaining the relevant textures. Another contribution of this paper is the definition of a new texture descriptor - the Gradient descriptor.

2. Background

Among the current approaches used in image processing to describe texture, the so called **statistical approach** [5-11] is the widely used because it produces good results with low computational costs. This method considers the distribution of gray levels and their inter-relationship. The pixel values are used to construct numerical structures which are associated to the texture pattern of the image. This pattern is based mainly on the inter-relationship between one pixel and its neighbors.

Co-occurrence matrix. Generally, the problem of texture discrimination based on statistical approach consists on the analysis of a set of *co-occurrence matrices*. In this matrix, the indexes of rows and columns represent the given range of the image gray levels, and the value $P(i,j)$ stored at the position (i,j) is the frequency that gray levels i and j occur with, at a given distance and at a given direction. For instance, suppose we have the image represented by its gray level matrix shown left in Figure 1. Regarding the 0° direction and the distance 1, we will have the co-occurrence matrix shown right. For instance, the value of the co-occurrence $P(0,1) = 8$ was calculated by scanning the gray level matrix and, for each pixel with value 0, its left and right nearest neighbors were checked and $P(0,1)$ was incremented whenever a value 1 was found.
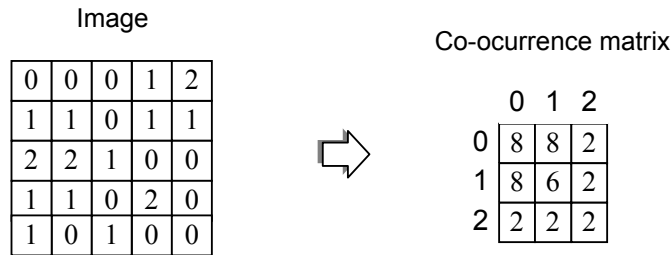

Figure 1. Image quantified in 3 gray levels, sampled in 5x5 pixels and its co-occurrence matrix for direction = 0° and distance = 1.

After these calculation is done, the matrix is reduced by dividing each value by normalization factors [5] rendering a matrix whose sum is equal to 1. One co-occurrence matrix is created for each pair direction-distance considered by the texture analysis.

Descriptor. Having a co-occurrence matrix, different properties of the pixel distribution can be obtained by applying mathematical operations on the matrix values. These operations are called *descriptors*. Each descriptor is related to a particular visual feature about texture.

Haralick et al. proposed a set of 14 descriptors [12]. Table 1 shows the most used ones. $P(i,j)$ is the value at position (i,j) in the co-occurrence matrix.

Image Signature. This is a numeric value or a set of them, which can be used to represent an image regarding one or more characteristics of it [4]. For example, one signature that can be assigned to an image is a vector of values obtained from the application of the Energy descriptor over its set of co-occurrence matrices. The image signature is generally used as parameter of comparison between two images.

3. Proposed Method

In order to apply similarity search onto regions of interest in medical images based on the statistical approach using texture representation, we propose a method that works is four steps as follows:

Step 1: *Obtain the co-occurrence matrices of each image.* The gray levels of the image are reduced to 16. For 0°, 45°, 90° and 135° directions, and distances 1, 2, 3, 4 and 5, calculate the corresponding co-occurrence matrix. This produces 20 matrices of 16x16 integer elements per image.

Step 2: *Obtain the values for the chosen descriptors.* For each co-occurrence matrix, the value for the descriptor (or descriptors) is calculated. For each image, the resulting descriptor values are stored in a matrix where the rows represent the directions 0°, 45°, 90° and 135° and the columns represent distances 1, 2, 3, 4 and 5.

Step 3: *Generate image signatures.* The image signatures are calculated from the descriptor matrix by averaging the values obtained with the different distances for each direction. Aiming at eliminating dependencies of image rotation, distances are calculated with different "rotations" on the elements of the signatures and the smaller one is adopted.

Step 4: *Compare the images through their signatures.* The signatures of two images are compared and the distance between them is calculated, using the Euclidean distance function on the elements of the signature.

Table 1. Texture descriptors proposed by Haralick

Descriptor	Equation	Meaning
Variance	$\sum_i \sum_j (i-j)^2 P(i,j)$	level of contrast of the image
Entropy	$\sum_i \sum_j P(i,j) \log P(i,j)$	suavity of the image
Energy	$\sum_i \sum_j P^2(i,j)$	uniformity of the image
Homogeneity	$\sum_i \sum_j P(i,j)/(1+|i-j|)$	homogeneity of pixels distribution
3rd Order Moment	$\sum_i \sum_j (i-j)^3 P(i,j)$	level of distortion
Inverse Variance	$\sum_i \sum_j P(i,j)/(i-j)^2$	inverse level of contrast

4. The Gradient Descriptor

A new descriptor was developed, which we have named as *Gradient*. It consists of generating one gradient vector from the co-occurrence matrix, whose indexes represent values of |*i-j*| (*i* and *j* are also indexes of the co-occurrence matrix), and whose content is the sum of the amount of occurrences in the elements with the same values of |*i-j*| in the co-occurrence matrix.

In the example shown in Figure 2, the image presents 16 pixels having neighbors with the same gray level, 20 pixels having neighbors with a difference of 1 gray level and 4 pixels having neighbors with a difference of 2 gray levels. Latter, these vectors are used to calculate the distances between images, weighing their values by the factor $(i-j)^2$, a "variance-like" factor.

The Gradient descriptor measures the **suavity** in the transition among pixels along the image.
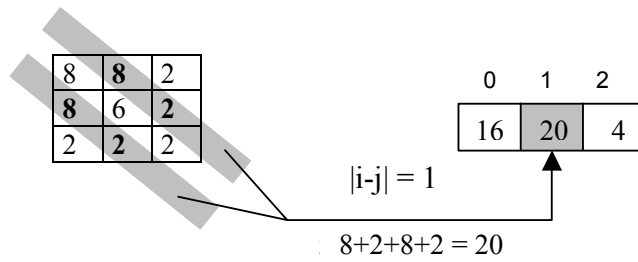
Figure 2. Vector composition for gradient descriptor

5. Experimental Approaches

A tool called **Texture Extractor** was developed to be used in the experiments executed to test the proposed method. The Texture Extractor provides an interface where the user can choose a query image as a reference and a set of candidate images stored in a previously assembled image database. The candidate images will be compared to the query image and then classified according to a similarity criterion. The user chooses a texture descriptor (or a combination of them), as well as a method to calculate the image signature and executes the feature extraction, which is followed by the classification of the images based on the calculated distances. All the descriptors of Table 1 were implemented in this tool.

Our intent was to test and validate the capacity of the proposed method to separate different human body tissues. A database of images was created, consisting of computerized tomography and magnetic resonance image sections. The images are representative elements of typical segments of different tissues: brain, spine, heart, lung, breast, adiposity, muscle, liver and bone. The database contains one hundred images, divided into eleven images of each tissue. Other databases were tested, but, due to space limitations, only the results achieved with this one is shown here. The other ones have generated similar results.

Two experimental approaches for getting the image signatures in the database were used:

1) One representative image of each group (tissue) was selected as the query image and then compared with all the others in the database. A different feature extraction and classification was executed for each representative image using all descriptors available (gradient, variance, entropy, energy, homogeneity, 3th order moment, inverse moment and a combination of gradient, entropy and homogeneity) individually. This approach was employed to compare the performance of the descriptors.

2) In this experiment, the goal was to analyze the method effectiveness in identifying specific tissues, in other words, what tissues can be automatically identified by it, with good accuracy. We decided to use the descriptor that has presented the best performance in experiment 1: the combined descriptor. All images in the database were used as query images in different tours. Then, the curve precision vs. recall was plotted. These plots were used to compare the tissue discrimination performance of the tool.

6. Results

Experiment 1. The values of precision and recall were obtained (as detailed in step 1 of section 3), and the areas under the curves were calculated. These measurements are presented in Table 2.

Table 2. Results of *precision* vs *recall* curves (areas) for each descriptor

Descriptor	Average Area	Standard Deviation	compared with Mean Value (%)
Combined	0,90	0,06	+32,3
Gradient	0,74	0,09	+8,8
Homogeneity	0,72	0,16	+5,9
Variance	0,69	0,11	+1,4
Entropy	0,64	0,23	-5,9
3th Moment	0,62	0,11	-8,8
Energy	0,61	0,24	-10,3
Inv. Variance	0,53	0,11	-22,1
Mean Value	0,68		

Considering these results, we can see that the Combined (Gradient, Entropy and Homogeneity) descriptor is superior to the others, followed by the descriptors Gradient, Homogeneity and Variance. Considering only single descriptors, our proposed descriptor Gradient was the best, with better values of area (the larger value of Table 2, column 1) and standard deviation (the smaller value of column 2) and with performance 8,8% above the mean (column 3).

Experiment 2. In this experiment, the precision and recall were calculated for every image in the database, using the Combined descriptor. The results of images pertaining to the same group were averaged and the issued curve was plotted for each tissue.

Based on these curves, shown in Figure 3, we can see the quality of the Combined descriptor in the identification of different tissues, and conclude that for the majority of tissues, good separation was reached. The achieved results showed that the proposed method is very good, presenting an image retrieval accuracy always over 90% for queries asking for similar images up to 20% of the database.
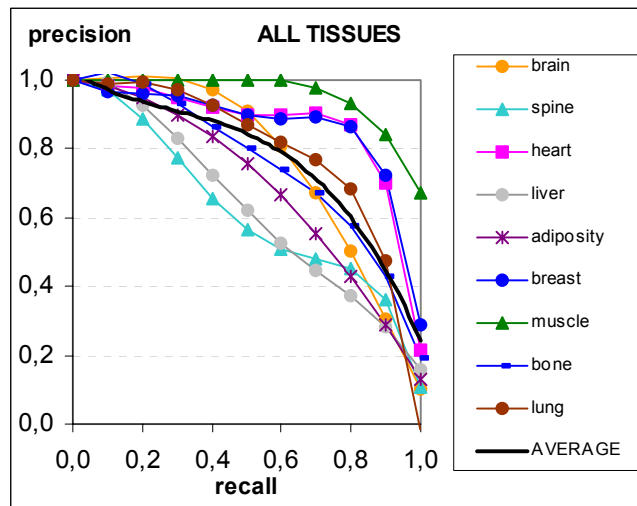

Figure 3. Precision vs recall for different tissues retrieval using the combined descriptor

7. Conclusions

This work presents a technique based on texture which combines the matrices of image gray levels to generate a single signature for images, which is used in similarity calculations.

A tool was implemented based on the presented technique to validate it through real images from different tissues of the human body, and to assist the study and analysis of medical images, aiming to be included in a PACS under development at the University Hospital.

The new *Gradient* descriptor was implemented, and compared with the other ones. The results have shown that its performance is better than all the other existing descriptors.

Two distinct experiments were performed: to determine the performance of different descriptors in the context of medical images; and to evaluate the precision vs. recall results for different tissue samples using the proposed method. The achieved results showed that the proposed method performs very well, presenting an image retrieval accuracy always over 90% for queries asking for similar images up to 20% of the database, which are the most common queries issued. They also qualify the methods implemented to be used in processes that involve wider contexts in medical imaging (integrated to segmentation methods, for instance), as well as in more specific contexts of detailed analysis of images about human body tissues, regarding the relevance carried by texture features in the field of medical image CBIR systems.

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