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Content Based Image Retrieval Using Local Binary Pattern Operator and Data Mining Techniques

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Abstract. Content based image retrieval (CBIR) concerns the retrieval of similar images from image databases, using feature vectors extracted from images. These feature vectors globally define the visual content present in an image, defined by e.g., texture, colour, shape, and spatial relations between vectors. Herein, we propose the definition of feature vectors using the Local Binary Pattern (LBP) operator. A study was performed in order to determine the optimum LBP variant for the general definition of image feature vectors. The chosen LBP variant is then subsequently used to build an ultrasound image database, and a database with images obtained from Wireless Capsule Endoscopy. The image indexing process is optimized using data clustering techniques for images belonging to the same class. Finally, the proposed indexing method is compared to the classical indexing technique, which is nowadays widely used.

Keywords. Image Retrieval, Local Binary Pattern, Ultrasonography, Wireless Capsule Endoscopy

Introduction

The past decade was marked by a significant progress in terms of computation techniques, leading to an almost exponential increase of generated data, which requires an optimum management of image databases. Nowadays, there are two different methods to find an image in an image database: the first and the most employed approach use a set of alphanumeric characteristics (metadata), while the second approach identifies an image using its informational content.

The first indexing approach is traditional, being based on attaching different numeric and alphanumeric characteristics to every image. Their ensemble will represent the indexing key of the image in the image database [1]. This process is laborious, time consuming, and presents the drawback that different users may describe differently the same image. These deficiencies in defining the indexing keys decrease the performances of this indexing and retrieval mechanism, thus making it less practical for very large databases.

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The second indexing approach [2] was proposed in 1992, being called content-based image retrieval (CBIR). Following this approach, the image characterization is performed by using feature vectors. These vectors, which are automatically built by applying different feature extraction algorithms, globally characterize the image properties defined by colour, texture, shapes. In this way, it is possible to index and retrieve a similar image to another image defined by the user.

CBIR systems have significantly changed the indexing and retrieval processes of images in databases. The global representation of the image informational content by using a feature vector led to the use of data mining techniques for image analysis, and the retrieval of key information. Thus, using n-dimensional feature vectors, it is possible to represent an image as a point in an n-dimensional space [3], allowing application of hierarchical indexing techniques [4, 5]. In this context, the use of various similarity techniques becomes possible [6].

In this paper, we review the CBIR concept. Subsequently, we propose a method for building the feature vector using the Local Binary Pattern (LBP) operator. In addition, we propose an image indexing method based on a hierarchical cluster structure, using the proposed LBP operator. This method is then validated by conducting a set of experiments on two medical image databases.

1. Content-based image retrieval systems. Architecture.

The classical architecture of an image retrieval system using the similarity of the informational content of images includes two sub-systems. The first sub-system is responsible with the definition of a feature vector. This vector is indexed within the database, together with the corresponding image. The indexing technique, where the feature vector is used as indexing key, is also specific to the class containing the image, as defined by the user. This sub-system works offline.

The second sub-system is responsible with the image database interrogation that takes place in successive steps. The user adds an image, and its corresponding feature vector is computed. In the next step, various metrics are applied to evaluate the similarity between the added image and those stored in the image database (e.g., the Euclidean distance). The most similar image is determined and visualized.

2. The proposed CBIR architecture

We propose a novel method to define, index, and retrieve images from a CBIR database. The method is structured into two levels: the first level defines the feature vector that globally represents the texture of an image, while the second level defines a novel method to index images in a CBIR image database. The proposed method consists of attaching a classification tree (generated by a data mining technique) to a data base. The classification classes are represented by the underling imaging diseases. An existed image is classically retrieved by using the LBP vector. In case of a new image, after LBP vector determination, the corresponding class (disease) will be computed, together with the similarity coefficient.

2.1. Feature vector definition

Several studies using LBP were performed in order to choose the optimum method. The image database CUReT [7], which contains more than 60 types of textures, each one with over 200 combinations obtained by changing perspectives and illuminations, was chosen. The experiments used 6 different textures (e.g., cotton, velvet, two variants of carpet, wood, paper), for every type having between 120 and 200 images. For the 6 different texture classes, 1025 images were selected.

In order to test the precision of the texture representation, the feature vectors were defined for all 1025 images. Afterwards, the feature vectors were analyzed using a supervised K-Means clustering technique. We used 66% of the images to determine the 6 classifiers (one for each texture type), the rest of 34% being used to test the precision of the classification operation.

2.2. Choosing the optimum LBP variant for the feature vector definition

The LBP operator may be considered a statistical and structural method for texture analysis [8]. It is notable that the operator allocates to each pixel the label (binary code) that best suites the neighborhood where it belongs, where neighborhoods may be considered as micro-textures.

Our study was performed in three phases. The first phase used a simple LBP operator, with 3x3 pixel regions in different variants. The results were employed in the second and third study phases. The second phase used (R, P) circular neighborhoods, adjusting both the radius R and the number of pixels P from the circular neighborhood. Finally, the third phase was the image division in blocks. We have used 4 and 6 blocks, for each block defining a feature vector. The blocks were computed by dividing the image into 4, respectively 6, zones of equal dimension. The image is represented by 4, respectively 6, feature vectors. The obtained results are presented in Table 1 (second phase results), and Table 2 (third phase results).

Table 1. Rate of success for a uniform LBP operator for different values of R and P (6 classes, 1025 images)

Operator LBP			Rate of success
R=1 P=8	No rotation	Non-uniform patterns	79.10%
R=1 P=8	Rotation	Non-uniform patterns	87.39%
R=1 P=8	No rotation	Uniform patterns	94.22 %
R=2 P=8	No rotation	Uniform patterns	92.60%
R=2 P=16	No rotation	Uniform patterns	82.48%

Table 2. Rate of success for a circular LBP operator applied to images divided in blocks (6 classes, 1025 images)

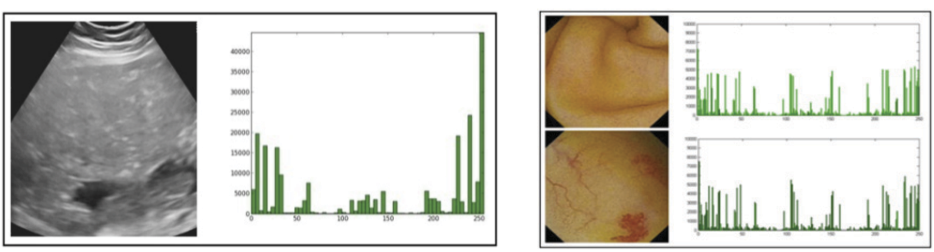
Operator LBP			Rate of success
Uniform R=1, P=8	4 blocks	Small resolution	94.22%
Uniform R=1, P=8	4 blocks	High resolution	99.43%
Uniform R=1, P=8	6 blocks	High resolution	99.75%

3. Results

We developed an application which builds two databases using the LBP operator for indexing purposes. The first one contains ultrasound images, and the second one contains images acquired during the Wireless Capsule Endoscopy (WCE) investigation of the digestive tract. In both cases, the image sets were divided into a training set and a testing set. Images from the training set were used to build the data base, as well as to generate the classification tree. The training set was used to verify the classification performance.

The application has four functional components. The first two components create and respectively update the image databases. The next two components are responsible for retrieving the most similar image with the one given by the user, and respectively, visualizing the results. When the most similar image is displayed, a similarity coefficient is also computed, which indicates the degree of informational content similarity. The Euclidean distance between the feature vectors was computed [9].

The first experiments were performed on a set of 310 ultrasound images belonging to 62 patients. For each patient, between 3 and 8 ultrasound images were selected at different moments of time. The initial image set was divided in two subsets. The first one was a training set with 205 images, and a testing set with the other 105 images. The second experiments were performed on a set of 300 WCE images representing either normal findings (e.g., normal intestinal mucosa – 150 frames), or lesions of the small bowel (e.g., telangiectasia, polyps, Celiac disease – 150 frames). The images were extracted from 35 video files obtained after the investigation with Olympus EndoCapsule EC® of 35 patients hospitalized in the 1st Medical Clinic from the Emergency Clinical County Hospital Craiova (all patients gave informed consent). The initial set was divided in two subsets: a training set with 200 images (containing both normal mucosa and lesions), and a testing set with the other 100 images. For both experiments, the training set was used to build the image database, and the indexing process was performed according to the feature vector obtained by applying the uniform circular LBP operator with $R = 1$ and $P = 8$. Figure 1 (a) presents an ultrasound image and the corresponding feature vector. Figure 1 (b) presents two WCE images and the corresponding feature vectors (the first image represents normal intestinal mucosa; the second image contains a telangiectasia lesion – a vascular lesion defined by a dilation of small blood vessels located near the surface of the intestinal membrane).



(a) (b)

Figure 1. (a) LBP signature for an ultrasound image (.bmp type, size 640x480 pixels, type circular uniform patterns in (R=1, P=8) neighborhood). (b) LBP signature for two WCE images, with normal finding and telangiectasia (.jpg type, size 288x288 pixels, type circular uniform patterns in (R=1, P=8) neighborhood).

For ultrasounds, it was considered that the input image and the retrieved image are similar if they belong to the same patient. For WCE images, it was considered that the input image and the retrieved image are similar if they both represent normal mucosa or they both contain one of the three lesions present in the database.

The study was performed in two phases. In the first phase, for all images in the testing set, the application retrieved the most similar image from the databases, and a comparison between them was performed to see if they belong to the same patient, for ultrasounds, or WCE class. For all 105 images in the ultrasound testing set, 92.2% correct classified images were obtained. For all 100 images from the WCE testing set, 87% correct classified images were obtained (Table 3).

In the second phase, the ultrasound testing set was used to build a number of 62 models of type patient, while the WCE testing set was used to build a number of 4 models of WCE classes. Each model is defined by a feature vector that represents the center of gravity of images defined by feature vectors. The Euclidean distance was used for the computation of the center of gravity. The models were added to each database. For the same ultrasound testing set, this phase ended with 96.1% correct identifications of the patient. For the same WCE testing set at this phase, a proportion of 88% correct identifications of the WCE class were obtained (Table 3).

Table 3. Rate of success for a uniform LBP operator with R=1 and P=8 applied on the testing sets of medical images: Ultrasounds and Wireless Capsule Endoscopy (WCE)

Image Data Base structure. Content **Rate of success for the retrieval of a similar image**	**Images, feature vectors**	**Images, feature vectors, model of image classes**
Ultrasounds (62 patients' models)	92.2%	96.1%
WCE images (4 models of WCE classes)	87%	88%

4. Conclusion

We proposed a novel architecture for a CBIR image database using a feature vector defined with a LBP operator and data mining techniques. Following this study, the most efficient way to globally represent the informational content present in an image is to define the feature vector using a circular LBP operator with radius 1 and 8 pixels neighborhood. Moreover, it is better to indirectly retrieve similar images from the databases using image models. This aspect significantly increases the accuracy of the retrieval process, and decreases the time for accessing information from the image database.

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