# Review of Features Used in recent Content-Based Radiology Image Retrieval systems

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## 1 Introduction

IMAIOS [1] is a young innovative company, providing on-line teaching solutions in the medical imaging field. Its database is quite impressive: over 20,000 images of various modalities (MRI, CT), and a unique anatomic atlas of 3000 images with 5000 captions (an example is shown in Figure 1).

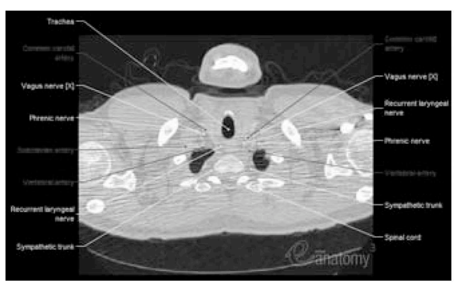


Figure 1: Image from IMAIOS anatomic atlas - *Copyright IMAIOS 2010*

This is a general trend: the number of digitally produced images has dramatically increased. This is particulary true in radiologic use: with numerous technologic improvements, an increasing number of images are captured from a patient with very high precision and resolution. A whole-body CT scan for example, which is commonly used for road accident patients, will release around 3000 images. At the same time, a strong need for storing, indexing and retrieving these huge amounts of data has emerged.

[1]http://www.imaios.com

A Content-Based Image Retrieval system aims to retrieve the most similar images to a query from a database. Classical retrieval systems retrieve a result from a textual query, which cannot describe precisely all the visual characteristics of an image. In CBIR systems, the query is an image. The main idea is to extract some ”features” from the images, which will be compared for retrieval.

In the field of medical practice, CBIR is often associated to Computer Aided Diagnosis (CAD). By integrating computer assistance in the diagnosis process, the goal is not to get rid of medical expertise but to improve its efficiency and accuracy.

First CBIR systems appeared in the 1980s. Still, most systems are academic, but there is a growing interest in this topic, as proven by the great deal of publications.

This article describes CBIR systems in the Section 2. In Section 3, we will review the features used in recent CBIR systems in radiology. Finally, discussion and conclusion can be found in Section 4.

# 2 General scheme of a CBIR system

Figure 2, presents the general framework, which processes in two phases. The first one is done before any query, it extracts some visual descriptors from the images in the database and stores them. The second one is the real-time retrieval phase. The user inputs a query image, from which descriptors are extracted and compared to the ones in the features database. The system finally retrieves most similar images. An example of retrieval is shown in Figure 3, and Table 1 gives an overview of a system attributes in a medical radiology context. Current trend is to design application-driven (and then very specific) systems, which makes their evaluation a significant problem.

| | |
|---|---|
| **Image Modality** | Radiography, Ultrasonography (US), Computer Tomography (CT), Magnetic Resonance Imaging (MRI). |
| **Data content** | Specific (for example x-ray spine images or mammographies) or general |
| **Application** | Specific diagnosis tasks (for example osteoarthritis) or general |
| **Query** | A single image, or an image associated with text information. |
| **Visual features** | List of the descriptors used for expressing the image content (described in section 3). |
| **Distance measure** | In order to express the similarity / dissimilarity between two images. |
| **Improvements** | Learning method, and/or relevance feedback from the user |
| **Graphical User Interface (GUI)** | The user interface is significant, if the system is aimed to work in a clinical context. |
| **Performance** | In terms of sensitivity and specificity of the retrieval, and its speed. |

Table 1: Characteristics of CBIR systems in a medical radiology context

# 3 Existing systems

This section presents some recent choices made for retrieval systems on radiology images during the 2008-2010 publication period. Reviews with older materials can be read for more information on the subject (Akgl *et al*., 2009; Long *et al*., 2008). First, visual features are enumerated, then other characteristics of CBIR systems are described.

## 3.1 Features review

There are two kinds of descriptor: for general or specific purpose. ***Specific features*** can only be extracted in a precise application (for example inter-vertebral disc shape

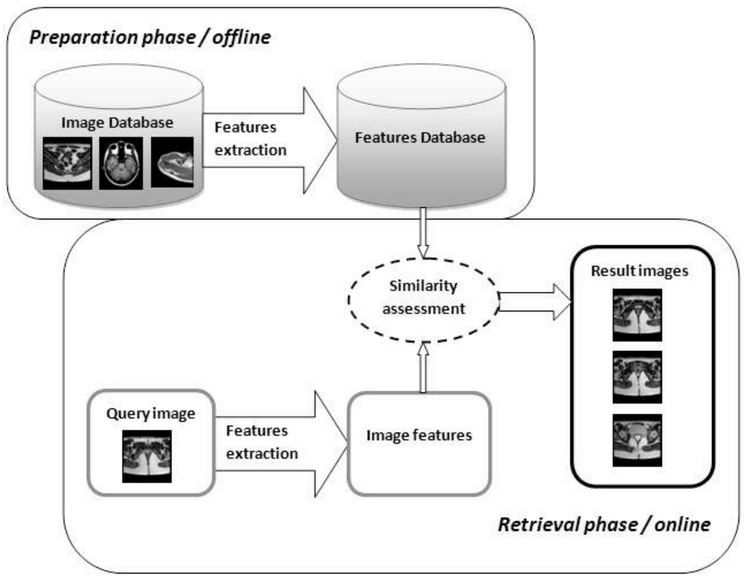


Figure 2: General framework CBIR systems

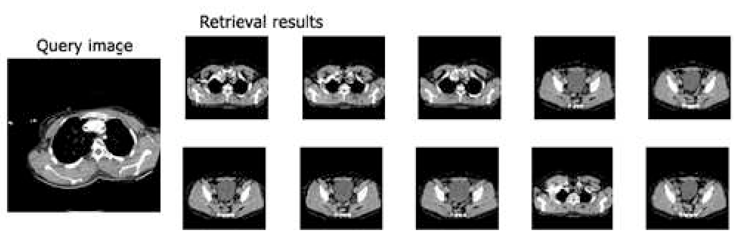


Figure 3: Retrieval example: the system has returned the 10 most similar images to the input

profiles used in Lee *et al*. (2009)), whereas ***general features*** can be extracted from any image. The features describe either ***color, texture or shape***. They are computed: ***on the whole image***, ***on each block*** obtained by dividing the image in small patches of equal size, or ***on Regions Of Interest*** (ROIs), which have been beforehand delineated (segmented) regions. The segmentation process may be manual or automatic. Table 2 gives an overview of the different features used in the last two years published materials, and Figure 4 presents their hierarchy.

### 3.1.1 Color Features

**Histograms**, which represent the grayscale or color distribution of an image, commonly characterizes color in an image. The histogram itself can be considered as a feature Bugatti *et al.* (2009), on the original image or after a frequency layer decomposition (Wu *et al.* (2009)), or it can be used to calculate statistical descriptors, such its mean, standard deviation and skewness (asimmetry) (see Ribeiro *et al.* (2009); Xue *et al.* (2008)). Modified histograms, which represent various windowings of the original image as in Bugatti *et al.* (2009), may also be computed from the original distribution.

### 3.1.2 Texture

Exact texture definition is still not clearly established, as it is strongly related to human visual perception. In this section we will present here some features used in retrieval.

**Haralick descriptors** are 14 statistical values extracted from the Grey-Level Cooccurrence Matrix (GLCM) of the image (Haralick (1979)). The GLCM represents the spatial relationship of a given (distance, angle) couple, between pixel values. Haralick's descriptors are widespread in radiology image retrieval ( Ribeiro *et al.* (2009); Jin *et al.* (2009); Bugatti *et al.* (2009)), even if the computational cost of the method is high.

**Tamura descriptors** are 6 values or histograms calculated from the image: coarseness, contrast, directionality, line-likeness, regularity, and roughness. They are described in Tamura *et al.* (1976) and calculated in Caicedo *et al.* (2008) and Nino *et al.* (2008) systems.

**Local Binary Patterns** operator is a measure derived from local neighborhood thresholded intensities. An histogram can be used to represent the patterns. This method has been introduced by Ojala in Ojala *et al.* (1996), it is grayscale invariant, and is used in Caicedo *et al.* (2008); Nino *et al.* (2008).

**Wavelet Transform based descriptors** are computed after applying a wavelet transform. This function computes a collection of spatial-frequency representations of the image, called sub-bands, with different resolutions. Then, some descriptors can be extracted, in general in each sub-band: coefficients' histogram and generalized Gaussian distribution (Quellec *et al.* (2010)), statistical features (mean, energy, standard deviation) Jin *et al.* (2009); Kokare (2009); Xue *et al.* (2008). Various wavelet types are found in retrieval systems: Haar, Daubechies, Le Gall, Cubic B-spline, tree structured cosine-modulated...

At last, the **Invariant feature histogram** method presented in Caicedo *et al.* (2008); Nino *et al.* (2008) computes image invariant moments, which represent the texture in pixels neighborhood.

### 3.1.3 Shape

Shape analysis is a very active domain and several retrieval descriptors can be computed on it. The methods are based on the regions, or on the boundaries of the shape.

**Simple geometric descriptors** can be easily calculated over the shape or the boundaries: area, perimeter, extent, solidity, major and minor axis length, equivalent diameter, eccentricity, elongation, compactness, solidity... They are used in Xu *et al*. (2009); Park *et al*. (2009); Wei *et al*. (2009); Bugatti *et al*. (2009).

An image moment is a local weighted average of the image pixels' intensities. A function of these moments, chosen to be invariant to some manipulations Ribeiro *et al*. (2009), can be used as features called **Invariant moments**.

**Fourier Transform based methods** extract features after applying the Fourier Transform on the shape boundaries. The image in the frequency domain is obtained, where each point represents a specific frequency contained in the spatial domain image. Two features, fractal dimension and Fourier descriptors, can be extracted from this representation. The fractal dimension is calculated from the curve slope of the power spectrum average in Park *et al*. (2009). When the Fourier transform is applied on the shape boundary, the features, named as the Fourier Descriptors, are the modules of the coefficients obtained Xu *et al*. (2009). They are invariant to translation, rotation or scale modification.

**Frequency Layer Decomposition based descriptors** are computed after calculating the absolute value of the substraction of the original image with a Gaussian kernel. The result is decomposed in several sub-images, which are thresholded in various ways. Features are extracted from these sub-images. In Wu *et al*. (2009), the Moment Fourier Descriptor (MFD) is calculated. It is the combination of the Fourier transform and invariant moment, it can extract complex shape and is robust to geometrical deformations.

A featured named **Sobel histogram** is computed over the values obtained after applying the Sobel operator, which detects contours in an image.

**Procustes analysis** extracts a pre-shape from a Region of Interest (ROI) boundaries, by removing the variations in translation, rotation and scaling across them. Procustes distance evaluates the similarity between two pre-shapes (Xu *et al*. (2009); Qian *et al*. (2010); Xu *et al*. (2008)).

Two other feature extraction methods are based on **Partial Shape Representation** (Xu *et al*. (2008)): Line Segments and Multiple Open Triangles, after defining an open shape contour of ROIs . Line Segments are given by the connection of two adjacent points on the contour. Three features are calculated : the length, absolute orientation and relative orientation of each segment. For Multiple Open Triangles, open triangles are associated to each couple of coordinates of the shape. This is done by connecting a point to its predecessor and its successor. A point can have more than one predecessors or successors, in this case multiple open triangles are extracted for this point. The descriptors computed are : the angles and the lengths of the two sides of these open triangles, as well as the average of the individual angle similarities for each point of the shape.

## 3.2 Other characteristics of a CBIR system

**Similarity** between images is assessed by three kinds of methods. ***Direct comparison*** evaluates directly the similarity of two images with a statistical analysis (for example linear correlation (Deserno *et al*. (2008)).***Vector distance*** compares feature value vectors, with common metric distance functions as the Euclidean distance, the Canberra distance, the Manhattan distance... ***Classification*** assigns a label to the query image,

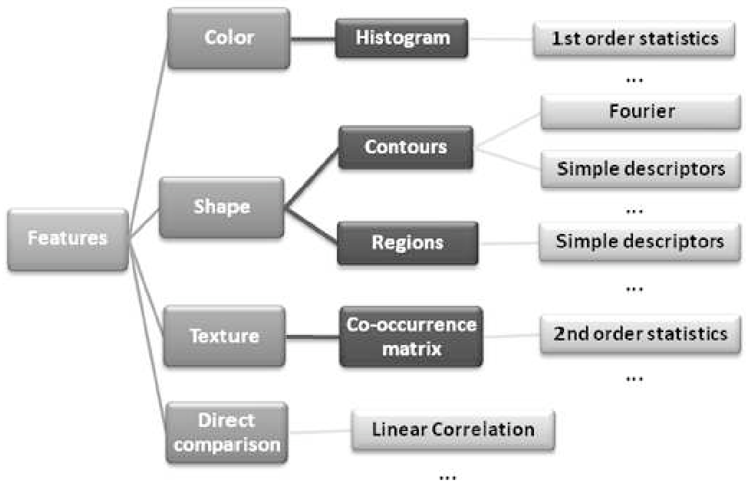


Figure 4: Hierarchical presentation of some features

| **GENERAL FEATURES** | | | |
|---|---|---|---|
| **Computed on the whole image** | | | |
| **Type** | **Pre-extraction** | **Features** | **Ref.** |
| **Color** | - | Grey-level histogram | Bugatti *et al*. (2009)Caicedo *et al*. (2008)Nino *et al*. (2008) |
| | - | Color histogram | Caicedo *et al*. (2008)Nino *et al*. (2008) |
| | Grey-level histogram | High and low attenuation histograms | Bugatti *et al*. (2009) |
| | Frequency Layer Decomposition | Y, Cb, Cr histogram | Wu *et al*. (2009) |
| | Discrete Cosine Transformation | Color Layout Descriptor | M.Rahman *et al*. (2008) |
| **Texture** | Grey-Level Co-occurrence Matrix | Haralick descriptors | Ribeiro *et al*. (2009)Mueen *et al*. (2007) |
| | - | Tamura descriptors | Caicedo *et al*. (2008)Nino *et al*. (2008) |
| | Wavelet Transform | Coefficients histogram | Quellec *et al*. (2010) |
| | | Generalized Gaussian distribution | Quellec *et al*. (2010) |
| | | Energy and Standard Deviation | Kokare (2009) |
| | Local Binary Patterns | Local Binary Patterns Histogram | Caicedo *et al*. (2008), Nino *et al*. (2008) |
| **Shape** | Frequency Layer Decomposition | Moment Fourier Descriptor | Wu *et al*. (2009) |
| | - | Edge Histogram Descriptor | M.Rahman *et al*. (2008)Mueen *et al*. (2007) |
| **Computed on each block after the image has been divided in small blocks of equal size** | | | |
| **Color** | - | Mean grey value | Avni *et al*. (2009), M.Rahman *et al*. (2008) |
| | - | Principal Component Analysis coefficients | Avni *et al*. (2009) |
| **Texture** | - | Wavelet Transform | Iakovidis *et al*. (2009) |
| | Grey-Level Co-occurrence Matrix | Haralick descriptors | M.Rahman *et al*. (2008)Mueen *et al*. (2007) |
| **Shape** | - | Edge Histogram Descriptor | Mueen *et al*. (2007) |
| **Computed on Regions Of Interest (ROIs)** | | | |
| **Type** | **Pre-extraction** | **Features** | **Ref.** |
| **Color** | Grey-level histogram | Histogram mean and standard deviation | Ribeiro *et al*. (2009) |
| | Color histogram (for each channel) | Histogram mean, standard deviation and skewness | Xue *et al*. (2008) |
| **Texture** | - | 2D Principal Component Analysis | de Oliveiraa *et al*. (2010) |
| | Grey-Level Co-occurrence Matrix | Haralick descriptors | Jin *et al*. (2009)Bugatti *et al*. (2009)Ribeiro *et al*. (2009) |
| | Wavelet Transform | Energy's mean and variance | Jin *et al*. (2009) |
| | | Coefficients' mean and standard deviation | Xue *et al*. (2008) |
| **Shape** | Fourier Transform | Fourier Descriptors | Xu *et al*. (2009) |
| | | Fractal dimension | Park *et al*. (2009) |
| | - | Simple Geometric Descriptors | Xu *et al*. (2009)Park *et al*. (2009)Wei *et al*. (2009)Bugatti *et al*. (2009) |
| | Pre-shape | Full or partial Procustes distance | Xu *et al*. (2009)Hsu *et al*. (2009)Qian *et al*. (2010)Zheng (2009)Xu *et al*. (2008) |
| | - | Invariant Moments | Ribeiro *et al*. (2009) |
| | Multiple Open Triangles | Length, Angle, Merging | Xu *et al*. (2009), Xu *et al*. (2008) |
| | Line Segments | 2-norm length, absolute and relative orientation | Xu *et al*. (2008) |

| **SPECIFIC FEATURES** | | | |
|---|---|---|---|
| **Type** | **Pre-extraction** | **Features** | **Ref.** |
| **Color** | Grey-level histogram | Air, Dense structures, Lung structure | Bugatti *et al*. (2009) |
| **Shape** | 9-point vertebral contour | Mean and standard deviation of vertebra distance, Vertebra skewness | Lee *et al*. (2009) |
| | 36-point vertebral contour | Normalized inertias, Inter-vertebral disc shape profiles | Lee *et al*. (2009) |
| | Segmentation | Absolute and relative sizes | Xue *et al*. (2008) |

Table 2: Overview of the features used in CBIR systems in the radiological context

which corresponds to the most similar class of the image dataset, by applying for example k-nearest-neighbors-based algorithms (Park *et al*. (2009)).

CBIR systems accurracy can be improved by **training and / or relevance feedback**, which wil bel briefly introduced below.
The learning phase trains the system with statistical methods such as Association Rule Mining on the feature vectors of the reference database (see Ribeiro *et al*. (2009)). Association rules are obtained, which will be used in the retrieval phase. Another approach is to calculate features weight with training data, for example by using a Gaussian Mixture Modeling followed by the Expectation Maximization algorithm, as in Lee *et al*. (2009).
The relevance feedback consists of letting the user choose some relevant / irrelevant items. This choice can be made on the query, or on the results. The retrieval system is iteratively refined. Two techniques have been proposed for relevance feedback, that can be used separately or together. The first one is a probability estimation for calculating image similarity, by updating the weights of the features or re-estimate the probabilities as in Xu *et al*. (2009); M.Rahman *et al*. (2008), by a Bayesian rule, or by Expectation Maximization algorithm. The second one is named optimal adaptive learning (Support Vector Machine, used in de Oliveiraa *et al*. (2010); Wei *et al*. (2009); M.Rahman *et al*. (2008) or adaptive filters). Feedback is made on the current itteration, or using feedback history.

# 4 Discussion and conclusion

Current CBIR systems are not fully satisfactory. The choice of a feature combination is a difficult task, in particular because numerous improvements in image analysis have been made recently and therefore, the number of possible descriptors has exploded. They need to be tested in a retrieval context. Shape analysis especially is a very active field, with a large number of publications. Other defects are the gaps still existing between the needs and the systems, that lead to no real medical use of current CBIR systems Deserno *et al*. (2009). Causes are various: lack of communication between computer scientists and radiologists, specificity of the applications, inadequate performances, necessity to integrate the patient context in the process. Finally, the use of training and relevance feedback needs to be generalized, as it seems to improve systems performances. IMAIOS considers combining interesting features to create an innovative CBIR system.

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