Classification of Endoscopic Images Based on Texture Spectrum.

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ABSTRACT

This paper suggests a new framework for the discrimination of different texture regions in images using the information that comes from the texture spectrum. We calculate features based on the run lengths of the spectrum image representing the textural descriptors of the respective regions. These measures are used in a classification scheme based on the stability quotient measured between the different regions. This scheme is capable of the characterization among different texture regions within the same image offering a tool for the accurate discrimination among them. The proposed scheme has been successfully applied on different endoscopic images for the right classification between normal and cancer regions.

INTRODUCTION

A number of methods for the description of the texture have been proposed in the literature (Haralick 1979 – Rao 1990). A common aspect in most of them is the construction of an intermediate formulation, suitable for the description of the distribution of neighboring pixels in the image. Other methods aim to the transformation of the original image in another one, using filtering procedures in order to indicate special texture characteristics of the image. The texture spectrum was initially used as a texture filtering approach and has been introduced in the last few years (He and Wang, 1991). The key concept of this method is the computation of the relative intensity relations between the pixels in a small neighborhood and not on their absolute intensity values. The importance of the texture spectrum method is determined by the extraction of local texture information for each pixel and of the characterization of textural aspect of a digital image in the form of a spectrum. The application of the texture spectrum methodology to a given digital image, resulting to the texture spectrum which characterizes the original image, maintaining the image' s texture characteristics.

In the proposed methodology we use the texture spectrum transformation, consisted at first on the extraction of the textural information of neighboring pixels and consequently on the calculation of a set of statistical measures, describing each texture class. The values of these measures form the feature vectors of each texture class, to be used for the discrimination purpose of the proposed classification scheme. With the view to mathematically explain the discriminant results, we proceed to a clustering algorithm, calculating the sum of the average intra-class distance of each class, divided by the product of the average inter-class distance, between a pair of classes (Goldfarb, 1984). The maximization of the distance between the different classes and the minimization of the distance among the features within the same class, at the same time, is the major objective of the proposed methodology.

The description of the principles of the method exists in the next section. In section three there is a description of the algorithm of the proposed approach for the calculation of the feature vectors from the texture spectrum and the results of the application of this scheme, as well as the high discrimination ability achieved on endoscopic images, is described in section four. Finally the conclusions and possible extensions of the method are described at the last section.

TEXTURE SPECTRUM

This section gives a brief description of the principles used for the estimation of the texture spectrum.. The methodology is known in general as a filtering approach of the texture but it will be used here as a preprocessing procedure for the extraction of the textural features. The texture will be faced as an interwoven distribution of the intensities of the pixels. A statistical approach for the description of the texture properties seems more reasonable compared with a structural one (Julesz 1986). A complete definition of the texture spectrum employs the determination of values as the texture unit, the texture unit number and finally the texture spectrum.

Texture Unit

In a digital image the main goal is to extract the local texture information of a neighborhood of pixels. In our case the size of the neighborhood is 3*3 pixels. This pattern of the image, consisting by 9 pixels, is denoted by a set of nine elements, where each element represents the intensity value of one of the nine pixels. Representing the intensity value of the central pixel as V_0 and the intensity value of each neighboring pixel as V_i, the set that is considered as the smallest complete unit of the under consideration image is: $V = \{V_0, V_1, V_{2, \ldots ,} V_8\}$.

Considering the smallest positive value Ä within the neighborhood of zero, the corresponding texture unit is defined as: $TU = \{E_1, \ldots, E_8\}$, where

$$E_i = \begin{cases} 0 \ \text{ if } \ V_i \le (V_0 - \Delta) \\ 1 \ \text{ if } \ (V_0 - \Delta) \prec V_i \le (V_0 + \Delta) \\ 2 \ \text{ if } \ V_i \succ (V_0 + \Delta) \end{cases} \qquad (1)$$

for $i = 1,2, \ldots, 8$.

Texture Unit Number

From the formula (1) above, each element can be assigned one of three possible values so the total number of possible texture units for the eight elements can be estimated as $3^8 = 6561$. Texture unit number is defined according to the following equation:

$$NTU = \sum_{i=1}^{8} E_i \times 3^{i-1} \qquad (2)$$

where NTU varies from 0 to 6560.

The set of 6561 texture units corresponds to the relative gray level relationships between a pixel and its neighbors in all possible directions; that is the local texture aspect of a given pixel in accordance with its neighbors. The basic idea of the texture spectrum approach is to transform an image using the texture units and to characterize the global texture of an image by its texture spectrum. The texture spectrum can then be defined as the occurrence frequency function of all the texture units.

The global texture characteristics of the image , are maintained to the corresponding texture spectrum and the resulting image, confirming that the textural spectrum approach can be used with success to texture characterization and texture classification.

FEATURES EXTRACTION AND CLASSIFICATION SCHEME

The characterization of the texture has as purpose to produce a set of measures, appropriate to identify the different types of textures and to create discriminant texture subspaces. The principal idea of a texture classification scheme is to describe each texture class by a set of features. As it has been mentioned above, by the calculation of the texture units, the original image is transformed according to the relative gray level relationships between neighboring pixels, producing at the end, unique characteristics for each texture class. The runs of linearly adjacent pixels having the same (or in a range) gray levels, that may occur along some given direction offer an effective tool for the extraction of features (Siew et.al 1989).

Considering P(i, j) as the number of runs of length j of gray level i and N as the total number of points in the image, we can define the following numerical measures:

1) Long Run Emphasis:

$$LRE = \sum_i \sum_j \left[j^2 \ P(i, j) \right] / \sum \sum P(i, j)$$

2) Short Run Emphasis:

$$SRE = \sum_i \sum_j \left[P(i, j) / j^2 \right] / \sum \sum P(i, j)$$

3) Gray Level Nonuniformity :

$$GLNU = \sum_i \left[\sum_j \left[P(i, j) \right] \right]^2 / \sum \sum P(i, j)$$

4) Run Length Nonuniformity :

$$RLNU = \sum_j \left[\sum_i \left[P(i, j) \right] \right]^2 / \sum \sum P(i, j)$$

5) Run Percentage:

$$RPC = \sum_i \sum_j P(i, j) / N^2$$

The measures defined above, are proposed for the identification of different classes of textures and determine the characteristics of each class, as they rely on the differences in the spatial arrangement of gray levels of neighboring pixels.

A clustering algorithm is then used to evaluate the ability of the proposed scheme to discriminate among the different texture categories. A requirement from the applications is to choose such measures that will produce non-overlapped -in an ideal case- texture subspaces. The borders of these subspaces will then be estimated, using the proposed technique, so any other vector will be easily classified in one of the texture classes by examining the distances of this vector with the other classes.

The clustering method used (Goldfarb, 1984), is based on the calculation of the average intra-class distance of each of the classes, divided by the average inter-class distance between that class and one of the others.

The average intra-class distance is defined as :

$$P(\Delta \grave{u}) = \frac{2}{n(n-1)} \sum_{i=2}^{n} \sum_{j=1}^{i-1} \Delta \grave{u}(q_i, q_j) \qquad (3)$$

where n is the number of the features of each texture class, i and j are successive pixels, q_i,q_j are the feature vectors of each point within the subspace and Äù is the Euclidean distance for this pair of pixels.

The average inter-class distance between two classes, is defined as follows:

$$R(\Delta \grave{u}) = \frac{1}{n\bar{n}} \sum_{i=1}^{n} \sum_{j=1}^{\bar{n}} \Delta \grave{u}(q_i, \bar{q}_j) \qquad (4)$$

where n and $\bar{n}$ is the number of the features of two different texture classes, i and j are pixels belonging each one to one of these classes and Äù is the Euclidean distance for this pair of pixels. Finally, the stability quotient for two classes distance, is defined as follows:

$$Z(\Delta \grave{u}) = \frac{P(\Delta \grave{u})}{R(\Delta \grave{u})} \qquad (5)$$

The purpose of the following algorithm is to keep the features of a class close to each other and the features of different classes far apart.

ALGORITHM

The framework described above, aims to the transformation of any digital image from the point of view of texture units and texture spectrum. Considering a digital image stored in a square raster form, each pixel is surrounded by eight neighboring pixels. We use a window of 3x3 size in order to extract from the corresponding neighborhood in the image, the local texture information contained even in small regions.

The first step is to calculate the texture units according to the procedure described in the following paragraph:

a) Scanning of the original image using a 3x3-sliding window, representing the smallest complete texture neighborhood.
b) Calculation of the corresponding unit according to formula (1), for each region of the image, focusing on the relative gray level relationships between the central pixel and its neighbors in all eight directions.
c) For each 3x3 pattern of the image, we compute the texture unit number, using the formula (2).
d) The resulted texture unit numbers form the texture spectrum of the image.

The texture spectrum approach described above, transforms the original image in such a manner that each 3x3 neighborhood, is replaced by the corresponding to this region its texture unit number. As it is clear for the above described scheme, the emphasis is placed on the relative gray level relationships between pixels in a small neighborhood, maintaining at the same time the global texture characteristics of the image.

The general idea of texture analysis is the description of each texture class by a set of features. These features are determined as a set of measures to be used in a later phase for the discrimination among different types of textures. The main goal is to classify the texture classes, according to the set of features that relies on the differences in the spatial arrangement of gray levels of neighboring pixels. The determination of the features of each spectrum image, is completed in the following the next steps:

a) Collection of patterns from the texture spectrum, by extracting windows, of a pre-determined size, from the spectrum image. The size of the window, is determined at the beginning of the algorithm.
b) Computation of the set of the five measures according to the run lengths of the patterns of the spectrum image.
c) Plotting of all the possible combinations of three of the above measures, in order to estimate those combinations that can more effectively produce discriminant texture subspaces.

The primary goal of the proposed approach is to maintain all the features from a class close together, while at the same time, features from different classes far apart. This intention has been evaluated according to the stability quotient for two classes, which is considered to be a goodness measure for clustering classes.

So, for each class, we calculated the intra-class distance and its inter-class distance with another class, by following the formula (4) and (5). The stability quotient, according to equation (6) is near to zero when the features of a class are close together, while this class is not close to another class and is going to be near to one, in the opposite situation.

DISCUSSION AND RESULTS

The method described has been extensively applied on endoscopic images, containing lungs' cancer regions, where each one is represented by 512x512 pixels. Figure 1, shows at the left part the original endoscopic images and at the right part shows the images that resulted after the application of the texture spectrum approach. Comparing these figures, we note easily that the texture spectrum maintains the important structure of different texture classes and also preserves the textural information in the original images.

A set of five measures based on the relative gray level relationships between neighboring pixels has been calculated for each spectrum image. These measures are: Long Run Emphasis (LRE), Short Run Emphasis (SRE), Gray Level Nonuniformity (GLNU), Run Length Nonuniformity (RLNU), and finally, Run Percentage (RPC). Plotting all the possible combinations of the computed measures, of all the texture classes of an image, we estimated the discriminative capability of these measures. Studying the results, we have come to the conclusion that there are certain combinations of measures, that appears with less discrimination capability of regions with the same texture class. In figures 2 and 3, we can study some plots of possible combinations of the computed measures, as it concerns all the texture classes of the image. The values of these measures have been computed, after the application of the described method to the two images, showing in Figures 1 (a) and (c).

One step furthers, the stability quotient is calculated, in order to prove and mathematically the above results. For each combination of three measures, we have calculated the distance between features belonging at the same class, and the Euclidean distance, between pairs of classes. The quotient that results from each type of features, is stored to a vector (Fig. 2 and 3), fact that enable us to compare the results taken above, with the mathematical computation of the stability quotient.

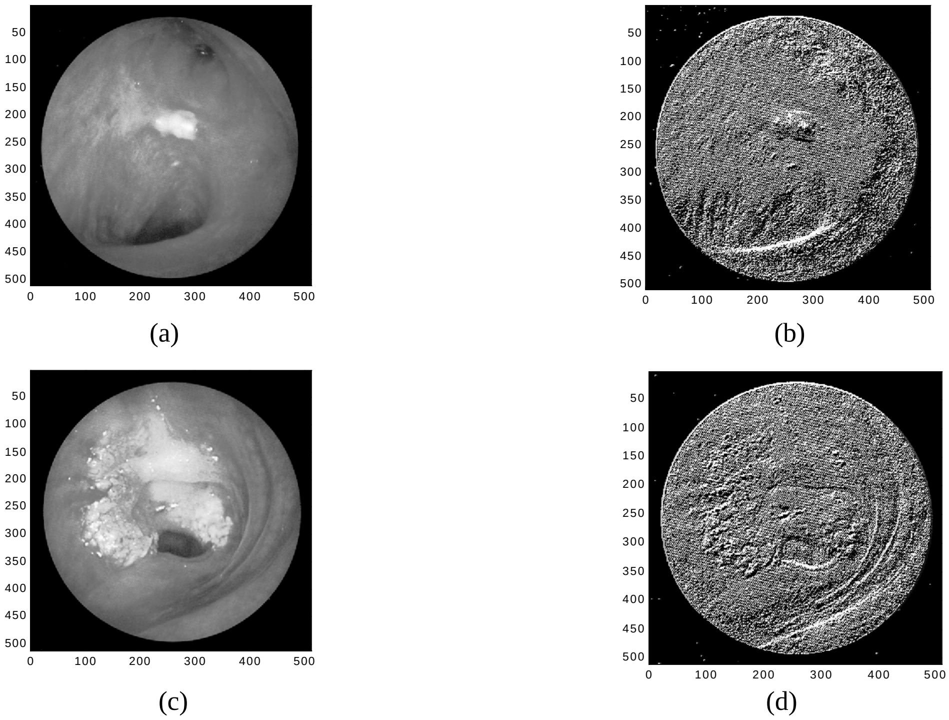


Figure 1. The original endoscopic images appearing at the left side and the corresponding spectrum images at the right side of the page. In these images, two different stages of cancer in the lungs are showed.

In general, the value of the stability quotient is near to zero, when the value of the intra-class distance is small, while at the same time the distance between two classes is significant. Same, as we can see from the plots, in cases that the features of a class are far apart, while the distance of two classes is small, the value of the stability quotient for the two classes is close to one.

CONCLUSIONS

This paper outlines a new approach to texture classification applied on lung endoscopic images. The key concept of this paper is to extract all the texture information of an image, by characterizing its textural aspect in the form of a spectrum. The innovation of the approach that is outlined in this paper, is the feature selection of the image based on the texture spectrum of the image. Taking into consideration that the texture spectrum method has been introduced for texture analysis, we decided to select features of the image that are estimated using the texture units, in order to estimate the success of this method. By combining these measures, we picked out a number of combinations of features, which divide the image into regions with the same texture information. The results obtained from the application of the method to different images were then confirmed by the computation of the stability quotient between two classes.

In the present work, we applied a texture characterization and a clustering method, to a transformed image, characterized by its texture spectrum, in order to distinguish the features with the most textural discriminative ability.

REFERENCES

Goldfarb L. (1984), "A unified approach to Pattern Recognition", *Pattern Recognition,* 17, 575-582.

Haralick R. (1979), “Statistical and tructural approaches to texture”, *Proceedings IEEE*, 67, 786-804.

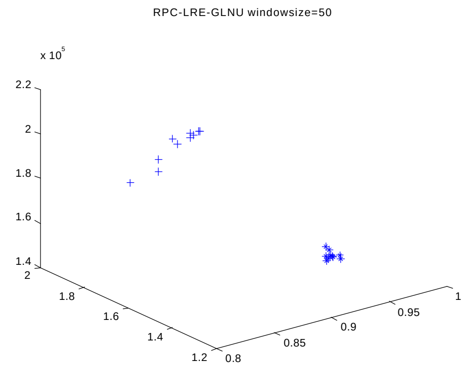
He D.C and Wang L.(1991), "Texture features based on texture spectrum", *Pattern Recognition*, 24, 1187-1195.

He D.C. and Wang L. (1990), "Texture unit, texture spectrum and texture analysis", *IEEE Trans. Geoscience and Remote Sensing,* 56, 61-66.

Julesz B. (1986), “Texton Gradients: Thetextonn theory revisited”, *Biological Cybernetics*, 54, 245-251.

Rao A.(1990), “*A taxonomy for texture description and identification*”, Springer-Verlag, New York.

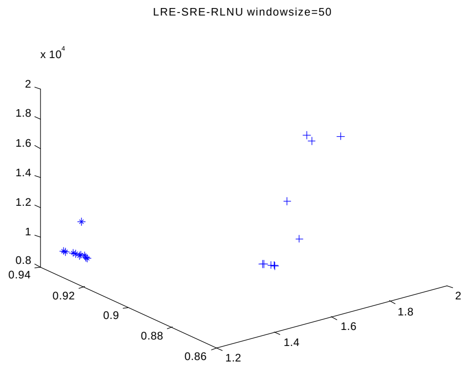
Siew L.H., Hodgson R. M. and Wood E. J.(1988), "Texture measures for carpet wear assessment", *IEEE Trans. on Pattern Analysis and Machine Intelligence,* 10, 92-105.



(a)

RPC – LRE – GLNU

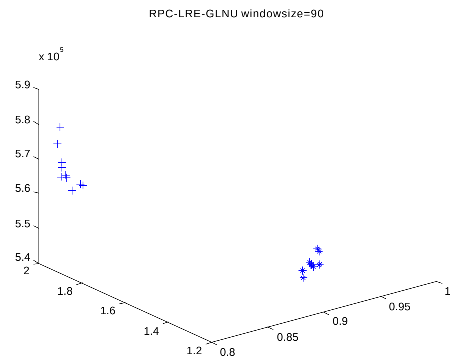
Windowsize =50	Normal (+)	Cancer (*)
Normal (+)	Undefined	0.479
Cancer (*)	0.090	Undefined



(b)

LRE – SRE- RLNU

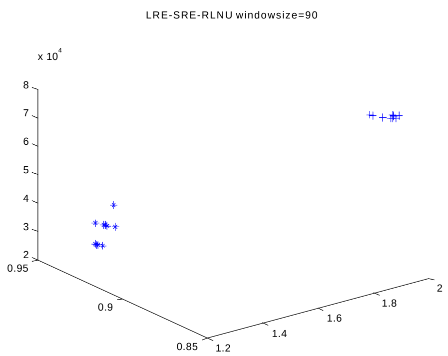
Windowsize =50	Normal (+)	Cancer (*)
Normal (+)	Undefined	1.802
Cancer (*)	0.214	Undefined



(c)

RPC – LRE – GLNU

Windowsize =90	Normal (+)	Cancer (*)
Normal (+)	Undefined	0.584
Cancer (*)	0.279	Undefined

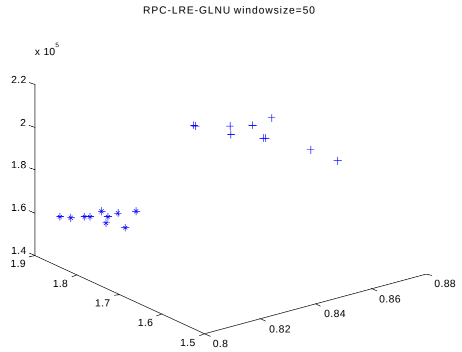


(d)

LRE – SRE- RLNU

Windowsize =90	Normal (+)	Cancer (*)
Normal (+)	Undefined	0.016
Cancer (*)	0.225	Undefined

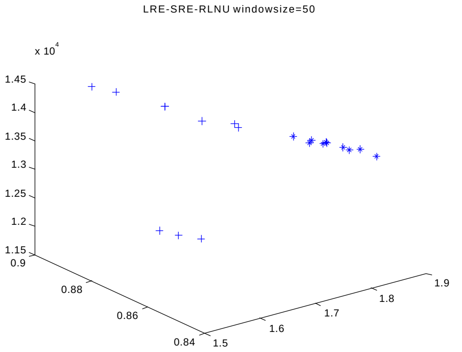
Figure 2. 3-D plots of the measures RPC-LRE-GLNU and LRE-SRE-RLNU for the image Fig. 1(a). Besides the plots, that have been computed for different sizes of the window, the corresponding stability quotient has been computed and confirmed the results, as the side matrixes show.



(a)

RPC – LRE – GLNU

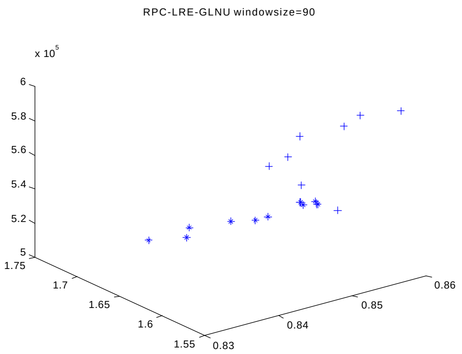
Windowsize =50	Normal (+)	Cancer (*)
Normal (+)	Undefined	0.253
Cancer (*)	0.118	Undefined



(b)

LRE – SRE- RLNU

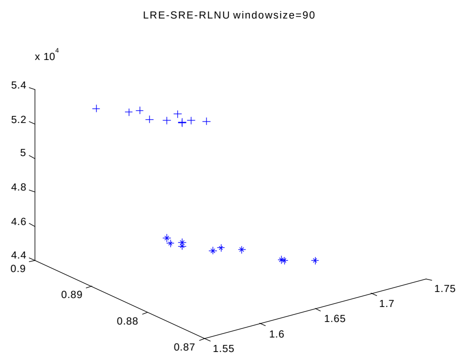
Windowsize =50	Normal (+)	Cancer (*)
Normal (+)	Undefined	2.294
Cancer (*)	0.225	Undefined



(c)

RPC – LRE – GLNU

Windowsize =90	Normal (+)	Cancer (*)
Normal (+)	Undefined	1.474
Cancer (*)	0.603	Undefined



(d)

LRE – SRE- RLNU

Windowsize =90	Normal (+)	Cancer (*)
Normal (+)	Undefined	0.071
Cancer (*)	0.102	Undefined

Figure 3. 3-D plots of the measures RPC-LRE-GLNU and LRE_SRE_RLNU for the image Fig. 1(c). Besides the plots, that have been computed for different sizes of the window, the corresponding stability quotient has been computed and confirmed the results, as the side matrixes show.