On Fuzzy Texture Spectrum for Natural Microtextures Characterization

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Abstract

Texture is an important spatial feature, useful for segmenting objects in an image. Texture Spectrum is a statistical approach to texture analysis. In this paper we proposed a Texture-based approach that considers the vagueness of the images and has into account the human beings.

Keywords: Texture analysis, Texture Spectrum, Fuzzy sets.

1 Introduction

Texture segmentation has long been an important topic in image processing. Basically, it aims at segmenting a textured image into several regions with the same texture features. An effective and efficient texture segmentation method will be very useful in applications like the analysis of aerial images, biomedical images and seismic images as well as the automation of industrial applications.

In the field of image segmentation, an automatic texture classification process is necessary. The information from texture can be added to other characteristics such as color or brightness in order to achieve a more robust segmentation. A number of methods for the description of the texture have been proposed in the literature ([1], [4]-[6]). A common aspect in most of them is the construction of an intermediate formulation, suitable for the description of the distribution of neighbouring 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.

Texture spectrum has been introduced in the last few years ([2], [3]), and was initially used as a texture filtering approach. The key concept of this method is the computation of the relative intensity relations between the pixels in a small neighbourhood 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 results into the texture spectrum, which characterizes the original image maintaining the image's texture characteristics.

In present work we propose an approach based on the texture spectrum method, which considers the vagueness within the data for getting a robust microtexture characterization method.

The paper is organized as follows: first, the texture spectrum technique will be briefly presented. The power of this technique and his limitations will be discussed. Secondly, the classification will be improved by means of using fuzzy numbers. Thirdly, a concrete example will illustrate the article, giving some real results. Finally, a conclusion will reveal the power of the spectrum method used together with the fuzzy theory.

2 Texture Spectrum Method

A complete definition of the texture spectrum employs the determination of values as *Texture Unit* and *Texture Unit Number*. The basic unit of the method is defined by a central pixel and its eight neighbors, forming a 3x3 pixel square. This minimal square image has the local texture information of the central pixel in all the directions.

2.1 Texture Unit -TU

In a digital image the main goal is to extract the local texture information of a neighbourhood of pixels. In our case the size of the neighbourhood is 3x3 pixels. This pattern of the image, consisting by 9 pixels, is denoted by a set V of nine elements, $V=\{V_0, V_1, V_2,\ldots, V_8\}$, where V_0 represents the intensity value of the central pixel and V_i ($1\leq i\leq 8$) the intensity value of each neighbouring pixel.

The smallest complete unit which best characterizes the local texture aspect of a given pixel and its neighborhoods, in all eight directions of a square raster, is *Texture Unit* (TU) that is defined, as in [1], by TU={E_1, E_2, …,E_8}, where:

$$E_i = \begin{cases} 0 & if \quad V_i < V_0 \\ 1 & if \quad V_i = V_0 \; ; \quad 1 \le i \le 8 \\ 2 & if \quad V_i > V_0 \end{cases} \tag{1}$$

and each element E_i occupies the same position as pixel *i*. An example is shown in Fig. 1.

92	87	83
93	92	96
90	89	95

(a)

1	0	0
2		2
0	0	2

(b)

Figure 1: (a) Grey levels of an image part.
(b) Texture Unit associated to the central pixel.

2.2 Texture Unit Number - N_{TU}

As to each element of the *TU* can be assigned one of three possible values 0, 1 or 2, the total number of *Texture Units* is 3^8=6561. These *Units* can be labelled and ordered in different ways; here we will label each *TU* as a 3-base number, named *Texture Unit Number*, N_{TU} according to next formula:

$$N_{\mathrm{TU}} = \sum_{i=1}^{i=8} E_i \cdot 3^{i-1} \tag{2}$$

where *i* is the position of the *Texture Unit* box, and E_i is the value of the box (0, 1 or 2).
Moreover, the 8 elements can be ordered differently. If they are ordered clockwise, as shown in Fig. 2, the first element can take eight possible positions, from the top left *a* to the middle left *h*, and then the 6561 texture units can be labeled by the abode formula under eight different ordering ways (from *a* to *h*).

Neighborhood

92 *a*	87 *b*	83 *c*
93 *h*	92	96 *d*
90 *g*	89 *f*	95 *e*

Texture Unit

1	0	0
2		2
0	0	2

TU Number

N_{TU}=4591

V={92, 92, 87, 83, 96, 95, 89, 90, 93} TU={1, 0, 0, 2, 2, 0, 0, 2}

Figure 2: Transformation of a neighbourhood to a Texture Unit and its Texture Unit Number.

2.3 Texture Spectrum-TS

The basic idea of the *Texture Spectrum* approach [2] is to transform an image using the *TU*s and characterize its global texture by the *Texture Spectrum*, *TS*, which is defined as the occurrence frequency function of the *TUs*, and is evaluated in a region of the image to deduce its texture-type. The power of this method [7] is based on the fact that each texture-type has associated a particular *Texture Spectrum*, with particular peaks. Similarly, given a *Texture Spectrum*, it is possible to deduce from which kind of texture it was obtained. So, for example, Fig. 3 corresponds to a part (40x40 pixels) of a white blood cell of the microscopic image of Fig. 11, and its *Texture Spectrum* is represented in Fig. 4. The spectrum was obtained evaluating the *Texture Unit* of each pixel, and then representing them as a frequency distribution.

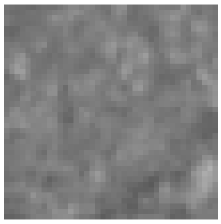

Figure 3: Part of a White Cell (40x40 pixels) of Fig. 11.

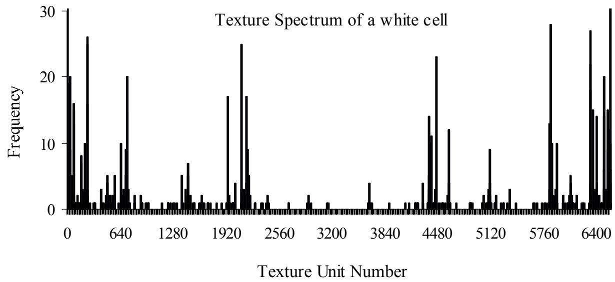

Figure 4: Texture Spectrum of Fig. 3.

For getting a better understanding of the usefulness of the *Texture Spectrum* we have considered also the 40x20 pixels' image of a red cell (Fig. 5) of the microscopic image of Fig. 11, for which the Texture Spectrum is shown in Fig. 6.

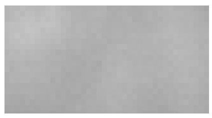

Figure 5: Part of a Red Cell of Fig. 11.

Having a look at histograms of Figs. 4 and 6 we can realize that there are a lot of inexistent *Unit Textures*. In fact, from the possible 6561 *TU's* values, only 461 and 497 respectively are present. A more detailed study indicates that the absent *TU's* involve ones in their *Texture Unit*, which is the case when neighbors and central pixels have the same grey level value.

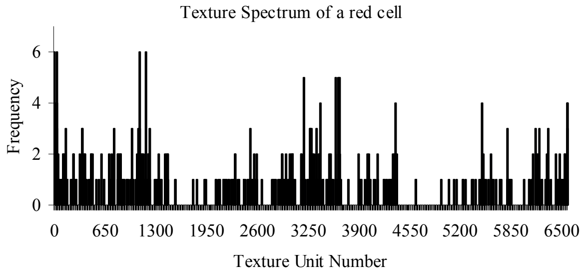

Figure 6: Texture Spectrum of image 5 (red cell)

Even if the human eye see two neighboring pixels as equal, in natural images occurs rarely that they have exactly the same intensity value. However, the desirable situation would be that in homogeneous images appear a lot of ones in the *Texture Units* , because that is what the human eye perceives.
In short, if there is a lack of ones, the UT will take only values of 0 and 2, which means that the possible real number of different textures are 2^8 instead of 3^8, that is 256 instead of 6561. The spectrum will be never totally covered, thus the power of the method is misused.
Here we propose a solution that takes into account this fact and is addressed to improve the use of the entire spectrum, considering the vagueness introduced within the image by different sources.

3 Fuzzy Texture Spectrum-FTS

With the aim of solving aforementioned problem, in this section we will make use of fuzzy techniques to assign values of 1 in the unit textures accordingly to human eye perception. The main idea of the proposed solution consists in assigning the value 1, in the *Texture Unit*, not only when both the central and neighbor pixel have the same gray level, but also when they are *similar enough*. This conception of *similar enough* is not a clearly defined edge, but a vague idea. It is actually when the crisp definition is not accurate that we should apply fuzzy numbers.

First we will introduce the method that we propose to assign values to the boxes of what we will say a *Fuzzy Texture Unit* (FTU). The same values 0, 1 or 2 will be given, but using fuzzy functions. Then, the way we will sum all the values to create the *Fuzzy Texture Spectrum* (FTS) will be explained.

3.1 Fuzzy Texture Unit Boxes-FTUB

Using fuzzy techniques provides a more flexible way of assigning values to the *TU* boxes E_i. From now on E_i will not be a unique value 0, 1 or 2, but it will have the three values associated at the same time, each one to its own degree. Each particular degree will be calculated with the aid of a membership function that has to be defined. Therefore, we will consider *Fuzzy Texture Unit Boxes* (FTUB) FE_i that are defined as follows:

$$FE_i = \{\mu_0(V_i), \mu_1(V_i), \mu_2(V_i)\}; \quad 1 \le i \le 8 \tag{3}$$

Wherein $\mu_0(V_i)$, $\mu_1(V_i)$ and $\mu_2(V_i)$ are the membership degrees of V_i to the fuzzy sets 0, 1 and 2 respectively.

For getting accurate results, the three membership functions should be obtained from real data, i.e. from real images. As already said, the desirable situation would be assigning a 1 when the two pixels have *similar enough* intensity levels, which is the case of major homogeneity zones, but not the textured ones. From a fuzzy view point, we expect a high value of μ_1 together with low values of μ_0 and μ_2 in the case of homogeneous images. On the other hand, textured images would be characterized by low values of μ_1 and high values of μ_0 and μ_2, what should indicate differences of intensity in neighboring pixels. So, it will be necessary to collect data from both types of images in order to define the membership functions that best fit our purpose.
The first step for getting the membership functions consists on studying the intensity differences between two neighbor pixels in homogeneous and textured images. Following with the initial example, the values are extracted from the microscopic blood cell image of Fig. 11, which is the type of image to be studied and characterized.
Due to the fact that textured and non textured zones appear mixed within the image, a previous partition is necessary to consider the red cells and the background (homogeneity) by a hand and the white cells (texture) by another hand. Once separated, the differences between two neighbor pixels are evaluated and added in a frequency distribution. Fig. 7 shows the frequency distribution of the intensity differences between two neighbor pixels in homogeneous (blue triangles) and textured (red squares) zones. The x-axis represents the intensity differences and the y-axis the frequencies in a total of 2000 evaluations for each case.

As expected, the blue curve, representing the intensity differences in homogeneous images, is narrower than the red one, i.e. the intensity values are globally more similar inside the unit texture.

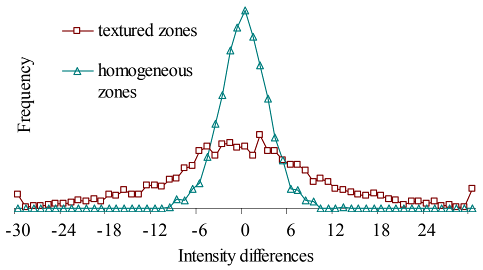

Figure 7: Frequency distribution of the intensity differences between two neighbor pixels in homogeneous and textured zones.

Three membership functions (Fig.8) should be defined from these data: μ_0 giving the degree to which the evaluated pixel is darker than the central one; μ_1 that gives the gray level similarity degree; and μ_2 indicating the degree to which the pixel has lighter intensity. So, if x is the difference in intensity given in x-axis, the membership functions are defined as:

$$\mu_0 = \begin{cases} 1 & if \quad x \le -4 \\ \dfrac{-(x+1)}{3} & if \quad -4 < x < -1 \\ 0 & if \quad x \ge -1 \end{cases} \tag{4}$$

$$\mu_1 = \begin{cases} 0 & if \quad x \le 4 \\ \dfrac{x+4}{3} & if \quad -4 < x < -1 \\ 1 & if \quad -1 \le x \le 1 \\ \dfrac{4-x}{3} & if \quad 1 < x < 4 \\ 0 & if \quad x \ge 4 \end{cases} \tag{5}$$

$$\mu_2 = \begin{cases} 0 & if \quad x \le 1 \\ \dfrac{x-1}{3} & if \quad 1 < x < 4 \\ 1 & if \quad x \ge 4 \end{cases} \tag{6}$$

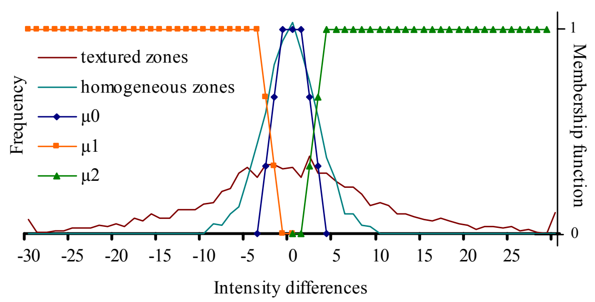

Figure 8: Fuzzy Functions for the Fuzzy Unit Texture Boxes

Once we have a method to calculate the FTUB, which is now a set of three values $FE_i \equiv \{\mu_0, \mu_1, \mu_2\}$, we will proceed to introduce how they are used to determine the *Fuzzy Texture Spectrum*.

3.2 Fuzzy Texture Unit

In a similar way to the *TU*, the *Fuzzy Texture Unit* (*FTU*) is defined by:

$$FTU = \{FE_1, FE_2, FE_3, FE_4, FE_5, FE_6, FE_7, FE_8\} \tag{7}$$

The problem now is how to add all these values to obtain a *Fuzzy Texture Spectrum (FTS)*.

In the crisp method, each pixel had a texture unit associated, so the *Texture Spectrum* was constructed adding the *TUs* of the entire image's pixel. However, as we haven't characterized a pixel by single *TUs*, but by *FTUs*, each having its particular membership degrees, the *Fuzzy Texture Spectrum* has to be obtained adding the membership values given by the *Fuzzy Texture Unit*s.

Unlike the crisp method, when considering a pixel, multiple parts of the *Texture Spectrum*, corresponding to different texture units, can be incremented simultaneously. The increment of a *Texture Unit Number* will be obtained multiplying the membership values of the *Fuzzy Texture Units*.

For a better understanding of the proposed technique, given the 3x3 pixel square of Fig. 9-a, the *FTUs* associated to the central pixel are calculated. In Fig. 9-b we have written the values of the *FTUB* obtained using equations (4) to (6) for $\mu_j(V_i) \neq 0$.

(a)

92	87	83
93	92	96
90	89	95

(b)

μ_1=1	μ_0=1	μ_0=1
μ_1=1		μ_2=1
μ_1=2/3 μ_0=1/3	μ_0=1	μ_2=2/3 μ_1=1/3

Figure 9: (a) Grey levels of an image part. (b) *FTU*s associated to the central pixel

So, considering all the membership values' combinations, the central pixel has associated four *FTU* (bold numbers show the differences between the *FTUs*), each having its corresponding *NTU*

$$FTU1 = \{1_1, 0_1, 0_1, 2_1, \mathbf{2}_{2/3}, 0_1, \mathbf{1}_{2/3}, 1_1\}; \quad N_{TU1} = 3133$$
$$FTU2 = \{1_1, 0_1, 0_1, 2_1, \mathbf{1}_{1/3}, 0_1, \mathbf{1}_{2/3}, 1_1\}; \quad N_{TU2} = 3052$$
$$FTU3 = \{1_1, 0_1, 0_1, 2_1, \mathbf{2}_{2/3}, 0_1, \mathbf{0}_{1/3}, 1_1\}; \quad N_{TU3} = 2404$$
$$FTU4 = \{1_1, 0_1, 0_1, 2_1, \mathbf{2}_{1/3}, 0_1, \mathbf{1}_{1/3}, 1_1\}; \quad N_{TU4} = 2323$$

The degree to which each *TU* will be considered in the *FTS* is obtained multiplying the eight membership values:

$$FTU1 = \{1_1, 0_1, 0_1, 2_1, 2_{2/3}, 0_1, 1_{2/3}, 1_1\}; \quad \mu(N_{TU1}) = \mathbf{4/9}$$
$$FTU2 = \{1_1, 0_1, 0_1, 2_1, 1_{1/3}, 0_1, 1_{2/3}, 1_1\}; \quad \mu(N_{TU2}) = \mathbf{2/9}$$
$$FTU3 = \{1_1, 0_1, 0_1, 2_1, 2_{2/3}, 0_1, 0_{1/3}, 1_1\}; \quad \mu(N_{TU3}) = \mathbf{2/9}$$
$$FTU4 = \{1_1, 0_1, 0_1, 2_1, 2_{1/3}, 0_1, 1_{1/3}, 1_1\}; \quad \mu(N_{TU4}) = \mathbf{1/9}$$

In short, when evaluating the pixel, the *Fuzzy Texture Spectrum* will be incremented in the four *Texture Numbers* N_{TU1}, N_{TU2}, N_{TU3} and N_{TU4} with weights 4/9, 2/9, 2/9 and 1/9 respectively.

The process of calculating all the texture units associated to a pixel and then the increment in the texture spectrum is performed for all the pixels of the image for obtaining the *Fuzzy Texture Spectrum*. In the case of Fig.3 the *FTS* is shown in Fig. 10. Compared with the TS of Fig.4, it can be observed that the *FTS* is more distributed within the values, i.e. there are more values involved, and the peaks are lower, what agree with the visual textural inspection.

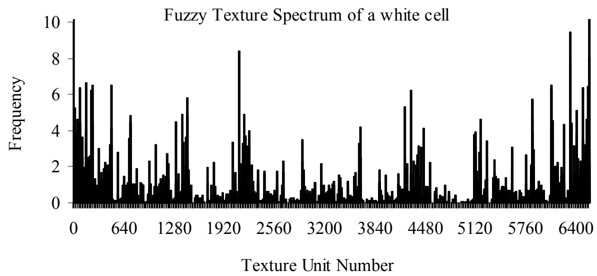

Figure 10: Fuzzy Texture Spectrum of Fig. 3.

4 Fuzzy Texture Spectrums Similarity

The *Fuzzy Texture Spectrum* here presented is intended to achieve an automatic recognition of a concrete textured image. The main goal is to distinguish the white cells, which are the textured big ones within a microscopic blood image (Fig.11). As white cells have a particular texture, they have also a particular *Texture Spectrum* ([7]) that can be used for white cells recognition. In the proposed approach we will compare the *FTS* model of Fig.10 with the obtained for different 20x20 pixels' groups of Fig.11. If the *FTS* are similar, the evaluated part corresponds to a white cell, in other case this part of the image is not of a white cell. In general, a spectrum won't be coincident with another, but will have some similarities and the more similar the spectrums the greater the evidence of texture.

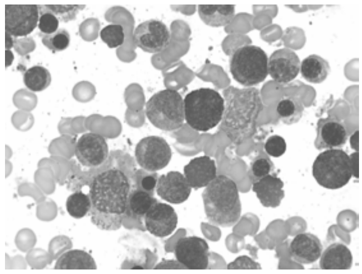

Figure 11: Microscopic blood cell image

So, the goal is determining the similarity of two texture spectrums and decide whether an image part, whose texture spectrum is compared with a prototype, belongs or not to a texture category. For solving this problem we can use minimum square techniques applied to all the values or just some characteristic values such as the peaks.
Going back to the example, the first step consists in describing the white cell's FTS prototype. To do it we will use a peak recognition method. So, we must to determine the characteristic peaks and, at the same time, refuse the peaks present in other textures. In general, the properties present in the whole image have to be rejected for giving more emphasis to the particularities.

We obtained the FTS of five white cells, five red cells and five parts of the background (20x20 square pixels) of Fig. 11. The peaks appearing in the white cells' FTS were identified in the other spectrums. Finally we considered 8 peaks appearing only in the case of white cells as characteristic peaks, that correspond to FTUs having 2 adjacent darker and six lighter pixels than the central one, and whose Texture Unit Numbers are: N_{TU1}=8, N_{TU2}=24, N_{TU3}=72, N_{TU4}=216, N_{TU5}=648, N_{TU6}=1944, N_{TU7}=4376 and N_{TU8}= 5832. A possible configuration of the texture unit is shown in figure 12, all the texture units have the same distribution but in a different orientation.

0	0	0
0		2
0	0	2

Figure 12: Characteristic TU of a white cell texture.

As the texture is not directional the eight possible peaks have the same importance therefore the values of the peaks can be added together. The value of this sum will be proportional to the white cell membership. After analyzing the 20x20 pixel squares of Fig.11, the white cell FTS membership function is defined as plotted by Fig.13.

As the procedure is repeated for all the possible 20x20 pixels squares of the image, a single pixel will have a total of 400 evaluations. So, the final membership degree of a pixel to White Cell is the average of all of them, while the pixels situated in the edges and corners have a special processing.

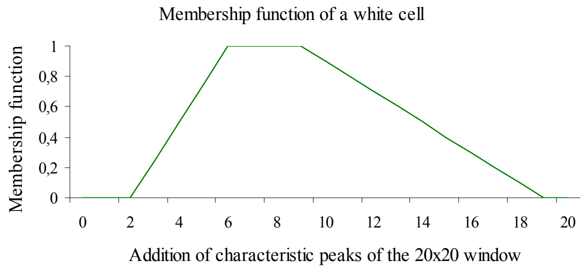

Figure 13. White cell FTS membership function obtained from the addition of the characteristic peaks.

5 Results

Here we will present the results obtained applying the proposed method to the image of Fig.11. So, the membership degree of the image pixels to the White cell texture are represented in the image of Fig. 14, wherein whiter gray levels correspond to higher membership values. If this image is superposed over the original image (Fig. 11), and then makes transparent the lighter pixels, the resultant image shows that there is a correspondence between white cells and light pixels, as is shown by Fig. 15.

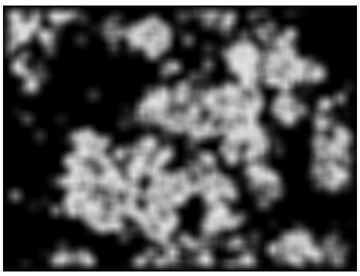

Figure 14. White cells texture membership values. Membership degrees are proportional to intensity.

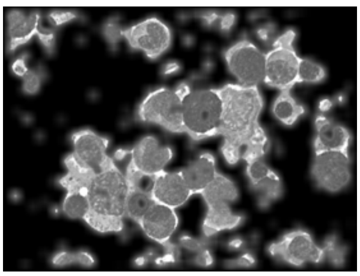

Figure 15. Superposition of Fig. 11 and Fig. 14

6 Conclusions

The texture spectrum method introduced by He and Wang [2] performs texture characterization by terms of using the information of a pixel neighborhood. The neighborhood representation is done by means of the *Texture Unit*, which may be influenced by external factors such as noise. We have developed a new solution introducing fuzzy techniques to calculate the *Fuzzy Texture Unit* and the *Fuzzy Texture Spectrum*, exemplified with a microscopic blood image. The fuzzy technique allows a better representation of the real texture and uses a wider band of the *Texture Spectrum*, otherwise misused in case of noise.

New forms of comparison and texture detection will be studied in future work. The *Fuzzy Texture Spectrum* method will be applied to distinguish texture in other image types. The characterization can be done comparing the particular *Fuzzy Texture Spectrum* of an image part with a standard one in global terms or using a set of peaks as we did here

References

[1] R. Haralick, “Statistical and tructural approaches to texture”, *Proceedings IEEE*, 67, 1979, pp. 786-804.

[2] D. C. He and L.Wang, “Texture unit, texture spectrum and texture analysis”, *IEEE Trans. Geoscience Remote Sensing*, vol. 28, Issue 4, 1990, pp. 509-512.

[3] D. C. He and L.Wang, “Texture features based on texture spectrum”, *Pattern Recognition*, vol. 24, Issue 5, 1991, pp. 391-399.

[4] A.Rao, “*A taxonomy for texture description and identification*”, Springer-Verlag, New York, 1990.

[5] A. R. Rao, N. Bhushan and G. L. Lohse, “The relationship between texture terms and texture images: a study in human texture perception”, Proc SPIE, vol 2670, 1996, pp.206-214.

[6] M. Tuceyran and A.K. Jain, “*Texture analysis”*, in “*Handbook of Pattern Recognition and Computer Vision”*, C.H. Chen, L.F. Pau and P.S.P. Wang (Eds.), chapter 2, 235-276, World Scientific, Singapore, 1993.

[7] L.Wang and D. C. He, “Texture classification using texture spectrum”, *Pattern Recognition*, vol. 13, Issue 8, 1990, pp. 905-910.