Computerized methods for the assessment and characterization of the inflammatory bowel diseases and colon cancer from ultrasound and endoscopic images

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Abstract: - The inflammatory bowel diseases (IBD) are severe, chronic and recurring disorders, requiring continuous patient monitoring. We aim to develop computerized methods for the noninvasive assessment of the bowel inflammation based on ultrasound images. In this work, we study the role of the textural parameters in characterizing different types of inflammatory bowel diseases and the colorectal tumors. Also, the time intensity curves (TIC) are post processed through mathematical modeling, in order to emphasize the behavior of the contrast agent for the considered affections. The relevant textural and TIC parameters are determined through specific methods, and then they are assessed individually and in combination for performing automatic diagnosis. B-mode and contrast-enhanced ultrasound images (CEUS) of biopsied patients are used. The information obtained from the endoscopic images is taken into consideration, as well. The patients were suffering from the following diseases: Crohn's disease, ulcerative recto-colitis, colon cancer.
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Key-Words: - **inflammatory bowel diseases, colon cancer, ultrasound images, contrast enhancement, endoscopic images, computerized assessment, textural parameters, time-intensity curves, automatic diagnosis**

1 Introduction

The inflammatory bowel diseases (IBD) are a group of disorders that frequently mark the population of the developed countries. Their evolution is frequently chronic, with activation peaks and remission periods, elements that are conditioned by the rapidity of the diagnosis, by the follow-up efficiency and by the therapeutic means. There are several clinical, laboratory and paraclinical parameters used to assess the activity phase. Most used clinical scores are the Crohn's Disease Activity Index (CDAI) and Truelove Witts. Together with laboratory parameters, they can assess to some degree the activity but are not enough accurate [1]. The standard methods of diagnosis and of inflammatory phase assessment are the endoscopic, radiologic and histopathology exams, but these are invasive. Also, they only provide information from the mucosal layer. Computer tomography and magnetic resonance imaging are elective imagistic methods, but they are less accessible and quite expensive. Ultrasonography has similar potential in diagnosis, but with advantages like: noninvasively, reduced cost and the possibility of repeatability [1], [2], [3]. Our aim is to develop new methods of activity assessment in inflammatory bowel diseases, based on ultrasonography examination, combined with some modern techniques like vascular contrast enhancement and computer-aided analysis of images. The texture is considered, as an important visual feature, able to provide subtle information. In our work, we develop texture-based methods in order to emphasize the features that characterize each inflammatory bowel disease and the digestive tumors. Both relevant feature selection and automatic recognition, performed through feature selection and pattern classification methods, are involved. Contrast-enhanced ultrasound (CEUS) provides us the means to study vascular flows and perfusion inside bowel walls. The time-intensity curves (TIC) extracted from contrast clips are an efficient instrument of quantification; thus, we try to extract relevant parameters from them. The endoscopic images are analyzed as well, being able to provide a rich amount of information concerning the inflammatory bowel disease and the digestive tumors.

2. The state of the art

In [4] the authors analyzed the fluorescent images of the colonic tissue based on textural parameters derived from the Grey Level Cooccurrence Matrix (GLCM), in order to distinguish the colonic healthy mucosa versus adenocarcinoma. A modified version of Multiple

Discriminant Analysis was used for dimensionality reduction, such that only four final features resulted. A minimum Mahalanobis Distance, a Linear Discriminant Classifier and a simple evaluation 'score' method were used for performing two-category classification and provided 95% accuracy. In [5] the authors used the Grey Level Cooccurrence Matrix (GLCM), together with morphological features (shape, orientation), in order to characterize the malignant and benign tissues from biopsy slides of patients with colon cancer. The Support Vector Machines (SVM) method with a 3rd degree polynomial kernel provided very satisfying classification results (above 90%). Textural features such as the skewness and the kurtosis of the image intensity histogram, together with RGB color features, were used in order to perform the segmentation of the bowel lumen from endoscopic images [6]. The computerized image analysis techniques, and also the textural parameters in conjunction with classifiers, were also widely used for the classification of various kinds of tumors from medical images [7], [8], [9]. However, in the case of the inflammatory bowel diseases, the computerized techniques are poorly implemented and there is no systematic study of the relevant features that characterizes each type of disease. We aim to perform this in our work, through the methods illustrated bellow.

3. The inflammatory bowel diseases and their aspect in ultrasound and endoscopic images

Bowel inflammation is a common disorder found in several intestinal diseases, ranging from malignant to purely inflammatory ones. There is a group of intestinal diseases, known as Inflammatory Bowel Diseases (IBD), that have unknown causes, but are important because of their severity. The Crohn's disease (CD) and Ulcerative colitis (UC) are the most frequent forms. The inflammation extends to all the layers in Crohn's disease, and only to the mucosa in the Ulcerative colitis. Concerning the case of the Ulcerative colitis, hypoechoic lesions that correspond to the ulcerations appear. Patients with inflammatory bowel diseases present, alternatively, periods of remission and of activity. The evolution is marked by the onset of complications, among which some of major severity, so that the assessment of the inflammation activity and of the treatment response is crucial in monitoring these patients. Concerning the features of the Crohn's disease, the characteristic visual appearance is that of a "target" image, corresponding to the transversal bowel section taken on a specific part of the bowel, where the walls are thickened over 4 mm, having a circumferential, stenotic aspect (Fig.1). In the acute form, a removal of the separation between the composing layers, because of edema and inflammation, is being noticed. In the chronic form, the composing layers appear as being distinct. The dominant process at histological layer is that of fibrosis, which generates an echo-poor halo surrounding a central echogenic zone [10]. Ulcerative colitis is a mucosal disease, the halo being a less prominent feature (Fig. 2). [11] Inflammatory or neoplastic bowel pathology is associated with the thickening of the bowel wall. The colorectal tumors (Fig.3), although distinct from inflammatory bowel diseases, share a lot of characteristics with the latter, like wall thickening and increased vascularity. However, like every tumor, they are characterized by the heterogeneity of the tissue structure and by the complexity and irregularity of the vessel structure [12].

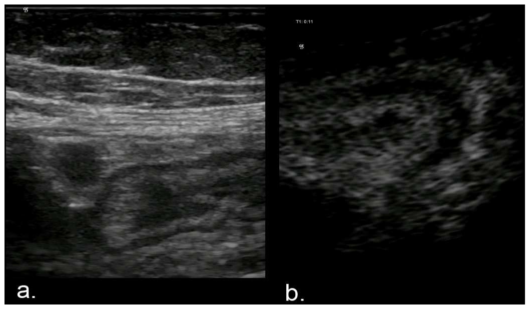

Fig 1. Crohn's disease. Native (a) and contrast enhancement (b)

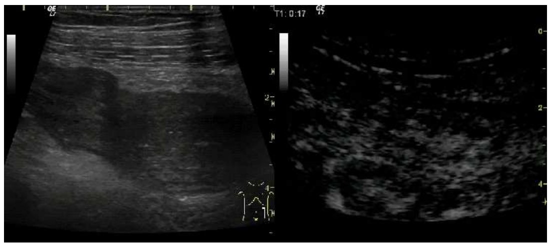

Fig 2. Ulcerative recto-colitis, before treatment (a) Native, (b) Contrast enhancement

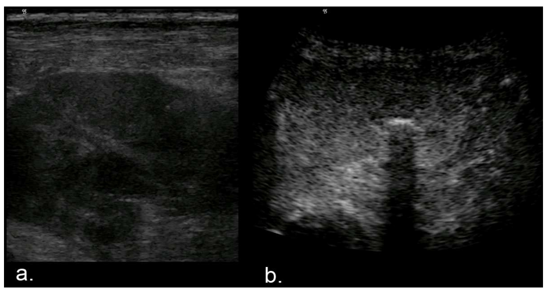

Fig 3. Colorectal tumor, native (a), showing high contrast uptake (b)

Within endoscopic images, edema and eritema are frequent in the case of the Crohn's disease. In the case of edema, a white blur appears on the mucosa, in the affected region, while in the case of eritema, a slight red color is specific. Concerning the aspect of ulcerative colitis in endoscopic images, small lesions corresponding to the ulcerations appear. They usually have a white color, because their coverage with fibrin. The tumors appear as a local inflammation or a prominent region within the bowel wall. The characterization of the specific visual aspect for the Crohn's disease and for the ulcerative colitis, through computerized techniques, is the subject of analysis in this work. Some eloquent images are depicted bellow:

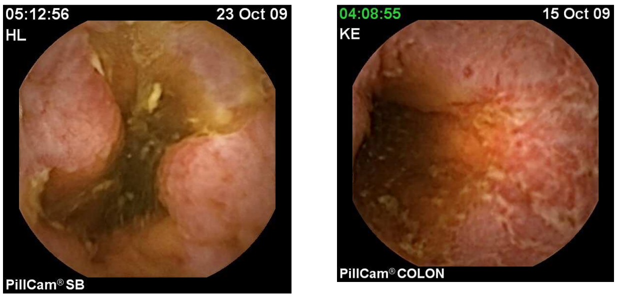

Fig. 4. Crohn's disease – a. Edema; b. Edema and eritema

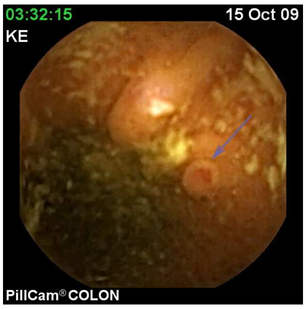

Fig.5. Ulcerative colitis - ulceration

4. Proposed methods

In our work, we compute a number of potentially useful textural parameters, we select the most relevant ones by specific methods, and then we assess the possibility of automatic diagnosis of the considerred inflammatory bowel diseases, by providing the relevant features at the inputs of some powerful classifiers.

4.1.Methods for textural parameter computation

First order statistics, as well as second order statistics, edge-based statistics, fractal based methods and multi-resolution methods were considered. *The first order statistics* of the grey levels, appropriate for liver and tumor tissue characterization, were the mean grey level, the maximum and minimum of the grey levels and the autocorrelation index, a texture granularity measure [13]. *The second order statistics* of the grey levels were provided by the *Grey Levels Co-occurrence Matrix (GLCM),* which computed, for each possible pair of grey levels ($g1$, $g2$), the number of pairs of pixels, of intensities $g1$ and $g2$, being in a spatial relationship given by a specified displacement vector $(\vec{dx}, \vec{dy})$, as results from (1):

$$C_D(g_1,g_2)=\#\{((x,y),(x',y')): \\ f(x,y)=g_1, f(x',y')=g_2, |x-x'|=dx, \\ |y-y'|=dy, \mathrm{sgn}(dx\cdot dy)=\mathrm{sgn}((x-x')\cdot(y-y'))\} \quad (1)$$

We computed the GLCM probability matrix [14] in our implementation. The parameters that we computed from GLCM, considered as being able to best characterize the tumor tissue, were: contrast, variance, local homogeneity, correlation, energy and entropy [14]. *The edge-based statistics,* edge-frequency and edge-contrast, also provided useful information, as they computed the relative number of separations between regions with different intensity values (edge frequency) and also the relative amount of the difference between these regions (edge contrast) [13]. *The variability in edge orientations* was also taken into consideration [13]. *The fractals* provided a measure of the grey level structure complexity in the region of interest. We computed the Hurst coefficient, as described in [15]. For emphasizing *the textural microstructures* of the liver and tumor tissue, we applied the Laws convolution filters in order to detect: *levels, edges, spots, waves, ripples* [13]. We used *the Wavelet transform* for the decomposition of the signal spectrum in components having various frequencies, and for the analysis of the signal at various resolutions. We considered the Haar function as basis for the Wavelet transforms [15]. The decomposition was performed at two levels: at the first level, the signal components were computed on the original image; at the second level, the decomposition was performed for each component obtained on the first level: low-low, low-high, high-low and high-high. Then, we computed the Shannon entropy value of the grey levels for each component [15], using (2):

$$Entropy = -\sum_{x=1}^{N}\sum_{y=1}^{M}|I(x,y)|\log_2|I(x,y)| \quad (2)$$

All the features were computed on regions of interest having 50x50 pixels in size. They were independent of orientation and scaled with the size of the region of interest.

4.2. Selection of the relevant textural features

The values of the textural features described above are used as inputs for classifiers like Bayesian Belief Networks in order to analyze their relevance and the recognition rates obtained. *The method of Bayesian Belief Networks* is suitable for establishing probabilistic causal influences between features, as it builds a dependency network represented as a Directed Acyclic Graph (DAG). The nodes represent the features, and the links between the nodes correspond to the causal dependencies between the features, expressed as conditional probabilities. A complex mechanism of inferences is also implemented, in order to compute the probabilities of the values for children, depending on the values of their indirect parents [16]. The Bayesian Belief Networks are also used to compute the probability distribution of each textural feature [16]. The method of Correlation based Feature Selection (CFS) [17] was also used, as it provided very satisfying results in our former experiments, as the method of Bayesian Networks also did. The CFS method eliminates the redundant, dependent features, choosing those that are the most correlated with the class parameter. For each analyzed subset s, a merit is computed. A complete set of feature subsets is analyzed and the subset that has the highest merit is selected. We also used the method of Decision Trees, C4.5 algorithm [16], for feature selection.

4.3. Performing automatic diagnosis of the inflammatory bowel diseases

During the validation phase, the most appropriate pattern classification methods were used in order to make an objective evaluation concerning the set of relevant features. The Multilayer Perceptron method [17] was implemented, as our experiments demonstrated that it was the most accurate. The method of *Artificial Neural Networks* is inspired from the human perception, so it aims to build a structure that respects the model of a human neural network. In the majority of cases, it has three or more layers, being called Multilayer Perceptron. Usually, for training the network, the classical *backpropagation* algorithm is used. According to Kolmogorov, any continuous function, designed to separate the data into classes, can be expressed through an artificial neural network having three layers and a big enough number of hidden units (nodes situated on the second layer) [17]. The classification performance was evaluated using specific accuracy parameters like the recognition rate (percent of correctly classified instances), the sensitivity (TP rate), the specificity (TN rate) and the area under ROC (AUC) [17].

4.4. Time Intensity Curves (TIC)

Visual information from contrast enhanced ultrasound images (CEUS) can be stored as short, uncompressed clips and the information can be interpreted both subjectively and numerically by means of Time-Intensity Curves (TICs). As their name suggests, TICs display the evolution of absolute signal intensity (dB), averaged from a chosen region of interest, along the axis of time (s from the injection of contrast), given a relatively constant spatial location [3]. Our protocol for CEUS examination consists in: (1) Obtaining a good US section with the most altered bowel segment, if possible combined with digestive contrast (water enema); (2) Switching to pulse-inversion contrast mode with low MI (<0,2) and low gain (exclusion of tissue echoes); (3) Injecting 4,8 ml SonoVue i.v. in bolus followed by a 10 ml saline flush and starting the timer on the machine; (4) Saving two 30s long consecutive clips (arterial and early venous phases) in the same location, followed by bowel screening for focal changes; (5) Subjective assessment of the enhancement's intensity, speed and layer involvement; (6) TIC saved from the region of the anterior bowel wall with data exported as tables; (7) For the sake of data standardization, all the curves were aligned on the y-axis so that the origin would correspond to I = 0dB (Absolute intensities are not important); (8) Non-linear curve fitting using Edgeworth-Cramer Peak equation, effective for multiple peaks, is performed. Several parameters are calculated: Peak intensity (PI), Time to Peak Intensity (TTP), Maximum ascending gradient (GRAD), Area Under the Curve (AUC) [3].

5. Experiments and discussions

The dataset used in order to perform the selection of the relevant textural features for the differentiation of inflammatory bowel diseases contained the following classes: Crohn's disease, ulcerative recto-colitis and colorectal tumors. Each class contained 10 patients, and for each patient 3 images were considered. The images were acquired using a GE Logiq 7 ultrasound machine, with broadband transducers using frequencies of 5,5 and 9 MHz. Both B-mode and contrast enhanced ultrasound images were considered. Rectangular regions of interest, having 50x50 pixels in size, were selected on the bowel wall. The textural parameters mentioned in section 4.1 were computed on these regions, by our medical image processing application developed in the Visual C++ 8.0 environment. The values of these parameters were stored in Weka 3.5 specific files.

5.1. Selection of the relevant textural features from B-mode ultrasound images

The textural features that mark the differentiation between the activity forms of various inflammatory bowel diseases are illustrated in Table 1. The selection of the relevant textural features was performed in the Weka 3.5 environment [18]. The method of Bayesian Belief Networks was implemented, with K2 search and BMA estimation. The J48 method for Decision Trees, standing for the C4.5 algorithm, was implemented, as well.

Table 1. Relevant textural features for the differentiation between Chron's Disease and Ulcerative Recto-Colitis

Feature Selection Method	Relevant textural features
Bayesian Belief Networks	Autocorrelation index, Edge orientation variability, Hurst index, Wavelet_Entropy7_lh, Wavelet_Entropy8_lh, Directional gradient variability, Laws Edge mean, Laws Edge Frequency, Wave Frequency, Wavelet Mean
Decision Trees	Autocorrelation index, Edge frequency
CFS	GLCM homogeneity, Autocorrelation index, Hurst fractal index, Wavelet_Entropy7_lh, Wavelet_Entropia8_lh,Wavelet_Entropy6_hl Wavelet_Entropy7_hl Directional gradient variability, edge frequency, wave frequency, wavelet mean

Also, the Correlation-based Feature Selection (CFS) method was applied in Weka 3.5, in conjunction with genetic search. Within *Table 1*, the textural features that are relevant for the differentiation between the Crohn's Disease and Ulcerative recto-colitis are illustrated. We can notice that all the applied selection methods revealed almost the same features as being important for the differentiation between the two considered diseases. These are the autocorrelation index, an indication of the texture granularity, and the edge frequency, the last parameter being correlated with the Laws edge frequency [13]. *From the probability distribution tables* provided by the Bayesian Belief Network method illustrated bellow, it results that the frequency and variability of the local features and textural microstructures, in particular, the edge frequency pre-sents higher values in the case of the Crohn's Disease, than in the case of ulcerative colitis (*Table 2*). The reason is the thickening of the bowel wall layers, due to inflammation, which is much emphasized in the case of the Crohn's Disease and makes the separation walls between these layers become more obvious. The case of differentiation between the Crohn's disease and the other kinds of tissues (ulcerative rectocolitis and colorectal tumors) was also taken into consideration. The relevant textural features detected by the methods of CFS and Bayesian Belief Networks were the following: GLCM energy, GLCM entropy, GLCM variance, mean of the grey levels, edge contrast, Hurst coefficient and the Wavelet entropies.

Table 2. Probability Distribution table for edge frequency

Class	Most probable interval	Probability
Ulcerative colitis	(-∞, 0.141585]	0.828
Crohn's disease	(0.141585, ∞)	0.828

The case of differentiation between the ulcerative rectocolitis and other kinds of tissues (Crohn's disease and colorectal tumors) was also taken into consideration. The relevant textural features detected by the methods of CFS and Bayesian Belief Networks were the following: autocorrelation index, edge orientation variability, wavelet entropies at the first and second level, Laws spot average, Laws wave frequency. Within *Table 3*, the relevant textural features that mark the difference between the colorectal tumors and other kinds of tissues are illustrated. The second class contains instances of the textural features computed in the case of the Crohn's Disease and Ulcerative Colitis. It results that the features like the mean of the grey levels, the Haralick parameters of GLCM (GLCM energy, GLCM entropy, GLCM contrast), the properties of the local features (edge contrast, directional gradient variance, Laws wave mean) and the entropies computed after applying the Wavelet Transform are important for the recognition of the colorectal tumors. The Wavelet entropy has higher values for the colorectal tumors, indicating the chaotic nature of the tumor tissue.

Table 3. Relevant textural features for the differentiation between colorectal tumors and other kind of tissues

Method	Textural parameters
Bayesian Belief Networks	GLCM energy, GLCM entropy, GLCM contrast, Mean grey level, Edge contrast, Wavelet_entropy5_ll, Wavelet_entropy6 _ll, Wavelet_entropy5_lh, Wavelet_entropy6 _lh, Wavelet_entropy5_hl, Wavelet_entropy6_hl, Wavelet_entropy5_hh, Wavelet_entropy6_hh, Directional gradient variance, Wave mean
Decision Trees	GLCM_energy
CFS	Edge contrast, Wavelet_entropy6_ll, Wavelet_entropy5_lh, Directional gradient variability, Wave mean

5.3 Selection of the relevant textural features from contrast enhanced ultrasound images (CEUS)

Table 4. Relevant textural features for the differentiation between IBD from CEUS images

Considered classes	Relevant textural features
Crohn's disease/other tissues	Autocorrelation index, Edge orientation variability, Wavelet_entropy7_ll, Wavelet_entropy7_lh, Wavelet_entropy7_hh, Wavelet_entropy8_hh, Laws spot mean
Ulcerative recto-colitis/other tissues	GLCM correlation, GLCM variance, Wavelet_entropy8_hh, Gradient magnitude
Colo-rectal tumors/other tissues	GLCM homogeneity, GLCM energy, GLCM entropy, GLCM variance, Maximum grey level, Laws level frequency, Laws spot mean

The textural features which are relevant for the differentiation between the considered inflammatory bowel diseases are illustrated in *Table 4*. These features were computed from static images, captured in the early venous phase, when the contrast agent has filled the bowel walls. The CFS method, in conjunction with genetic search was implemented in Weka 3.5 [18] for feature selection.

5.4. Analysis of Time-Intensity Curves (TIC) and relevant parameters

The TIC parameters obtained from the fitted curves were compared between several classes of examinations. We have compared the values of time-to-peak (TTP), maximum ascending gradient (GRAD) and area under the curve (AUC) [3] between patients diagnosed with ulcerative colitis (UC), Crohn's disease (CD) and colorectal cancer (CC) (*Table 5*). There was no parameter capable of differentiating between UC and CD.

Table 5. Statistical differences between TIC parameters and their relevance in differentiating between ulcerative colitis, Crohn's disease and tumors

	Pathology comparison: Ulcerative colitis vs. Crohn's disease vs. Malignant tumors					
	UC average	CD average	CC average	p UC-CD	p UC-CC	P CD-CC
Time To Peak	23,76	23,65	33,68	0.99	0.002	0.007
maximum GRADient	0.47	0.45	0.96	0.63	0.03	0.08
Area Under the Curve	246,4	247,5	339	0.98	0.05	0.12

Table 6. Mean comparison and its' statistical relevance for IBD follow-up before and after treatment

	IBDs before and after treatment		
	"Before" average	"After" average	p
Time To Peak	18,06	24,66	0,1
maximum GRADient	0.55	0.37	0,05
Area Under the Curve	345.4	174.6	0.07

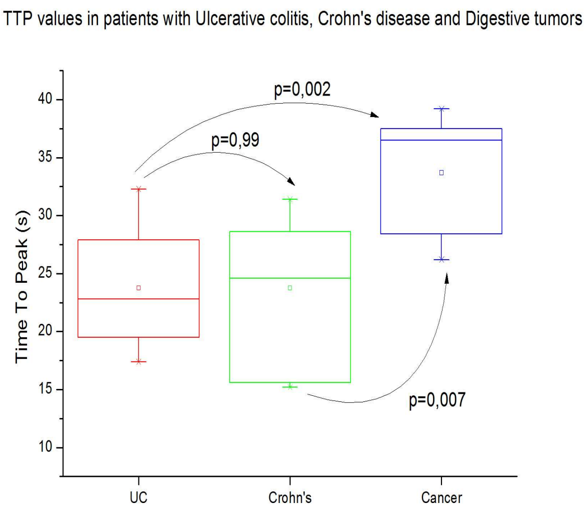

Fig 4. Distribution of TTP values between main pathology classes

However, the distinction of both UC and CD from malignant tumors was possible using most parameters, with the best performance (p<0,01) belonging to TTP. (Fig. 4). UC was overall easier to differentiate from CC. The t-Student's statistical test [16] was used in these studies. An important test concerned the assessment of IBD cases treated with corticoids. Using t-Student's paired test [16], statistical significant differences were obtained between examinations before and after treatment (*Table 6*). The best parameters for this purpose were AUC and, especially GRAD.

5.5. Endoscopic image analysis and selection of the relevant features

The textural features described within the paragraph 4.3 were computed on the endoscopic images, after performing their conversion to grayscale. The feature selection methods were applied in a similar manner with those used in the case of ultrasound images. In the case of the Crohn's disease, the images belonging to 25 patients were used for analysis. The textural features which were relevant for the differentiation between edema and eritema were selected, in order to analyze the severity of the disease. These features are illustrated in the table bellow:

Table 7. The relevant textural features for the differentiation between edema and eritema

Feature selection method	Relevant textural features
Bayesian Belief Networks	GLCM homogeneity, GLCM energy, GLCM entropy, GLCM contrast, Autocorrelation index, Edge orientation variability, Wavelet entropy1, Wavelet entropy2, Directional gradient variability, Laws edge frequency
Decision Trees	Ege orientation variability
Correlation-based Feature Selection (CFS)	GLCM homogeneity, GLCM energy, GLCM contrast, Autocorrelation index, Wavelet_Entropy1, Wavelet_Entropy2, Edge frequency

We can notice the importance of the GLCM homogeneity, of the GLCM energy, which is correlated with the GLCM homogeneity, of the autocorrelation index, indicating differences in granularity between edema and eritema, and also of the entropies computed on multiple resolution levels, after applying the Wavelet Transform. The edge orientation variability is more increased in the case of eritema, indicating the variations in intensity level of the bowel wall regions, only some of them having a red color appearance.

In the case of the ulcerative colitis, the images belonging to 20 patients were analyzed. We selected the textural features which were relevant for the differentiation

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between the ulcerations (the specific elements in the case of the current disease) and the mucus regions (which have a similar visual appearance with that of the ulcerations). The table bellow describes these features:

Table 8. The relevant textural features for the differentiation between ulcerations and mucus

Feature selection method	Relevant textural features
Bayesian Belief Networks	GLCM homogeneity, GLCM energy, GLCM entropy, GLCM contrast
Decision Trees	GLCM homogeneity
Correlation-based Feature Selection (CFS)	GLCM homogeneity, GLCM energy, GLCM entropy, Wavelet_Entropy8_ll

We notice again the importance of the GLCM homogeneity parameter, which has more increased values in the case of ulcerations, and more decreased values in the case of the mucus, due to the tacky nature of this liquid.

5.6. Performing automatic diagnosis based on textural parameters

In order to perform automatic recognition of the inflammatory bowel diseases, the method of Multilayer Perceptron (MLP) was used in the Weka 3.5 environment. The following parameters were chosen for MLP: the number of hidden layers was chosen as being the arithmetic mean between the number of classes and the number of input features; the learning rate was 0.2, in order to get a high accuracy learning, but to avoid overtraining, while the momentum was 0.8 [16]. In the case of the differentiation between the Crohn's disease and ulcerative recto-colitis, the recognition rate was 90%, the sensitivity (TP rate) was 90%, the specificity (TN rate) was 90% and the area under the ROC curve was 94%. In order to perform differentiation between the Crohn's disease and other kinds of tissues (ulcerative recto-colitis and colorectal tumors), the recognition rate was 85%, the sensitivity (TP rate) was 90%, the specificity (TN rate) was 80%, while the area under ROC was 90%. In order to perform differentiation between the ulcerative recto-colitis and other kinds of tissues (Crohn's disease and colorectal tumors), the recognition rate was 75%, the sensitivity (TP rate) was 80%, the specificity (TN rate) was 70%, while the area under ROC was 80%. In the case of differentiation between colo-rectal tumors and other kinds of tissues, the recognition rate was 78.54%, the sensitivity (TP rate) was 85.7%, the specificity (TN rate) was 57.1%, and the area under ROC was 93.9%. When differentiating between the considered types of inflammatory bowel diseases from contrast-enhanced ultrasound images, the recognition rate was 80% in the case of the differentiation between the Chron's disease and tissues affected by other diseases, it was 80% for the comparison between ulcerative recto-colitis and other kinds of tissues, respectively 85.71% when distinguishing the colorectal tumors from the other inflammatory bowel diseases. When considering the combination between textural and TIC parameters, provided at the input of the MLP classifier, in the case of differentiation between the Crohn's Disease and colonic cancer, the recognition rate was 90%, the TP rate (sensitivity) was 80%, the TN rate (specificity) was 95% and the AuC parameter had the value of 80%; when differentiating between colonic cancer and other kinds of diseases, the recognition rate was 85.71%, the sensitivity was 95.7%, the specificity was 71.4%, the AuC was 95.9%. Concerning the endoscopic images, the recognition rate in the case of differentiation between edema and eritema, obtained by applying the method of Multilayer Perceptron, was 98.8%, the TP rate (sensitivity) was 98%, the TN rate (specificty) was 90%, and the AuC was 98%. When differentiating between ulcerations and mucus liquid, the recognition rate was 78.57%, the TP rate was 85.7%, the TN rate was 71.4%, and the AuC was 85.7%.

6. Conclusion

The textural parameters are able to emphasize the important features concerning the differentiation between various inflammatory bowel diseases. The features that best characterize the Crohn's disease in acute form indicate a higher frequency of the local features and of the textural microstructures, a lower value of the homogeneity, and an increased value of the entropy. The acute form of ulcerative recto-colitis is put into evidence by the autocorrelation index, which is a granularity measure, by the variability of the directional gradient, by the wavelet entropies and by the Laws textural microstructures. The colorectal tumors are best characterized by parameters indicating the complex and chaotic structure of the tumor tissue. The recognition rate obtained in the case of differentiation between the Crohn's disease and ulcerative recto-colitis is high, its value being 90%, while in the other cases the classification accuracy is situated around 80%. These increased values confirm the efficiency of the textural parameters in performing the characterization of the inflammatory bowel diseases, and differentiation between the considered diseases. The time-intensity curves showed different patterns between inflammatory bowel diseases and colorectal tumors, translated mainly by an increased TTP and AUC for the latter. However, contrast enhancement provided similar images of UC and Crohn's disease, but the textural parameters proved to be able to solve this problem, leading to a recognition accuracy of 90% in this case. The results for the patients treated with corticoids showed a clear decrease in GRAD and AUC after treatment, with statistical relevance. The textural parameters also showed their role in the case of endoscopic image analysis. The accuracy of the IBD automatic diagnosis based on textural parameters is also high. The color-based (RGB) features will be considered as well in our future developments. We also aim to further increase the classification accuracy by considering a larger number of patients/class, and to study the behavior of the relevant textural parameters in contrast-enhanced ultrasound images, as a function of the time elapsed after the injection of the contrast liquid, for each inflammatory bowel disease and in the case of the colorectal tumors.

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