

Content-Based Image Retrieval: A Comprehensive User Interactive Simulation Tool for Endoscopic Image Databases

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Received: December 17, 2017 / Accepted: May 11, 2018 / Published online: June 30, 2018

Abstract

Until few years ago, radiological methods were widely used for the examination and investigation of the digestive tract. Today, wireless capsule endoscopy represents an innovative, noninvasive, effective solution that does not imply a risk of irradiation. Due to the impressive number of images captured on the entire “trip” covered by the video capsule, diagnostic accuracy is greatly improved, also allowing the visualization of certain areas of the digestive tract that were previously inaccessible. Captured images can be analyzed by a specialist who can identify lesions or possible active bleeding within the digestive tract. This paper presents the implementation of a recovery system for endoscopic images based on Content-Based Image Retrieval (CBIR) technique.

Keywords: Wireless capsule endoscopy; Content-Based Image Retrieval (CBIR) system; Local Binary Pattern; Intensity histogram; Color Coherence Vector

Introduction

In the field of medical imaging, computer science is always present through the continuous evolution of software applications designed to acquire medical images, to improve quality and clarity of images, always in correlation with hardware systems that produce more accurate and effective images, while controlling the radiation doses through shorter time exposures.

The investigation of the digestive tract using wireless capsule endoscopy (WCE) represents an imagistic method that allows the exploration of the entire small intestine - an area that is not easy to reach with traditional endoscopic procedures. This method does not imply radiation and does not cause discomfort for patients or provoke them any pain [1]. Due to the impressive number of images that result following this investigation, a reliable database is required, together with search algorithms that must be faster, more efficient and ready to deliver the expected results in a much shorter time. This may reduce the work of the examiner when looking for the desired medical data. Visual functions not only allow the recovery of cases with similar patient diagnoses, but also perform identification of cases of visual similarity, with different diagnoses.

For the human eye, a picture is a form of representation of the surrounding reality based on sensations acquired with the help of senses, while system information technology defines it as a two-dimensional signal. It is expressed by the mathematical function $f(x, y)$, where x and y are coordinates in a two-dimensional horizontal, respectively vertical, plane. Coordinates give every pixel within an

image a specific value in that point. A digital image is basically a two-dimensional matrix with numbers ranging from 0 to 255. All numbers correspond to particular values of the function $f(x,y)$, considered at any point.

Content-Based Image Retrieval (CBIR) technique has been developed to facilitate management of large image collections, and also to provide help with clinical care, biomedical research and education [2-6].

Retrieval techniques are implemented according to the following steps:

1. Define a specific image descriptor: at this stage, a particular feature of the image is selected for description: color or texture.

2. Index the data set: after defining the image descriptor, it is applied for each image from the data set for feature extraction, followed by memorization in a storage file (CSV file), allowing further comparison for similarity verification.

3. Define the array of similarity: image similarity can be used with different options like Euclidean distance, cosine distance, and chi-square distance.

4. Search: the final step is to perform a real search. The user will send an image query to the system, and it will extract features from that image.

The aim of the study was to develop a recovery system based on CBIR technique for endoscopic images.

Material and Method

Our study set included 1000 images from a patient admitted in 2015 to the 1st Medical Clinic within the County Emergency Hospital of Craiova, who was investigated with Olympus EndoCapsule EC for anemia associated with iron deficiency, after inconclusive upper and lower endoscopy. This set was completed with 120 WCE images obtained from public databases. All files were stored in an SQL database.

Image Descriptors

Modern times require rapid growth for image databases; also the demand for image processing and database querying increased significantly. An effective tool to process images by analyzing their content was needed. In image recovery techniques based on content, images are indexed by their visual components, such as color, texture, shapes.

The feature set is generated to express the contents of the images in the database, forming the characteristic vector. Similarity measurement is computed based on the distance (difference) between the interrogated image and each image from the database. The image that has the smallest distance from the interrogated image is indicated as similar [7].

Histogram Intensity

The histogram of a digital image is defined by a set of intensity levels expressed over a certain interval. Histogram intensity is commonly used to compare images, and it is computed by quantifying pixels' intensity in numbers for every gray shade [8]. For an 8 bit grayscale image, there are 256 different possible intensities, so the histogram will display graphically 256 numbers showing the pixels distribution, where 0 is the darkest shade (black), and 256 is the lightest hue (white). So for a unique grayscale image, $L = 256$, where L represents the number of different intensities.

To determine the pixel intensity histogram, it is necessary to convert first the color image to shades of gray (Figure 1). Histograms provide useful information related to brightness, contrast, dynamic and saturation effects, but they do not reflect the color distribution.

Local Binary Pattern

Local Binary Pattern (LBP) is a local operator, invariant to different shades of gray, which was introduced for image indexing purposes. For every pixel of a 2D image, the associated LBP value is computed using the gray values of its neighbors. The basic idea is to divide the image into regions

where each pixel is compared to those in its immediate vicinity, in terms of gray values. Thus, the image to be analyzed is transformed into a grayscale image, before applying any other method for image analysis.

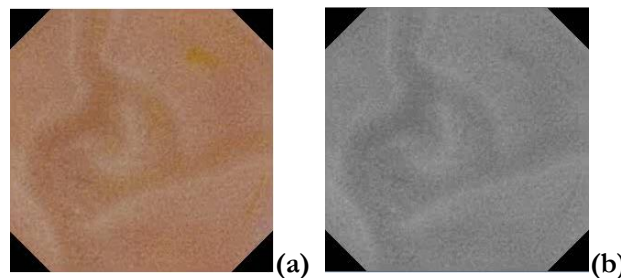


Figure 1. (a) Image acquired during WCE investigation. (b) Image converted to grayscale mode.

Simple LBP Operator

The basic LBP operator is based on the fact that texture has two complementary components at the local level: one model and one power. The original version uses a block of 3×3 neighboring pixels. They are set according to the center pixel value, by multiplying the powers of 2 and then summing them. The result represents the central pixel tag. Because the neighborhood region is made up of 8 pixels, 256 different labels may be identified, based on the relative gray shade values in the center and the pixels in the block. Figure 3 illustrates the basic LBP operator block. A major benefit of the simple LBP implementation is that it captures very fine details from the image. However, this ability is also the biggest disadvantage of the algorithm – as it cannot capture details at different scales, but only at the fixed scale of 3×3 .

Derivatives of the original LBP - Circular Neighbors

Since the basic LBP operator can only be applied on a square block of 3×3 pixels, several extensions have been developed to manage the dimensions of variable interest regions. Therefore, to take into account multiple dimensions of the block, two new parameters were introduced, for a circular neighborhood, namely, the number of points P in a circular symmetric block (thus eliminating the computation on a square surface), and the circle radius R , which allows the method to be applied to different regions.

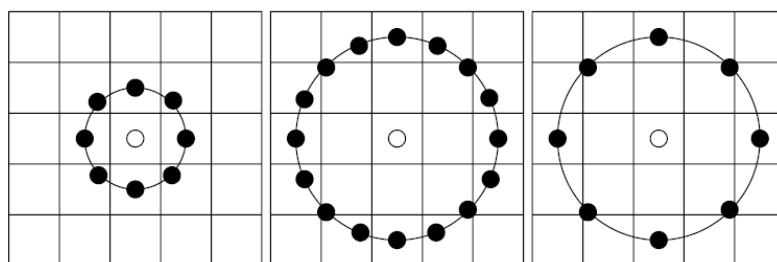


Figure 2. Circular neighborhoods (8,1), respectively (16,2), then (8,2). If a sampling point is not located within a pixel, then the corresponding points are interpolated in a bilinear manner.

A consequence of this improvement is the increased number of pixels involved in the final tag computation. They are determined based on the radius R , which identifies the distance between the center pixel and any neighboring pixel, but also the number of points P set on the circle with radius R . To include the values of all neighboring sampling points, for any radius and any number of pixels, linear interpolation is mandatory [9]. The notation is used to identify the regions of interest (P, R). Figure 2 illustrates three sets of neighbors for different values of P and R . From a dimensional point of view, the original LBP operator with a square 3×3 block may be considered a circular LBP operator

with radius 1 and 8 pixels equally distributed on the circumference, since the same 8 pixels are involved in the computation of the central tag.

Color Coherence Vector

The color coherence vector (CCV) technique implies a division process where pixels of a certain color is assigned to a group of coherence, associated with how much time they belong to that same color region; otherwise, the pixels are considered to be part of incoherent groups [10]. The first step in composing a vector with pixels belonging to a coherent group is similar to the one specific to histogram composition. For the CCV method, each image is characterized by a three-dimensional vector. Subsequently, vectors results are compared to find images similar to the one selected in the query.

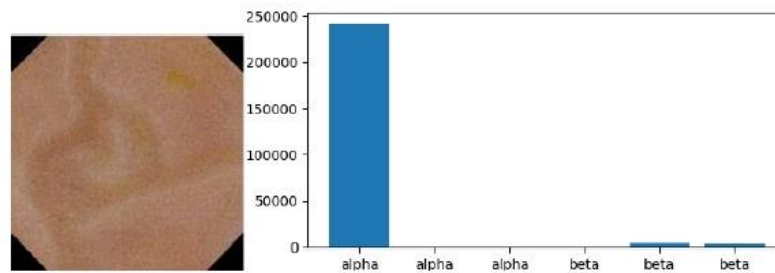


Figure 3. Endoscopic image and histogram with color coherence vector (alpha-coherent pixel, beta-incoherent pixel).

CCV divides each pixel's region of the color histogram into two parts. Pixels displaying a certain color are defined as coherent or incoherent. A coherent pixel is part of a group of pixels with the same color, while an incoherent pixel does not belong to a similar group. The connected components were computed for all groups of pixels. If the same color group contains more consistent pixels than a threshold value defined in advance, it belongs to the pixels of consistency, and the rest of the pixels are incoherent.

Results and Discussion

Finding similar images based on content assumes that the first step is to correctly extract the characteristics of all images present in the database, corresponding to a specific search method, and to retain them in an external file. Once the images' features were extracted, during a query they are compared to the data corresponding to the image being interrogated and results in a list of images that show color or texture similarities, according to the chosen method. Images retrieved after applying a content-based search model are displayed in an application called "EndoHealth" that facilitates the user interaction.

"EndoHealth" is a web application with different methods that help the identification of similar images within a database (Figure 4). The user can access the functions of this application only if he has an account, with a valid username and a password. After authentication, the main page contains two tables: one with 1000 images from the investigation with the wireless capsule, and one with public images.

The user can find an image by applying different attributes, such as ID, Name or Link. After the image is set, the user can find similar images with it, if he chooses one method among the available ones: Histogram Intensity, Color Coherence Vector or Local Binary Pattern.

The CBIR methods were applied both to the images from the public DB and images from the investigation with the wireless capsule. The query image is presented in Figure 5 (a), while the resulted images after querying with histogram intensity method, with color coherence vector and local binary pattern are shown in Figure 5 (b) and Figure 5 (c), respectively.

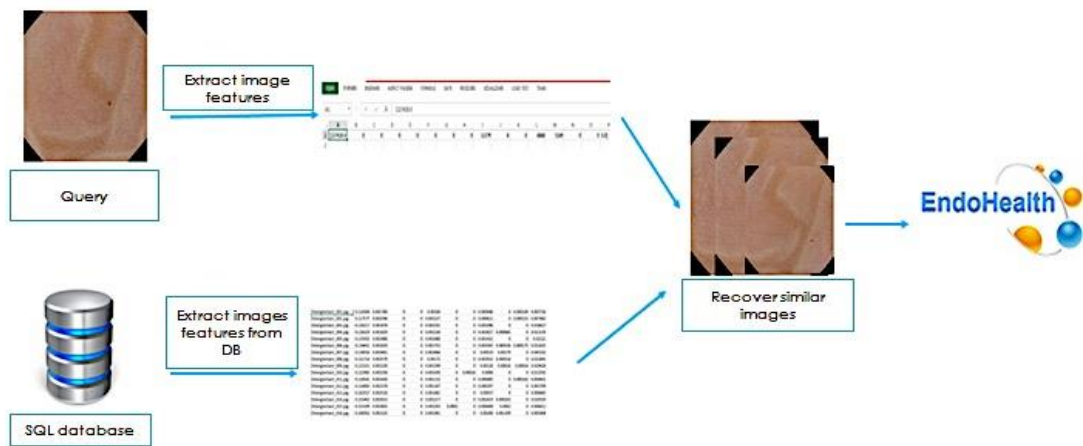
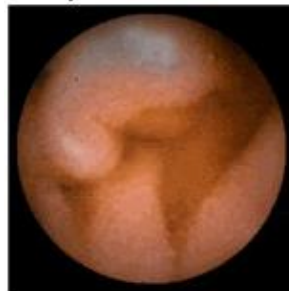
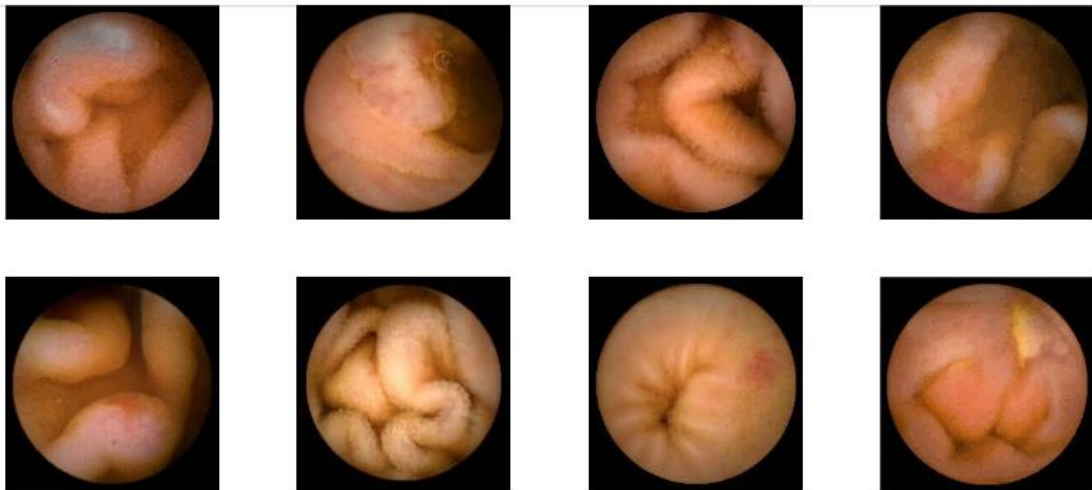


Figure 4. System architecture.

When applying the model based on Local Binary Pattern, the application can identify the pathology. Including the same query image, the resulted image is presented in Figure 1 (d).

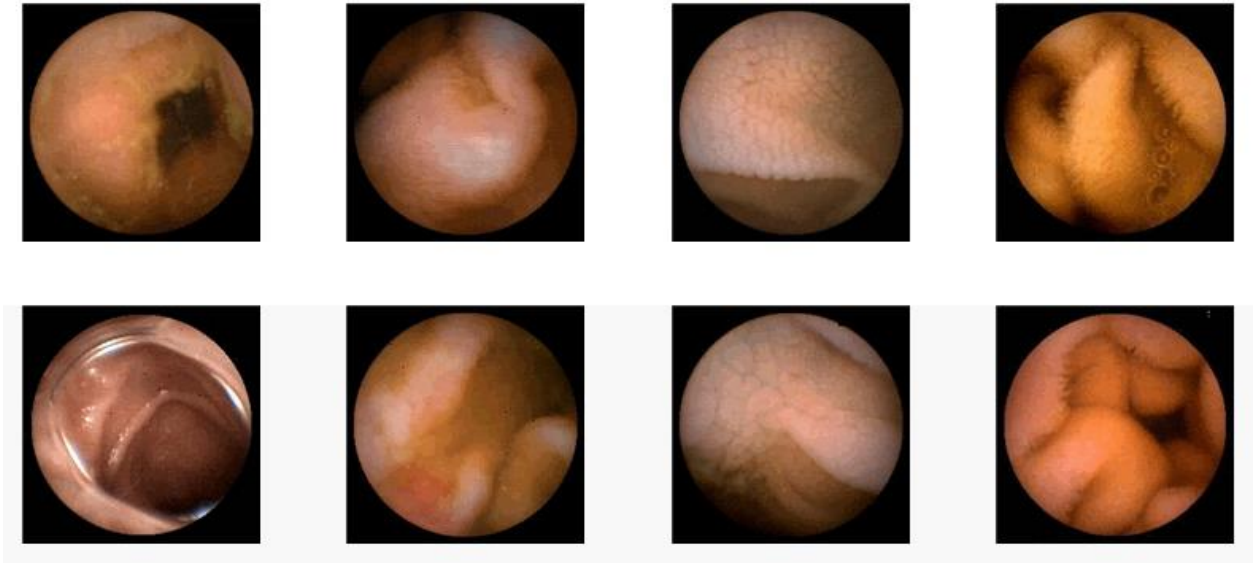


a) Query image



b) Results after querying with histogram intensity method

Figure 5. Example of interrogation with a DB with public images



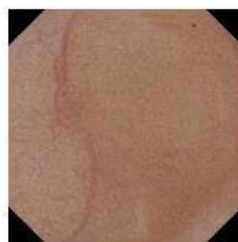
c) Results after querying with color coherence vector



d) The result after querying with the local binary pattern

Figure 5. (continued) Example of interrogation with a DB with public images

For WCE images, we applied the same querying methods as for the public image database. The query image is presented in Figure 6 (a). The retrieved images using the histogram intensity method is shown in Figure 6 (b), while the retrieved images using the method based on color coherence vector are presented in Figure 6 (c).

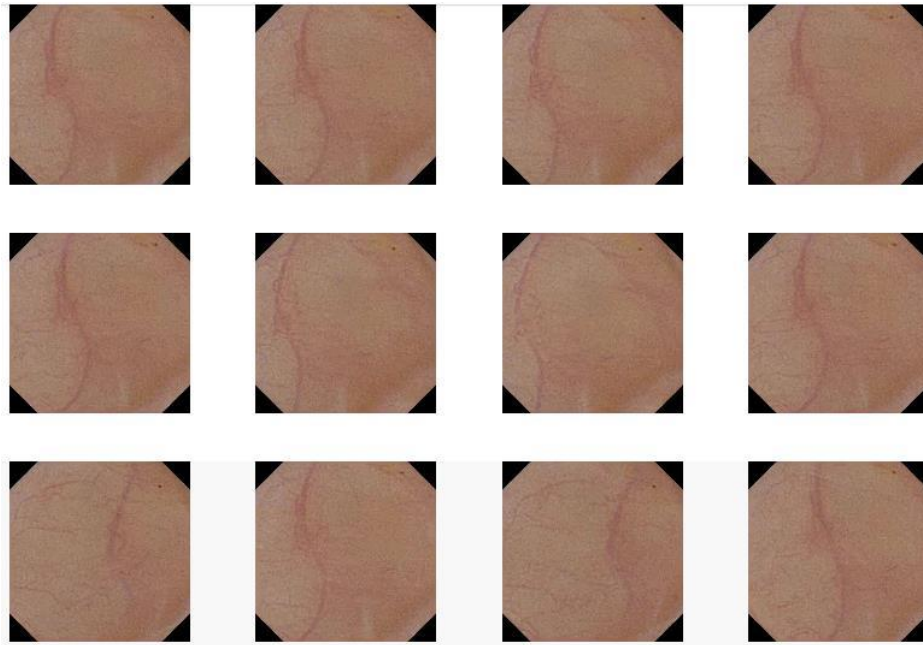


a) Query image

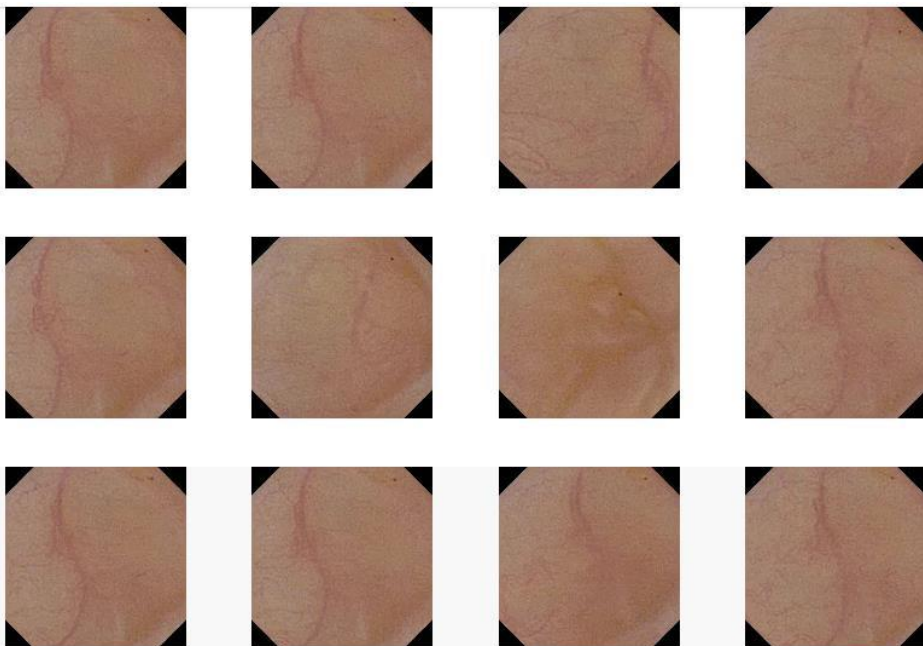
Figure 6. Example of interrogation with WCE images

When applying the method based on local binary pattern, the application identifies the pathology in the image. The resulted image is presented in Figure 6 (d).

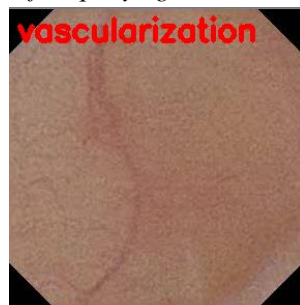
The results obtained using the methods based on histogram intensity and color coherence vector were similar to the application proposed by [11]. Additionally, our application integrates the local binary pattern method, allowing to also identify the pathology from the query image.



b) Results after querying with histogram intensity method



c) Results after querying with color coherence vector



d) The result after querying with the local binary pattern

Figure 6. (continued) Example of interrogation with WCE images

One limitation of the study is that images are not loaded into the application. Future studies include an extension of the current application, to include a module that may receive as input the entire video resulted from endoscopy and extracted the total number of images, also analyzing the presence of potential lesions present within the digestive tract. Once developed, this module may monitor more patients to see the progress or regression of pathology over a treatment.

Conclusion

Our proposed CBIR system is accessed through a user-interactive web application. Using the application, similar images from the investigation with the wireless capsule can be easily retrieved. Also, the implementation of the local binary pattern method allows also identifying the pathology which corresponds to the query image.

List of abbreviations

LBP – Local Binary Pattern
WCE – Wireless Capsule Endoscopy

Conflict of Interest

The authors declare that they have no conflict of interest.

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