Texture analysis using complex system models:
fractal dimension, swarm systems and non-linear
diffusion

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Análise de texturas usando sistemas complexos: dimensão fractal, multiagentes e difusão não-linear

Tese apresentada ao Instituto de Ciências Matemáticas e de Computação – ICMC-USP, como parte dos requisitos para obtenção do título de Doutor em Ciências – Ciências de Computação e Matemática Computacional. VERSÃO REVISADA

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To my beloved wife Iuliia.

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“ Happiness is not something you postpone for the future,
it is something you design for the present;
if it does not knock, build a door.”
(Jim Rohn)

RESUM O

BRANDOLI, B. M.. Texture analysis using complex system models: fractal dimension, swarm systems and non-linear diffusion. 2016. 115 f. Doctoral dissertation (Doctorate Candidate Program in Computer Science and Computational Mathematics) – Instituto de Ciências Matemáticas e de Computação (ICMC/USP), São Carlos – SP.

A textura é um dos principais atributos visuais para a descrição de padrões encontrados na natureza. Diversos métodos de análise de textura têm sido usados como uma poderosa ferramenta para aplicações reais que envolvem análise de imagens e visão computacional. Entretanto, os métodos existentes não conseguem discriminar com sucesso a complexidade dos padrões de textura. Tais métodos desconsideram a possibilidade de se descrever estruturas de imagens por meio de medidas como a dimensão fractal. Medidas baseadas em fractalidade permitem uma interpretação geométrica não-inteira que possui aplicações encontradas em áreas como matemática, física, e biologia. Sobre esta lacuna metodológica, a hipótese central desta tese é que texturas presentes na natureza podem ser medidas como superfícies fractais irregulares devido à sua geometria complexa, o que pode ser explorado para fins de análise de imagens e visão computacional. Para superar tais limitações, avançando o estado da arte, esta tese se inicia com uma análise das características de texturas baseada em caminhadas aleatórias de agentes sobre superfícies de imagens. Esta primeira análise leva a um método que combina dimensão fractal com caminhadas de agentes sobre a superfície de imagens. Em uma segunda abordagem, usa-se a difusão não-linear para representar imagens de texturas em diferentes escalas, as quais são descritas via dimensão fractal para fins de classificação de imagens. Em uma terceira proposta, emprega-se a dimensão fractal sobre múltiplas escalas derivadas de uma mesma imagem com o propósito de se realizar a descrição multi-escala de texturas. Um dos propósitos específicos foi a detecção automática de doenças em folhas de soja. Por último, as características de textura foram exploradas segundo uma metodologia baseada em redes complexas para análise de aglomeração de partículas em imagens de nanotecnologia. Os resultados alcançados nesta tese demonstraram o potencial do uso de características de textura. Para tanto foram usadas técnicas de dimensão fractal de Bouligand-Minkowski, multiagentes Artificial Crawlers e difusão não-linear de Perona-Malik, os quais alcançaram eficácia e eficiência comparáveis ao do estado da arte. As contribuições obtidas devem suportar avanços significativos nas áreas de engenharia de materiais, visão computacional, e agricultura.

Palavras-chave: análise de textura, dimensão fractal, sistemas multi-agentes, difusão anisotrópica, redes complexas.

ABSTRACT

BRANDOLI, B. M.. Texture analysis using complex system models: fractal dimension, swarm systems and non-linear diffusion. 2016. 115 f. Doctoral dissertation (Doctorate Candidate Program in Computer Science and Computational Mathematics) – Instituto de Ciências Matemáticas e de Computação (ICMC/USP), São Carlos – SP.

Texture is one of the primary visual attributes used to describe patterns found in nature. Several texture analysis methods have been used as powerful tools for real applications involving analysis and computer vision. However, existing methods do not successfully discriminate the complexity of texture patterns. Such methods disregard the possibility of describing image structures by means of measures such as the fractal dimension. Fractality-based measures allow a non-integer geometric interpretation with applications in areas such as mathematics, physics, and biology. With this gap in mind, the central hypothesis of this thesis is that textures can be described as irregular fractal surfaces due to their complex geometry; such geometry can be exploited for image analysis and computer vision. By exploring such possibilities, pushing the limits of the state-of-the-art, this thesis starts with an analysis of texture features achieved by means of agents on image surfaces. To do so, we used the Bouligand-Minkowski fractal dimension, swarm-system Artificial Crawlers, and non-linear diffusion of Perona-Malik, techniques that led to methodologies with efficacy and efficiency comparable to the state-of-the-art. Our first method combines fractal dimension with random walks on the surface of images. In a second approach, non-linear diffusion is used to represent texture images at different scales, which are described via their fractal dimension for image classification purposes. In a third proposal, we employ fractal dimension concepts over multiple scales derived from the same image for a richer texture description. One of the purposes is the automatic detection of diseases in soybean leaves. Finally, texture characteristics were exploited in a method based on complex networks used to analyze the agglomeration of particles in nanotechnology images. The results achieved in the four methodologies described in this thesis demonstrated the potential of using texture features in tasks of classification and pattern recognition. The contributions of this work shall support significant advances in materials engineering, computer vision, and agriculture.

Key-words: texture analysis, fractal dimension, swarm system, non-linear diffusion, complex networks.

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LIST OF PUBLICATIONS

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INTRODUCTION

1.1 Context and Motivation

Texture is an important visual attribute in computer vision with many areas of applications. Recently, texture analysis has been widely applied to remote sensing ([CORPETTI; PLANCHON, 2011](#); [GONG et al., 2014](#)), industrial inspection ([KIM; LIU; HAN, 2011](#); [TSANG; NGAN; PANG, 2016](#)), medical image analysis ([SERRANO; ACHA, 2009](#); [ERGIN; KILINC, 2014](#); [ZAGLAM et al., 2014](#)), face recognition ([FU et al., 2010](#); [MEHTA; YUAN; EGI AZARIAN, 2014](#)), among many others. Although the human visual system can easily discriminate textural patterns, the description by automatic methods has been a great challenge. Indeed, there is no universally accepted definition of texture. It is usually referred to as a repetitive pattern that can vary according to the size, which produces different tactile sensations associated with roughness, coarseness, and regularity. Furthermore, texture patterns are related to the physical properties of surfaces present in images, making them a powerful tool for image analysis.

Texture analysis has been an active research field in the last decade. The proposed methods have been grouped according to the mathematical aspects used to handle the patterns present in the images. There are five major categories: structural, statistical, spectral, model-based, and agent-based. The structural methods rely on primitives that provide a symbolic description of the images ([CHEN; DOUGHERTY, 1994](#)). The idea comes from concepts on mathematical morphology, which describes an image by evolving morphological operations with different sizes of structuring elements ([SERRA, 1983](#)), a useful technique to handle shapes in textures.

Statistical methods represent textures by the spatial distribution of the gray-level pixels in the image. One of the best methods of this category, and still very popular, is co-occurrence matrices ([HARALICK; SHANMUGAM; DINSTEIN, 1973](#); [HARALICK, 1979](#)). In the same line, Dmitry Chetverikov ([CHETVERIKOV, 1999](#)) introduced the technique named interaction

map. Similarly, Ojala et. al. ([OJALA; PIETIKÄINEN; MÄENPÄÄ, 2002](#)) proposed a method that describes images based on the occurrence of gray values on circular local neighborhoods; it is named local binary patterns (LBP). Xiaoyang et al. ([TAN; TRIGGS, 2010](#)) extended the idea of LBP to local ternary pattern (LTP), which considers the magnitude of pixel derivatives along with its sign to generate the ternary code. In the work of Hadid et al. ([HADID et al., 2015](#)), the authors present a comparative study using 13 variants of local binary patterns for gender classification.

Model-based methods were proposed with the assumption that textures can be represented by mathematical models, including stochastic models of Markov random fields ([CROSS; JAIN, 1983](#); [CHELLAPPA; CHATTERJEE, 1985](#)) and fractality ([MANDELBROT, 1977](#)). Particularly, fractal geometry has drawn great attention on the task of describing textures ([TRICOT, 1995](#)). The main reason is because fractal geometry is able to describe irregular or fragmented shapes of natural phenomena, as well as other complex objects that traditional Euclidean geometry is not able to describe. The fractal concept is expressed by the time-domain statistical scaling laws and is characterized by the power-law behavior of physical systems. This idea makes use of the geometrical interpretation of objects and takes into account the degree of regularity of the structure related to its physical behavior ([MANDELBROT, 1983](#)). Recently, Goncalves et al. ([GONCALVES; MACHADO; BRUNO, 2014](#)) proposed a hybrid fractal-swarm method for texture analysis.

Most of the methods used in texture analysis are restricted to the analysis of the spatial relations over small neighborhoods, or they are based on the extraction of global features of the whole image on a single scale. As a consequence, they do not perform well in high-complex geometry textures. In contrast, spectral methods or signal processing methods, including Fourier analysis ([AZENCOTT; WANG; YOUNES, 1997](#)), Gabor filters ([GABOR, 1946](#); [BIANCONI; FERNÁNDEZ, 2007](#)), wavelet transform methods ([DAUBECHIES, 1992](#); [MALLAT; ZHONG, 1992](#)), were developed inspired by evidence that the human visual system describes images by the frequency domain. However, the Fourier transform lacks spatial information, what impairs its potential for image description. Although Gabor filters present joint image resolution in both the spatial and frequency domains, they do not describe well coarse textures; this is because the energy of such textures is concentrated in subimages of lowest frequencies ([XU; WU; CHEN, 2010](#)). In contrast with Gabor filters, wavelets decompose a texture image into a set of frequency channels. However, wavelet analysis is basically a linear analysis and suffers from uniformly-poor resolutions over different scales and from its non-data adaptive nature, since the same wavelet basis is used to analyze all the data ([HUANG; LONG; SHEN, 1996](#)).

1.2 Goals and Contributions

The goal of this thesis is to propose solutions to overcome the drawbacks of current texture analysis methods, as observed in the literature. To reach this goal, we have proposed new methods for texture description based on complex systems, including fractal dimension, swarm systems, non-linear diffusion models, and complex networks. We have addressed two main issues found in typical statistical and model-based texture descriptors: (1) the lack of a multiscale representation to capture the richness of local features in different levels of observation; and, (2) although fractal descriptors proved to be a promising texture descriptor, current methods do not explicitly consider the neighborhood relation in terms of the gray levels of the texture. In this work, we evaluated our methods over four well-known texture benchmarks: Brodatz ([BRODATZ, 1966](#)), Vistex ([SINGH; SHARMA, 2001](#)), Outex ([OJALA et al., 2002](#)) and Usptex ([BACKES; CASANOVA; BRUNO, 2012](#)). In addition, our methods were compared with state-of-the-art texture methods, including Fourier descriptors, co-occurrence matrices, Gabor filters, and local binary patterns. The motivation to develop our methods is that they are suitable for real-world applications, as in material engineering and agriculture, leading to better or automatic decisions. As we show along the text, we focus on nanomaterial quality assessment and on plant disease identification in soybean leaves.

The first contribution of this thesis is a methodology for texture description. We carefully investigate all the steps of a swarm system method named artificial crawler, proposed first by ([ZHANG; CHEN, 2004](#); [ZHANG; CHEN, 2005](#)). The original method was proposed to have the iterative crawling step moving only in the direction of maximum pixel intensity, thus characterizing regions of high intensities in the image. However, in texture analysis, regions of low intensities are as important as regions of high intensities. For this reason, we proposed a new rule of movement that also moves the agents in the direction of lower intensity. We developed an improved method for assessing the quality of the silk fibroin scaffolds ([SHENZHOUE et al., 2010](#)) with two rules of movement: maxima and minima. Our goal is to provide an effective method to support visual analysis, thus reducing the subjectivity of the human analysis. We evaluated the potential of the silk fibroin by including glycerol in the solution during scaffold formation. This work was published in the Computational Science and Discovery Journal ([MACHADO; GONCALVES; BRUNO, 2014](#)) and is presented in Chapter 2.

The second contribution of this thesis is an extended methodology based on the energy information of the artificial crawler swarm system extracted from two rules of movement. Similar to the method proposed in Chapter 2, each agent is able to move to the higher intensities, as well as to lower ones. Although we can find the minima and maxima of images directly, the underlying idea is to characterize the path of movement during the evolution process. Our method differs from the original artificial crawlers since we quantify the state of the swarm system after stabilization by employing the Bouligand-Minkowski fractal dimension method ([TRICOT, 1995](#)). In the method, the energy information was considered the most important attribute due to its

capacity of representing the interaction between the movement of agents and the environment. This work was published in the journal *Physica A: Statistical Mechanics and its Applications* (GONCALVES; MACHADO; BRUNO, 2014) and is presented in Chapter 3.

The third contribution of this thesis is a multiscale texture descriptor based on non-linear diffusion. Many recent texture-analysis methods are developed to extract measures on a single scale. In contrast, we assume that an image texture reveals different structures according to the scale of observation, so that the scale concept of multiscale representation is of crucial importance (MACHADO et al., 2016a). Thus, we iteratively represent the original image in a set of new images. Inspired by the work of Yves Meyer (MEYER, 2001), where images are combinations of both oscillatory (texture) and geometrical (cartoon) patterns, we get two components for the derivative images. At each iteration step, we estimate the average and deviation of the Bouligand-Minkowski descriptors computed over the two components. We then combine the measures from both components to compose our feature vector. The Bouligand-Minkowski fractal dimension is adopted here due to its precision in quantifying structural properties. Experimental results over four well-known texture datasets reveal a superior performance of our method. This work was first published in the Proceedings of the 13th International Conference on Advanced Concepts for Intelligent Vision Systems with Gabor filters (MACHADO; GONCALVES; BRUNO, 2011). Later, a new research involving fractal descriptors was submitted to the Pattern Recognition Journal (MACHADO et al., 2016a) and is presented in Chapter 4.

The fourth contribution of this thesis is the application of the method proposed in Chapter 4. In this case, we assume that a leaf image presents different details according to the scale of analysis, which is suitable to describe fractal-like structures as observed in leaves. Accordingly, we propose a multiscale fractal descriptor that is applied over derivative images obtained by means of anisotropic diffusion. In our methodology, the gray levels of an image correspond to the energy diffusion at different levels represented in new derivative images. We split each new derivative into geometrical and oscillatory parts. Subsequently, we estimate the Bouligand-Minkowski fractal dimension of each component and combine the features to perform texture classification. Experiments indicate that our approach can successfully identify soybean leaf diseases and can also be used as a front-end application to non-experts or agronomists. In addition, our method was compared to the state-of-the-art texture methods showing superiority for recognition of soybean leaf diseases. This work (MACHADO et al., 2016b) has been integrated to the mobile application called BioLeaf - Foliar Analysis¹ (MACHADO et al., 2016c), which was submitted for software registration at the Brazilian agency National Institute of Industrial Property (INPI). Both the methodology and the mobile application description were submitted to the Computer Electronics and Agriculture Journal. Details are presented in Chapter 5.

Finally, the fifth contribution of this thesis is a complex network approach for particle agglomeration analysis in nanoscale images. In this work, instead of assuming that a nanoscale

¹ BioLeaf can be freely downloaded at <<https://play.google.com/store/apps/details?id=upvision.bioleaf>>

image is a textured surface, we have modeled the nanoparticles like vertices of a graph, while connections are created according to a thresholding for density estimation over a certain radius. For each nanoparticle, we calculate its density. Two particles are linked, defining an edge, only if their distance is smaller than a given radius and its density is higher than a given threshold. This work has been submitted to the Information Sciences Journal ([MACHADO et al., 2016d](#)) and it is presented in Chapter 6. Furthermore, this work was integrated into an expert system, named NanoImageAnalyzer, and it was submitted for software registration also at INPI.

1.3 Structure of the Text

This thesis is organized in seven chapters:

- In Chapter 2 we describe the improved artificial crawler method applied to material assessment of silk fibroin scaffolds;
- In Chapter 3, we present the basis for the fractal dimension and the proposed fractal-swarm method. We describe the method for texture analysis based on the Bouligand-Minkowski fractal dimension of artificial crawlers;
- In Chapter 4, we assumed that texture information can be significantly improved if different scales are considered during the image texture description;
- In Chapter 5, we extend the method proposed in Chapter 4 to the identification of soybean foliar diseases;
- In Chapter 6, we present a complex network approach for nanoparticle agglomeration analysis in nanoscale images;
- Finally, we provide conclusions and future directions of the thesis in Chapter 7. We reformulate the main contributions with emphasis on the results we have obtained and on the perspectives for future work.

INOVATIONS ON ARTIFICIAL CRAWLERS FOR TEXTURE ANALYSIS

2.1 Introduction

Silk fibroin is extracted from the cocoons of the silkworm *Bombyx mori*. It has recently been used as a protein biomaterial for the formation of scaffolds for a number of applications of biomedical sciences due to its high capacity to regenerate bones and tissues. Besides, it has good mechanical properties in terms of flexibility, for growth and adhesion used on human prosthesis (ALTMAN et al., 2003; SHENZHOU et al., 2010). Such properties have motivated researchers to investigate different silk fibroin scaffolds by adding glycerol (SHENZHOU et al., 2010). However, they are not able to determine the correct amount of glycerol because the mix can alter the silk fibroin molecules interactions, damaging the result on its surface. Therefore, our texture analysis methodology emerges as a framework for testing the proper concentration of glycerol.

As pointed out in Chapter 1, there exist several texture methods ranging from different domains. Despite the fact that there are several texture methods, they do not effectively capture the richness of patterns of the silk fibroin scaffolds. This is because patterns present a complexity surface information. This chapter presents a methodology for classifying surface properties of silk fibroin scaffolds by using the texture analysis attribute. The method proposed here is based on the artificial crawler model (ZHANG; CHEN, 2004; ZHANG; CHEN, 2005), and it was named artificial crawler-MinMax, short AC-MinMax. Differently to the original method, we propose a new rule of movement that not only moves artificial crawler agents toward higher intensity, as well as to lower ones. We confirm that this strategy increases the discriminatory power and overcomes the traditional methodology.

This chapter is organized as follows. Section 2.2 describes the original artificial crawler model in details. The proposed method to characterize texture images is presented in Section 2.3.

Section 2.4 discusses the experimental setup and the results for two experiments. Computational complexity is discussed in Section 2.5. Finally, conclusions are given in Section 2.6.

2.2 Artificial Crawlers Model

The texture method proposed in this study is based on the artificial crawlers model proposed in (ZHANG; CHEN, 2004; ZHANG; CHEN, 2005). Their agent-based model was first proposed in (ZHANG; CHEN, 2004) and then extended in (ZHANG; CHEN, 2005). In order to describe this model, let us consider an image that consists of a pair $(\mathcal{I}; I)$ – a finite set $\mathcal{I}$ of pixels and a mapping I that assigns to each pixel $p = (x_p, y_p)$ in $\mathcal{I}$ a intensity $I(p) \in [0; 255]$. Also, let us consider a neighborhood $h(p)$ that consists of pixels q whose Euclidean distance between p and q is smaller or equal to $\sqrt{2}$ (8-connected pixels):

$$\begin{aligned} h(p) &= \{q \mid d(p; q) \leq \sqrt{2}\} \\ d(p; q) &= \sqrt{(x_p - x_q)^2 + (y_p - y_q)^2} \end{aligned} \quad (2.1)$$

In image analysis, the artificial crawlers model assumes that each agent occupies one pixel of the image. At each time t , artificial crawler $A_t^i = \{e_t^i; p_t^i\} \forall i \in [0; N]$ is characterized by two attributes. The first attribute e_t^i holds the current level of energy. Such energy can either wax or wane their lifespan according to energy consumption and influence of the environment. The second attribute p_t^i is the current position of the artificial crawler in the image. The artificial crawlers act upon an environment. In images, the environment is mapped as a 3D surface with different altitudes that correspond to gray values in the z-axis. Higher-intensity pixels supply nutrients to the artificial crawlers (increase its energy), while lower-altitudes correspond to the land. Figure 1 shows a textured image and the peaks and valleys where the artificial crawlers can increase or decrease its energy life.

The N artificial crawlers begin with equal energy e_{nit} and are placed randomly on the surface (pixels) of the textured image:

$$\begin{aligned} p_0^i &= \text{rand}(\mathcal{I}) \\ e_0^i &= e_{nit} \end{aligned} \quad (2.2)$$

Then the evolution process starts following a set of specific rules. The aim of the artificial crawler is to move to areas of higher altitudes to absorb energy and sustain life. This way, the next step $p_{t+1}^i = f(p_t^i)$ depends on the gray level of its neighbors according to Equation 2.3. First, the artificial crawler settles down if the gray levels of its eight neighbors are lower than its own level (Figure 2 (a)). Second, the artificial crawler moves to a specific pixel if there exist one of its eight neighbors with unique higher intensity (Figure 2 (b)). Third, if there exists more than one neighbor with higher intensity, an artificial crawler moves to the pixel that was already

Figure 2 – Example of the three possible steps of artificial crawlers considering its eight neighbors. In (a), the artificial crawler i settles down (represented by the x-symbol in red color) the maximum in case of its intensity is lower than the intensity of the eight neighbors. In (b), the artificial crawler moves to the pixel of the highest intensity in case of its eight neighbors has an unique higher intensity pixel, and in (c), when the artificial crawler has more than one option of movement, i.e., the higher intensity pixels is not unique. In this case, the artificial crawler moves to a pixel that has already been occupied by another agent. Otherwise, it moves to either of the pixels of the highest intensity.

i.e. A_{t+1}^i eats up A_{t+1}^j if $p_{t+1}^i = p_{t+1}^j; e_{t+1}^i \geq e_{t+1}^j; i \neq j$. This law is inspired by nature and assumes that the artificial crawlers with higher energy are more likely to reach the peaks of the environment.

The evolution process converges to an equilibrium state when no further artificial crawlers are in movement (they are dead or settled down). In the original method, features are extracted using the number of artificial crawlers at each iteration and colonial properties. Each texture image is represented by four curves of evolution: (1) curve of living artificial crawlers, (2) curve of settled artificial crawlers, (3) curve of colony formation at a certain radius and (4) scale distribution of colonies. This representation has two significant drawbacks: (i) the extraction of this vector is very time-consuming due to the colony estimation, and (ii) the artificial crawlers move only in the direction of the maximum intensity, thus characterizing regions of high intensities in the image only.

2.3 An improved Artificial Crawlers Model

The original artificial crawler consists of moving a group of agents to a neighbor pixel towards to the highest intensity. Although the images were characterized with such model, the underlying idea does not extract all the richness of textural pattern. Our method differs from the original artificial crawler model regarding movement: each agent is not only able to move to the higher altitudes as well as to lower ones. It allows the model to extract the details present in peaks and valleys of the images.

First, the agents move to higher intensities as the original artificial crawler method. Thus, the artificial crawlers are set in a textured image using the rule of maximum intensity. Throughout the paper, this rule of movement will be referred as max. We can observe that the original artificial crawler method only models the peaks of a textured image. To obtain a robust and effective

texture representation, we propose to move artificial crawlers toward lower intensities – this rule of movement will be referred throughout the paper as min. In our method, artificial crawlers are randomly placed in the image with initial energy e . Then, the movement step is modified as follows:

$$\forall_i : e_i^t > e_{\min}; r_i^{t+1} = f(r_i^t)$$

$$f(r) = \begin{cases} r_i^t; & \text{if (a) is satisfied} \\ r_{\min}^t; & \text{if (b) is satisfied} \\ r_m^t; & \text{if (c) is satisfied} \end{cases}$$

- (a) Agents settle down if the grey level of its 8-neighbors are higher than itself.
- (b) Agents move to a specific pixel if there exist one of its 8-neighbors ($r_{\min}^t$) with lower intensity
- (c) If there exist more than one neighbor with lower intensity, an agent moves to the pixel that already was occupied (r_m^t).

The multi-agent systems using the rule of movement min is characterized as the original method by using the number of live agents at each time. Considering that now we have two rules of movement, the final feature vector of our method is composed by the concatenation of the curves of live agents for the rules max and min according to Equation 2.5.

$$j = [\max; \min] \quad (2.5)$$

In order to obtain the final feature vector, we run our method for the maximum of intensity as well as the minimum one. Although this strategy doubles the computing time, it allows extracting the details present in peaks and valleys of the images.

Figure 3 shows the curves of the evolution process for two classes using the two rules of movement: min and max. In this case, we set 14,000 artificial crawlers on its surface with 40 iterations along the stabilization process. We took the ten samples of two classes of textures from the album the Brodatz (BRODATZ, 1966), namely classes D4 and D7, to illustrate the feature separability of the proposed method. In Figure 2b is shown the number of live agents versus the number of iteration using the rule of movement min. Similarly, in Figure 2c, the curves are shown for the rule of movement max. This experiment shows that the original method, which uses only the min rule of movement, can fail in discriminating textural patterns. Further, this result can corroborate the importance of both rules of movement in the texture modeling.

2.4 Experimental Results

In this section, we demonstrate the effectiveness of the proposed method. We first outline details of the experimental setup, and then, experiments carried out on two datasets are discussed:

(a) Texture classes D4 (Class 1) and D7 (Class 2).

(b) min

(c) max

Figure 3 – Comparison of the proposed descriptors for 20 images, seen in (a), divided in two image classes of the Brodatz album: namely D4 and D7. In (b) is shown the curve with the number of alive agents for the rule min of movement, while in (c) the curves are computed with the rule max. It is worth noting in the plot of the letter (b), artificial crawlers move by using the rule min, the original propose cannot discriminate properly the two texture images due to its high variability intra-class in class 2.

Brodatz and silk fibroin. In Section 2.4.2 is described the whole process for image acquisition of silk fibroin scaffolds. Besides, we show comparative results with different texture methods.

2.4.1 Experimental Set up

The proposed method was first evaluated over texture classification experiments by using images extracted from Brodatz album (BRODATZ, 1966). This album (BRODATZ, 1966) is a well-known benchmark for evaluating texture methods. In our experiments, we used a total of 40 classes, with 10 samples each, as used in (BACKES et al., 2010). The sub-images have 200×200 pixels with 256 gray levels. One example of each class is shown in Figure 4. Although this texture dataset is widely used, it is limited in what concerns scale, viewpoint, and illumination changes.

The texture classification was carried out for ten-fold cross validation to avoid bias. At each round, we randomly divide the samples of each class into ten subsets of the same size, i.e., nine for training and the remaining for testing. The results are reported as the average value over the ten runs. For classification, we adopted the model Linear Discriminant Analysis (LDA). The underlying idea is to maximize the Euclidian distance between the means of the classes, while

Figure 4 – Samples of 40 classes of the Brodatz dataset used in the experiments. Each class contains 10 images of 200×200 pixels and 256 gray levels.

minimizing the within-class variance. For further information we refer to (FUKUNAGA, 1990).

Linear Discriminant Analysis (LDA) (FIDLER; SKOCAJ; LEONARDIS, 2006) was selected since it is well founded in statistical learning theory and has been successfully applied to various object detection tasks in computer vision. LDA, originally proposed by Fisher, computes a linear transformation ($T \in \mathbb{R}^{d \times n}$) of D , which $D \in \mathbb{R}^{d \times n}$ is a matrix and d denotes the number of features and n number of samples.

We optimized two parameters of the artificial crawler model: the number of agents and the way that agents move in the evolution process. The number of agents placed on the pixels of the image was initially set to 1;000, varying from 1;000 to 35;000. In our experiments, all the agents were born with an initial energy e of 10 units and the loss for each iteration consumes 1 unit of energy. The absorption rate was set to 0.01 regarding the current pixel. For the survival threshold and the upper bound of energy were set to 1 and 12 units, respectively.

2.4.2 Performance Evaluation

Experiment 1: First, we perform an analysis of our method on the Brodatz dataset. Figure 5(a) presents the correct classification rate versus the number of iterations. The results for the original artificial crawler is shown as curve max while the results for our method is shown as curve min and max. For a complete comparison, we also provide the results for a method which

agents move to pixels with lower intensity – curve min. As can be seen, the proposed method provided the highest correct classification rates for all values of iterations. These experimental results indicate that the proposed method significantly improves performance over the traditional methods. We can also observe that the rule min provided higher rates than the rule max, given the idea that valleys are more discriminative than peaks in the Brodatz dataset.

Another important parameter of the artificial crawler methods is the initial number of agents. Figure 5(b) shows the correct classification rates versus the number of agents. As in the previous experiment, our method achieved the highest rates compared to the other two strategies. Again, the rule min provided higher rates than the rule max. Another important observation from Figure 5(b) is that by using a few agents, the methods achieved good classification results, which makes the artificial crawler methods suitable for real-time applications. Using these two plots, we can determine the best parameters of our method to $t_{\max} = 41$ and $n = 27k$.

Figure 5 – Comparison rules of movement for the movement of artificial crawlers, varying (a) the number of iterations and (b) the number of agents in the Brodatz dataset.

Table 1 shows the results of the proposed method and the comparison with well-known texture analysis methods. The first column shows the name of the methods, followed by the number of descriptors necessary to reach such rate. The third column illustrates the number of images correctly classified, and, finally, the ten-fold cross-validation of the correct classification rates. It is observed that our method outperforms the traditional methods of the literature. The highest classification rate of 98:25% with a deviation of $\pm 1:69$ was obtained by our method, which is followed by a classification rate of 95:25% with a deviation of $\pm 3:43$, obtained by the Gabor filter, one of the most traditional texture analysis method.

Experiment 2: In this experiment, we present a comparative study of our method to assess the quality of the silk fibroin scaffolds. Our goal is to provide an effective method to support the visual analysis, thus reducing the subjectiveness of conclusions based on the human analysis. The potential of the silk fibroin is enhanced by including glycerol solutions during scaffold

Method	ND	Images correctly classified	CCR (%)
Fourier descriptors	101	346	86.50 ($\pm 6:58$)
Co-occurrence matrices	40	365	91.25 ($\pm 2:65$)
Original artificial crawler	160	372	93.00 ($\pm 5:50$)
Gabor filter	48	381	95.25 ($\pm 3:43$)
Proposed method (AC-MinMax)	100	393	98.25 ($\pm 1:69$)

Table 1 – Experimental results for texture methods in the Brodatz dataset. ND means the number of dimensions of the feature space.

formation (SHENZHOUE *et al.*, 2010). In general, such concentration can range from 0% to 10% with step of 2:5%. This dataset contains 5 classes, each of ten 200×200 pixel images. Figure 6 shows three samples for each concentration.

Figure 6 – Samples picked randomly for the glycerol concentration of 2:5%. The first column corresponds to 0% of concentration, the second 2:5%, and so on up to 10%.

We perform the same experiment to determine the best parameters of iteration and number of agents in the Silk Fibroin dataset. Figure 7(a) presents the evaluation of the number of iterations t , while Figure 7(b) presents the evaluation of the number n of artificial crawler, for different strategies of movement: min, max and min $\cup$ max. Since the images have the resolution of 200×200 pixels, our method can be evaluated with randomly and deterministic initial setting of agents over the image surfaces. Using both plots, we found that the best results are achieved for $t_{\max} = 7$ and $n = 28k$.

In the silk fibroin dataset, our method achieved highest classification rates when compared with traditional texture analysis methods. The experimental results, presented in Table 2, shows that although the number of descriptors ND of our method is high (a hundred), our method achieved the highest classification rate of 96%, with deviation of $\pm 8:43$. Thereby we cannot affirm that it is superior when compared to other methods, these experimental results indicate that our method is consistent and can be applied in real-world applications.

Figure 7 – Comparison of artificial crawler methods for different values of (a) iterations and (b) number of agents in the silk fibroin dataset.

Method	ND	Images correctly classified	CCR (%)
Fourier descriptors	101	39	78.00 ($\pm 22:01$)
Co-occurrence matrices	40	47	94.00 ($\pm 9:66$)
Original artificial crawler	160	42	84.00 ($\pm 15:78$)
Gabor filter	48	31	62.00 ($\pm 19:44$)
Proposed method (AC-MinMax)	100	48	96.00 ($\pm 8:43$)

Table 2 – Experimental results for texture methods in the silk fibroin dataset. ND means the number of dimensions of the feature space.

2.5 Computational Complexity

The proposed method initiates n artificial crawlers and each one performs a walk with $t_{\max}$ steps. The steps of all artificial crawlers state to a complexity of $O(n \times t_{\max})$. Once we run the artificial crawlers for both rules, the computational complexity is given by $O(2 \times n \times t_{\max})$. For comparison, we have used ($n = 27k; t_{\max} = 41$) and ($n = 28k; t_{\max} = 7$) in the Brodatz and silk fibroin datasets, respectively. We can see that the artificial crawlers need a few steps to achieve the highest correct classification rates.

Although our strategy doubles the computational complexity, experimental results indicate that the proposed method significantly improves classification rate, e.g., from 93% to 98:25% on Brodatz dataset and 84% to 96% on silk fibroin dataset, over the original method. Furthermore, the proposed method still has a good complexity in comparison to the complexities of well-known methods for texture classification, such as the complexities of Gabor filters ($O((w \times h) \log(w \times h))$) and the co-occurrence matrices ($O(w \times h)$), where w and h correspond to the width and height of the image, respectively, and $(w \times h)$ is the number of pixels of the image. It should be noted that the number of artificial crawlers is, usually, less than the number of pixels, i.e., $n < (w \times h)$. For instance, $n = 27k$ and $(w \times h) = 40k$ in the Brodatz dataset.

2.6 Remarks of the Chapter

In this chapter, we presented a novel method based on artificial crawler for texture classification. We have demonstrated how the feature space can be improved by combining min and max curves, instead of using only the strategy for the maximum of intensity of the pixels. Although our method provides a feature vector with double of dimensionality, the correct classification rate was superior compared with the original method on the most popular benchmark for texture analysis. Furthermore, we successfully tested our strategy on silk fibroin scaffolds analysis. This strategy can be extended to explore different imaging applications. As part of the future work, we plan to focus on evaluating the deterministic sampling, i.e, each pixel of the image is initialized with an agent.

--- --- FRACTAL DIMENSION OF ARTIFICIAL CRAWLERS --- ---

3.1 Introduction

Swarm systems or multi-agent systems, have been long applied in computer vision (LIU; TANG, 1999; WONG; LAM; SIU, 2001; RODIN et al., 2004; GUO; LEE; HSU, 2005; JONES; SAEED, 2007; MAZOUZI; GUESSOUM; MICHEL, 2009). In texture analysis, the swarm system can be found in a select group of approaches, such as the deterministic tourist walk (BACKES et al., 2010; GONCALVES; BRUNO, 2013a; GONCALVES; BRUNO, 2013b), the ant colony (ZHENG; WONG; NAHAVANDI, 2003), and the artificial crawlers (ZHANG; CHEN, 2004; ZHANG; CHEN, 2005). The basic idea of the swarm algorithms consists of creating a system by means of the agent interaction, i.e., a distributed agent system with parallel processing, and autonomous computing. In this chapter, we propose a novel method for texture analysis based on the artificial crawlers model (ZHANG; CHEN, 2004; ZHANG; CHEN, 2005). This swarm system consists of a population of agents, referred here as artificial crawlers, that interact with each other and the environment, in this case, an image. Each artificial crawler occupies a pixel, and its goal is to move to the neighbor pixel of greater intensity. The agents store their current position in the image and a corresponding energy that can wax or wane their lifespan depending on the energy consumption of the image. The population of artificial crawlers stabilizes after a certain number of iterations, i.e., when there is no change in their spatial positions.

In the original swarm system (ZHANG; CHEN, 2004; ZHANG; CHEN, 2005), the artificial crawlers move only in the direction of the maximum intensity, thus characterizing regions of high intensities in the image. However, in texture analysis, regions of low intensities are as important as regions of high intensities. Therefore, we propose a new rule of movement that also moves artificial crawler agents in the direction of lower intensity. Our approach differs from the original artificial crawlers model in terms of movement: each agent is able to move to

the higher altitudes, as well as to lower ones. To quantify the state of the swarm system after the stabilization, we propose to employ the Bouligand-Minkowski fractal dimension method (TRICOT, 1995). The fractal dimension method is widely used to characterize the roughness of a surface, which is related to its physical properties. In (GONCALVES; BRUNO, 2013a), the authors have also used fractal dimension to characterize the agents. The main differences of this approach lie on the type of agents and the dilation process used to estimate the fractal dimension. First, the work of Goncalves et. al. proposed the use of deterministic partially self-avoiding walks; the agents do not interact with each other. We, on the other hand, use the artificial crawlers, which are based on agent interaction. Furthermore, this earlier work estimates the fractal dimension of the attractors found by the agents, while we estimate the fractal dimension based on the energy information and the spatial position of each agent after the stabilization.

We have conducted experiments in two datasets widely accepted in the literature of texture analysis: Brodatz and Vistex. Experimental results have shown that our method overcomes different traditional methods over the Vistex dataset. Besides, our approach significantly improves the classification rate compared to the original artificial crawlers method. The superior results rely on two facts: the fractal dimension estimation of the swarm system and the two rules of movement. On one hand, the use of both rules of movement characterizes both regions of the image's texture. On the other hand, the fractal dimension improves the ability of discrimination obtained from the swarm system of artificial crawlers. Moreover, the idea of the fractal dimension estimation can be used for other swarm systems.

The main contributions of this method are:

- a new rule of movement for the artificial crawlers method. The original method is less efficient to describe images because it moves the agents to higher intensities only. The proposed method describes images by using two rules of movement, i.e., the swarm system finds the minima and maxima of images.
- a new methodology to image description based on the energy information acquired from two rules of movement. Although we can find the minima and maxima of images directly, the underlying idea is to characterize the path of movement during the evolution process. In this case, the energy information was considered the most important attribute due to its capacity of representing the interaction between the movement of agents and the environment.
- to enhance the discriminatory power of our method, we use the energy information and the spatial position of each agent to estimate the fractal dimension of the image surface, we employed the fractal dimension of Bouligand-Minkowski.

This chapter is structured as follows. Here, we do not describe the artificial crawlers model since it was done in details in Chapter 2, Section 2.2. In Section 3.2, it is presented the

basis for the fractal dimension and the Bouligand-Minkowski method. A proposed method for texture analysis based on the fractal dimension of artificial crawlers is presented in Section 3.3. Finally, Section 3.4 reports the experimental results, followed by the conclusion of the chapter in Section 3.5.

3.2 Fractal Dimension

In 1977, Mandelbrot introduced a new mathematical concept to model natural phenomena, named fractal geometry (MANDELBROT, 1977). This formulation received a lot of attention due to its ability to describe irregular shapes and complex objects that Euclidean geometry fails to analyze. In contrast, fractal geometry assumes that an object holds a non-integer dimension. Thus, estimating the fractal dimension of an object is basically related to its complexity. The patterns are characterized in terms of space occupation and self-similarity at different scales. The interactive construction process of the Von Koch curve is a typical example of self-similarity of fractals (MANDELBROT, 1983).

The first definition of dimension was proposed by the Hausdorff-Besicovitch measure (HAUSDORFF, 1919), which provided the basis of the fractal dimension theory. He defined a dimension for point sets as a fraction greater than their topological dimension. Formally, given $X \in \mathbb{R}^d$, a geometrical set of points, the Hausdorff-Besicovitch dimension $D_H(X)$ is calculated by:

$$D_H(X) = \inf\{s : H^s(X) = 0\} = \sup\{H^s(X) = \infty\} \quad (3.1)$$

where $H^s(X)$ is the s -dimensional Hausdorff measure (in Equation 3.2).

$$H^s(X) = \liminf_{\delta \rightarrow 0} \sum_{i=1}^{\infty} |U_i|^s : U_i \text{ is a } \delta\text{-cover of } X \quad (3.2)$$

where $|U|$ stands for the diameter in $\mathbb{R}^d$, i.e $|U| = \sup\{x - y : x, y \in U\}$.

In image analysis, the use of the Hausdorff-Besicovitch definition may be impracticable (THEILER, 1990). An alternative definition generalized from the topological dimension is commonly used. According to this definition, the fractal dimension D of an object X is:

$$D(X) = \lim_{\epsilon \rightarrow 0} \frac{\log N(\epsilon)}{\log \frac{1}{\epsilon}} \quad (3.3)$$

where $N(\epsilon)$ stands for the number of objects of linear size ϵ needed to cover the whole object X .

There are a lot of algorithms to estimate the fractal dimension of objects or surfaces. The most known algorithms are: box-counting (RUSSELL; HANSON; OTT, 1980), differential box-counting (CHAUDHURI; SARKAR, 1995), e-blanket (PELEG et al., 1984), fractal model based

on Fractional Brownian motion (PENTLAND, 1983), power spectrum method (PENTLAND, 1983), Bouligand-Minkowski (TRICOT, 1995) among others; as well as extensions of fractals, such as multifractals (CHAUDHARI; YAN; LEE, 2004), multiresolution fractals (FLORINDO; BRUNO, 2016) and fractal descriptors (BACKES; CASANOVA; BRUNO, 2012; FLORINDO ANDRÉ R. BACKES; BRUNO, 2012). One of the most accurate methods to estimate the fractal dimension is the Bouligand-Minkowski method (TRICOT, 1995). The Bouligand-Minkowski fractal dimension $D_B(X)$ depends on a symmetrical structuring element Y :

$$D_B(X; Y) = \inf \{ I ; m_B(X; Y; I) = 0 \} \quad (3.4)$$

$$m_B(X; Y; I) = \lim_{e \rightarrow 0} \frac{V(\partial X \oplus eY)}{e^{n-I}}$$

where m_B is the Bouligand-Minkowski measure, e is the radius of the element Y and V is the volume of the dilation between element Y and boundary ∂X . In the Euclidean space, V is a smooth I -dimensional manifold imbedded in $\mathbb{R}^n$, such that $V \sim L e^{n-I}$. To eliminate the explicit dependence on the element Y , a simplified version of the Bouligand-Minkowski fractal dimension can be described by using neighborhood techniques as:

$$D_B(X) = \lim_{e \rightarrow 0} D_T - \frac{\log V(X \oplus Y_e)}{\log e} \quad (3.5)$$

For instance considering an object $X \in \mathbb{R}^3$, the topological dimension $D_T = 3$ and Y_e is a sphere of diameter e . Varying the radius e , it estimates the fractal dimension based on the size of the influence area V created by the dilation of X by Y_e .

3.3 Proposed Method

In this section, we describe the proposed method, named FDAC, which is based on the fractal dimension of artificial crawlers. Basically, our method can be divided into two parts: artificial crawlers are performed in the texture image and then the fractal dimension of these artificial crawlers is estimated. The next sections describe these steps of our method.

3.3.1 Artificial Crawlers Model in Images

Although the original artificial crawlers method achieves promising results, the idea of moving to pixels with higher intensities does not extract all the richness of textural pattern of the images. In the method proposed here, the independent artificial crawlers are also able to move to lower intensities (valleys). It allows the model to take full advantage and capture the richness of details present in the peaks and valleys of the images.

In the first step, the artificial crawlers move to higher intensities as the original method. Thus, artificial crawlers $A_T^i = \{p_T^i; e_T^i\}$ are obtained after the evolution process converges, where

T is the number of steps needed for the system to converge. The artificial crawlers which move to higher intensities will be referred to as $U_T^i = \{p_T^i; e_T^i\}$ and this rule of movement will be referred to as max. The same hold for crawlers that seek for lower values, in which case the rule of movement is referred to as min. Figure 8 shows an example of 1,000 artificial crawlers using the rules of movement max and min. The green marks stand for the final position (convergence) of the live artificial crawlers, while the red ones represent the final position of the dead artificial crawlers. As we can see, the live artificial crawlers can achieve the highest intensities. As important as the live artificial crawlers, the dead ones aggregate information from the surface of the environment.

Artificial crawlers are born in different areas of altitude and their migration activity either leads to gain or loss of energy. The energy of each agent is directly influenced by the absorption from the environment. For instance, let us suppose that the environment has two peaks, p_1 and p_2 , with different altitudes, a_{p_1} and a_{p_2} . If $a_{p_1} > a_{p_2}$, the energy of the agent that reached the peak p_1 is higher than the energy of another agent that reached the peak p_2 . It occurs because the energy absorption is higher for the agent that is climbing the peak p_1 . Therefore, we can say that the energy corresponds to the history of the agents' steps.

Figure 8 – The final position of 1,000 artificial crawlers, (a) by using the rule of movement max and (b) by using the rule of movement min. Green marks stand for live artificial crawlers while red marks represent dead artificial crawlers.

In Figure 8 (a), we can observe that the original method – detailed in Chapter 2 in Section 2.2 only describes the peaks of a given texture image. Differently, we propose to move artificial crawlers toward lower intensities as well. In this approach, artificial crawlers $Q_t^i = \{p_t^i; e_t^i\}$ are randomly placed in the image with initial energy e_{nit} . The evolutionary process is modified so that the next step of an artificial crawler is to move towards the lower intensity. This rule of

movement will be referred to throughout the chapter as min, which is described in Equation 3.6:

$$f(p_t^i) = \begin{cases} 8 & p_t^i; \text{ if } l(p_t^i) \leq l(p) \forall p \in h(p_t^i) \\ > & p; \text{ if } l(p) < l(p_t^i); l(p) < l(q) \forall p, q \in h(p_t^i); p \neq q \\ \cdot & p; \text{ if } l(p) < l(p_t^i); l(p) \leq l(q) \forall p, q \in h(p_t^i); p \neq q; p \text{ was visited} \end{cases} \quad (3.6)$$

An example of the artificial crawlers using the rule of movement min can be seen in Figure 8 (b). Again, green marks represent the final position of live artificial crawlers while red marks represent the dead artificial crawlers. These artificial crawlers complement the artificial crawlers that use the rule of movement max, aggregating more information about the surface.

In the end of this step, we have two populations of N artificial crawlers $U_T^i = \{p_T^i; e_T^i\}$ and $Q_T^i = \{p_T^i; e_T^i\}$ which correspond to the artificial crawlers using rules of movement max and min, respectively.

3.3.2 Fractal Dimension of Artificial Crawlers

In this section, we describe how to quantify the population of artificial crawlers using the fractal dimension theory. To estimate the fractal dimension using the Bouligand-Minkowski method, the population of artificial crawlers can be easily mapped onto a surface $S \in \mathbb{R}^3$, by converting the position $p_T^i = \{x_i; y_i\}$ and the energy e_T^i of each artificial crawler into a 3D point $s_i = (x_i; y_i; e_T^i)$. The energy is important because it contains the information related to the evolutionary process of the artificial crawlers. This mapping can be seen in Figure 9 (a). We should note that the Z axis is the energy of the artificial crawlers.

The Bouligand-Minkowski method estimates the fractal dimension based on the size of the influence area $|S_r|$ created by the dilation of S by a radius r . Thus, varying the radius r , the fractal dimension of surface S is given by:

$$D = 3 - \lim_{r \rightarrow 0} \frac{\log V(r)}{\log r} \quad (3.7)$$

where $V(r)$ is the influence volume obtained through the dilation process of each point of S using a sphere of radius r :

$$V(r) = |\{s' \in \mathbb{R}^3 \mid \exists s \in S: |s - s'| \leq r\}| \quad (3.8)$$

The dilation process is illustrated in Figure 9. A group of artificial crawlers is mapped into a 3D space, shown in Figure 9 (a). Each point of the 3D space is dilated by a sphere of radius r (Figure 9 (b) and (c)). As the value of radius r is increased, more collisions are observed among the dilated spheres. These collisions disturb the total influence volume $V(r)$, which is directly linked to the roughness of the surface.

(a) Artificial crawlers mapped onto a 3D space by converting the final position and the energy into a point in the surface.

Figure 9 – An illustration of the dilation process for the fractal dimension estimation of artificial crawlers. The final position of the artificial crawlers was obtained using the rule of movement max and maximum energy $e_{\max} = 30$.

From the linear regression of the plot of $\log r \times \log V(r)$, the Bouligand-Minkowski fractal dimension is computed by:

$$D = 3 - a \quad (3.9)$$

where a is the slope of the estimated line.

3.3.3 Feature Vector

Although the fractal dimension provides a robust mathematical model, it describes each object by only one real value D – the fractal dimension. This is a problem because it is known that objects with distinct shapes can have the same fractal dimension, for instance, the well-known fractals: Peano curve, Dragon curve, Julia set and the boundary of the Mandelbrot set have the same Hausdorff dimension equals to 2. To overcome this characteristic, the concepts of

fractal descriptors is adopted (FLORINDO; BRUNO, 2013). This way, the fractal dimension of the object is considered the entire curve of fractality. It provides a rich shape descriptor that can be successful to discriminate shapes and patterns.

In order to improve the discrimination power of our method, we use the entire curve $V(r)$ instead of using only the fractal dimension:

$$j_t = [V(1); \dots; V(r_m)] \quad (3.10)$$

where t is the rule of movement used by the artificial crawler and r_m is the maximum radius.

Considering that we have two rules of movement, the final feature vector is composed by the concatenation of $j_{\max}$ and $j_{\min}$ according to Equation 3.11. The feature vectors $j_{\max}$ and $j_{\min}$ are obtained by using the fractal dimension estimation of artificial crawlers U_T^i and Q_T^i after the stabilization, respectively.

$$j = [j_{\max}; j_{\min}] \quad (3.11)$$

The importance of using both rules is corroborated in Figure 10. Figures 10 (b) and (d) show the feature vectors by using $j_{\max}$ only, and Figures 10 (c) and (e) show the feature vectors by using $j_{\min}$ only. An example of those feature vectors is obtained for four different image classes, each with 10 samples, as shown in Figure 10 (a). The classes D16 and D18 are discriminated using the rule of movement max (Figure 10 (b)), while the rule of movement min is not able to discriminate those two classes accordingly (Figure 10 (c)). On the other hand, the classes D49 and D93 are only discriminated if the rule of movement min is used (Figure 10 (e)). These plots corroborate the importance of using both rules of movement for texture recognition.

3.3.4 Computational Complexity

In the proposed method, N artificial crawlers are performed in the image of size $W \times W$ pixels. The swarm system converges after M steps, which leads to a computational complexity of $O(NM)$. After stabilization, we propose to quantify the swarm system by means of the fractal dimension. To calculate the dilation process, the Euclidean distance transform (MEIJSTER; ROERDINK; HESSELINK, 2000) is a powerful and efficient tool. This transform calculates the distance between each point of the 3D space and the surface. Several authors (SAITO; TORIWAKI, 1994; MEIJSTER; ROERDINK; HESSELINK, 2000) proposed algorithms for computing the Euclidean distance transform in linear time. The time complexity is linear in the number of points of the 3D space, which is $O(W \times W \times e_{\max})$ – $W \times W$ is the size of the image and $e_{\max}$ is the maximum energy of the agents. Usually, the maximum energy $e_{\max}$ is a small number (e.g. in this work the maximum energy is 20). Thus, we can ignore $e_{\max}$ in the complexity, since $W \gg 20$ in image applications. Finally, the computational complexity of the proposed method is stated as $O(NM + W^2)$.

Figure 10 – An example of feature vectors using the rules of movement min and max. The classes of texture are only discriminated if both rules are used.

Let us discuss the best, worst and average case based on the number of steps of the swarm system. The best case considers that the swarm system converges in one step ($M = 1$). Thus, the computation complexity is $O(N + W^2)$. In the worst case, the swarm system takes more than N steps, however, it is stopped in $M = N$ steps without the stabilization. The worst case leads to a complexity of $O(N^2 + W^2)$. It is important to emphasize that the worst case rarely occurs, requiring a specific configuration of the texture image and even a random image does not produce this special case. In order to analyze the average case, in Figure 11, we plot the average number of steps needed to converge over 400 images. We can see that the two rules of movement min and max present similar behavior. Also, the number of agents does not influence the number of steps to converge (e.g. the difference between the average number of steps for $N = 5k$ and $N = 40k$ is only 1:03 steps). Given that $M \sim 13$ for $N = 50k$, the average case leads

to a complexity which is very close to the best case, $O(N + W^2)$, and it is a good complexity in comparison to the complexities of Gabor filters $O(W^2 \log W)$ and co-occurrence matrices $O(W^2)$.

Figure 11 – Average number of steps to converge using the rules of movement min and max. The average number of steps was averaged over 400 images.

3.4 Experimental Results

In order to evaluate the proposed method, experiments were carried out on image datasets of high variability. We first describe such datasets, the experiments to evaluate the parameters of our proposed method, and then the comparative results with the state-of-the-art methods. We performed experiments on the two most used image datasets of texture: Brodatz (see the description in Chapter 2) and Vistex datasets. To evaluate our method, we used the Brodatz dataset with 111 classes, with samples of 200×200 pixels and 256 gray levels.

The Vision Texture dataset (SINGH; SHARMA, 2001) (or Vistex) consists of natural colorful textures taken under several scales and illumination conditions. It contains 54 images captured with an original size of 512×512 pixels. Each image was split into sub-images with 128×128 pixels, with 16 samples per class, resulting in 864 images. Figure 12 shows four texture samples.

In our experiments, Linear Discriminant Analysis (LDA) (TIMM, 2002; FUKUNAGA, 1990) in a 10-fold cross-validation strategy was adopted in the task of classification, as described in Chapter 2, Section 2.4.

The features used in this method, and the parameter evaluation, are in the next section.

Figure 12 – Four classes of 54 texture surfaces of the Vistex dataset. Each class has 16 samples of 128×128 pixels and 256 gray levels.

3.4.1 Parameter Evaluation

In this section, we evaluate the three main parameters of our method: number of artificial crawlers N , maximum energy $e_{\max}$ and maximum radius r_m of the fractal dimension. The other parameters were set according to (ZHANG; CHEN, 2005), since their possible values do not affect the final success rate. Each artificial crawler is born with initial energy $e_{\text{nit}} = 10$, the survival threshold $e_{\min} = 1$ and the absorption rate $I = 0.01$.

Since the three parameters are dependent, to set a specific configuration we first vary them together to find out the best parameter setting. In this case, we vary the energy from 5k to 40k agents, with the maximum energy ($e_{\max}$) ranging from 5 to 35 and, by using radiuses from $\sqrt{5}$ to $\sqrt{40}$. We test on every possible setting to determine which values we must use in order to obtain the best classification rate. For the Brodatz dataset, the best parameters are $N = 30k$, $e_{\max} = \sqrt{15}$, $r_m = \sqrt{37}$, while for the Vistex dataset the best ones are $N = 15k$, $e_{\max} = 20$ and $r_m = \sqrt{38}$. Notice that the setting for both datasets are close to each other. For other datasets, we recommend using a number of agents N between 60% and 95% of the number of pixels, $10 \leq e_{\max} \leq 25$, and $\sqrt{30} \leq r_m \leq \sqrt{40}$. In Figure 13, we present the behavior for each parameter in texture classification. Since we want to evaluate the number of agents, then the maximum energy and the radius parameters were set according to the best setting previously identified. The success rates for the different numbers of artificial crawlers are shown in Figure 13 (a) and (b) for Brodatz and Vistex datasets, respectively. The number of artificial crawlers placed on the pixels was initially set to 5k with a coverage rate of 5%, varying from 5k to 40k for the Brodatz dataset and varying from 5k to 15k for the Vistex dataset due to the size of the samples

(128×128 pixels). We can observe that the highest success rate was obtained for $N = 30k$ and $N = 15k$ for the Brodatz and Vistex, respectively. Further, it was found that the combination of rules min and max significantly improve the success rate for all the numbers of artificial crawlers in both datasets. Also, the rule of going to the minimum intensity provides similar results to the original rule – max. These results suggest that the valleys and peaks are important to obtain a robust texture analysis.

Figure 13 – The plot for evaluating the number of artificial crawlers in the Brodatz and Vistex datasets.

The maximum energy of the artificial crawlers is evaluated in the plot of the Figure 13.

Figure 13 (c) presents the results for the Brodatz dataset while Figure 13 (d) shows the results for the Vistex dataset. The maximum energy parameter was evaluated by the fact that it limits the artificial crawler energy and, consequently, can limit the fractal dimension space. However, the experimental results show that different values of maximum energy do not influence the success rate considerably. The highest success rate was obtained for $e_{\max} = 15$ using the Brodatz dataset and for $e_{\max} = 20$ using the Vistex dataset. It can be noted that the same behavior for the rules of movement was obtained here, with the combination of rules providing the highest success rates.

In the plots of Figures 13 (e) and (f), the maximum radius of the fractal dimension estimation is evaluated. As expected, the success rate increases as the radius increases and stabilizes after a certain radius. The maximum radius $r_m = \sqrt{37}$ provided the highest success rate of 99.25% for the Brodatz dataset. For the Vistex dataset, a success rate of 95.95% was obtained with the maximum radius $r_m = \sqrt{38}$. Just as the preliminary results suggested, the combination of rules of movement provides the highest success rates.

3.4.2 Comparison with other Methods

The proposed method, which is enriched by the fractal dimension estimation of artificial crawlers, is compared to traditional texture methods, namely Fourier descriptors (AZENCOTT; WANG; YOUNES, 1997), co-occurrence matrices (PALM, 2004; HARALICK; SHANMUGAM; DINSTEIN, 1973), Gabor filter (BIANCONI; FERNÁNDEZ, 2007; JAIN; FARROKHNI, 1991; GABOR, 1946), local binary pattern (OJALA; PIETIKÄINEN; MÄENPÄÄ, 2002), and multi fractal spectrum (XU; JI; FERMLLER, 2009). Moreover, the texture method using the artificial crawlers proposed in (ZHANG; CHEN, 2005) was also used in this comparison. We considered the traditional implementation of each method and its parameter configuration as described below, which yields the best result.

Fourier descriptors: these descriptors are obtained from the Fourier transform of the texture image. Each descriptor is the sum of the spectrum values within a radius from the center. The best results were obtained by radius with increment by one. Thus, for an image of 200×200 pixels, 99 descriptors are obtained. More information about the Fourier descriptors can be found in (AZENCOTT; WANG; YOUNES, 1997).

Co-occurrence matrices: they are computed from the joint probability distribution between pairs of pixels at a given distance and direction. In these experiments, we consider the distances from 1 to 5 pixels, and the angles 0° , 45° , 90° and 135° . Energy and entropy were calculated from these matrices to compose a 40-dimensional feature vector (HARALICK; SHANMUGAM; DINSTEIN, 1973; PALM, 2004).

Gabor filters: it convolves an image by a bank of Gabor filters (i.e., different scales and orientations). In the experiments, a bank of 40 filters (8 rotations and 5 scales) was used. The energy of each convolved image is used to compose the feature vector; in this case a 40-

dimensional feature vector. Additional information can be found in (BIANCONI; FERNÁNDEZ, 2007; JAIN; FARROKHNI, 1991; GABOR, 1946).

Artificial crawlers: N artificial crawlers, as those explained earlier, are performed in a texture image. Four feature vectors are then calculated: (i) the number of live artificial crawlers at each iteration, (ii) the number of settled artificial crawlers at each iteration, (iii) a histogram of the colony size formed by a certain radius and (iv) the scale distribution of the colonies. Finally, the four feature vectors are concatenated to compose a single vector. A complete description of the original method can be found in (ZHANG; CHEN, 2004; ZHANG; CHEN, 2005).

Deterministic tourist walk: this method (BACKES et al., 2010) is an agent-based method that builds a joint probability distribution of transient and attractor sizes for different values of memory sizes and two walking rules. In the experiments below, we used memory sizes ranging from 0 to 5.

Fractal-DW: this method can be described in three main steps: (i) attractors are found by deterministic partially self-avoiding walks; (ii) fractal dimension of the attractors is estimated; (iii) feature vector is built based on the dilation process of the fractal dimension estimation. We have followed the parameters suggested in (GONCALVES; BRUNO, 2013a).

Multi Fractal Spectrum: this method (XU; JI; FERMÜLLER, 2009) extracts the fractal dimension of three categorizations of the image: intensity, energy of edges, and energy of the Laplacian. For each categorization, a 26-dimensional MFS vector of uniformly spaced values was computed, totaling a feature vector of 78 dimensions.

Uniform rotation-invariant local binary pattern: the LBP method (OJALA; PIETIKÄLÄNEN; MÄENPÄÄ, 2002) calculates the co-occurrence of gray-levels in circular neighborhoods. We used three different spatial resolutions P and three different angular resolutions R – (P, R) : $(8, 1)$, $(16, 2)$ and $(24, 3)$.

In Table 3 we present the comparison of the texture methods on the Brodatz dataset. The proposed method provided comparable results to the local binary patterns and fractal-DW, and results superior to the other state-of-the-art methods. Although LBP features perform slightly better than our method, the experiment indicates that the proposed method significantly improves the success rate over the original artificial crawlers, i.e., from 89.75% to 99.25%.

Despite that the Brodatz dataset is widely used for texture classification, it does not contain textures with changes in terms of lighting conditions and perspectives. Hence, to evaluate the methods over textures closer to real-world applications, we also compared the results for the Vistex dataset, which are presented in Table 4. In this experiment, our method provided the highest success rate of 95.95%, which is superior to the result of the local binary patterns. Our method also significantly improved the success rate compared to the original artificial crawlers. Besides, it can be noted that our method achieved reliable results according to the small standard deviations in both datasets.

Table 3 – The experimental results for texture methods in the Brodatz database.

Method	Images correctly classified	Success rate (%)
Fourier descriptors	346	86.50 ($\pm 6:58$)
Artificial Crawlers	359	89.75 ($\pm 4:76$)
Co-occurrence matrices	365	91.25 ($\pm 2:65$)
Multi Fractal Spectrum	373	93.25 ($\pm 2:37$)
Gabor filter	381	95.25 ($\pm 3:43$)
Deterministic tourist walk	382	95.50 ($\pm 3:12$)
Fractal-DW	398	99.50 ($\pm 1:05$)
Local binary patterns	399	99.75 ($\pm 0:79$)
Proposed method (FDAC)	397	99.25 ($\pm 1:69$)

Table 4 – Experimental results for texture methods in the Vistex database.

Method	Images correctly classified	Success rate (%)
Fourier descriptors	672	77.78 ($\pm 4:67$)
Artificial Crawlers	691	79.98 ($\pm 4:65$)
Co-occurrence matrices	663	76.74 ($\pm 4:91$)
Deterministic tourist walk	734	84.95 ($\pm 4:13$)
Multi Fractal Spectrum	747	86.46 ($\pm 3:48$)
Gabor filter	774	89.58 ($\pm 2:61$)
Fractal-DW	744	86.11 ($\pm 4:42$)
Local binary patterns	801	92.71 ($\pm 2:43$)
Proposed method (FDAC)	829	95.95 ($\pm 2:50$)

3.5 Remarks of the Chapter

In this chapter, we have proposed a new method based on artificial crawlers and fractal dimension for texture classification. We have demonstrated how the feature vector extraction task can be improved by combining two rules of movement, instead of moving only for the maximum intensity of the neighboring pixels. Moreover, a strategy using fractal dimension was proposed to characterize the final configuration of the movement performed by the artificial crawlers. The idea of our approach improves the ability of discrimination obtained from the swarm system of artificial crawlers.

Although traditional methods of texture analysis – e.g. Gabor filters, local binary patterns, and co-occurrence matrices – have provided satisfactory results, the method proposed here has proved to be superior for characterizing textures on the Vistex dataset. On the Brodatz album, our method achieves the third best performance, being slightly inferior to the local binary pattern and to the fractal-DW methods. Experiments on both datasets indicate that our method significantly improved the classification rate with regard to the original artificial crawlers method. As future work, we believe that performance gains can be achieved by means of descriptors that explore further features, for example, by using features that represent shape.

MULTISCALE FRACTAL DESCRIPTORS BY MEANS OF NON-LINEAR DIFFUSION

4.1 Introduction

Multiscale image methods are inspired by the human vision interpretation of a scene by considering different kinds of information according to the depth of the analysis (RIESENHUBE; POGGI, 1999; WALTHER; KOCH, 2007). Inspired by biological studies, multiscale methods perform a sequential and hierarchical image analysis, driven by a different understanding of the key concept of scale. In the case of texture description, the scale is usually related to the representation of the regions where the intensity changes performed by a filter convolution before feature extraction. Thereby, multiscale texture description methods address the effort to combine the spatial accuracy of fine-scale methods with the ability to deal with coarse-scale methods. It is commonly accepted that texture description performed at different scales can improve the result of image classification (GANGEH; ROMENY; ESWARAN, 2007; XU; WU; CHEN, 2010; XU et al., 2012). Nonetheless, some papers have investigated how to determine automatically the optimal scale for multiscale approaches (HEATH et al., 1997; LINDBERG, 1998; YITZHAKY; PELI, 2003), but no consensus has been reached.

Over the past few decades, many different approaches have been developed for multiscale image representation. Kang et al. (KANG; MOROOKA; NAGAHASHI, 2005), for example, proposed a method using multiscale local autocorrelation features for texture segmentation. However, their method consisted of extracting small windows of textures randomly sampled close to the corners of the image. In addition, they reduced the feature space to a subspace using principal component analysis. The same idea of creating a multiscale representation and reduce the space with principal component analysis was presented in (GANGEH; ROMENY; ESWARAN, 2007). Furthermore, Gangeh et al. (GANGEH; ROMENY; ESWARAN, 2007) used the linear Gaussian filtering to construct a multiscale representation that equally smoothes all the

regions of the image. In (XU; WU; CHEN, 2010), it was developed a multiscale blob feature extraction for texture classification. They described images in terms of blobs of binary values. In contrast to our proposal, (GANGEH; ROMENY; ESWARAN, 2007) and (XU; WU; CHEN, 2010) used the linear Gaussian scale space for image representation that does not preserve the image structures that are important to perform texture analysis. Similar to our proposal, Aujol and Chan (AUJOL; CHAN, 2006) decomposed an image into the sum of two components for texture segmentation; however, they do not construct a multiscale representation that has proved to be very important in texture classification (GANGEH; ROMENY; ESWARAN, 2007; XU; WU; CHEN, 2010; XU et al., 2012). Recently, Xu et al. (XU et al., 2012) combined SIFT-like feature descriptors estimated at multiple window sizes of multi-fractal spectrum in the task of texture description. Another fractal-based texture analysis was proposed by Florindo et al. (FLORINDO; BRUNO, 2013). Although their method is said to be performed in different scales, they basically divide an image recursively into four same-size parts, not truly constructing a multiscale edge-preserving methodology. In addition, feature selection was performed before texture classification. Very recently, (FLORINDO; BRUNO, 2016) proposed wavelet-fractal dimension for texture classification. Differently, we use the concept of scale for texture description. Unlike (FLORINDO; BRUNO, 2013; FLORINDO; BRUNO, 2016), we do not use any method for space selection or dimensionality reduction.

In this chapter, we hypothesize that an image texture reveals different structures according to the scale of observation, so that the concept of multiscale representation might be of potential importance in texture analysis. Considering this hypothesis, we propose a multiscale fractal descriptor using the Perona-Malik equation (PERONA; MALIK, 1990). More specifically, the gray levels of an image correspond to the heat diffused at different levels represented in new derivative images. Inspired by the work of Yves Meyer (MEYER, 2001), we split each new derivative into a geometrical, named cartoon, and textural part, named texture. Subsequently, we estimate the Bouligand-Minkowski fractal dimension of each component and propose to combine the features to perform the texture classification. Experiments using well-known texture datasets – Brodatz, Vistex, Outex and Usptex – illustrate the characteristics of the proposed method. In addition, our method is compared with the traditional texture methods, such as Fourier descriptors, co-occurrence matrices, Gabor filters and, local binary patterns. The results indicate the superiority of the proposed method for texture analysis.

The main contributions of this study are:

- A new methodology to image description based on the multiscale analysis constructed from the Perona-Malik diffusion equation. We named our approach of MFD-PM.
- More discriminatory power, as demonstrated in experiments on multiscale image representation over texture classification.
- Demonstration that the combination of cartoon and textural components is better to capture

the richness of patterns present in image surfaces, improving the texture classification.

The chapter is organized as follows. Here, we do not describe the Bouligand-Minkowski fractal dimension since it was done in details in Chapter 3, Section 3.2. A new method for texture analysis based on the fractal dimension of multiple image scales is presented in Section 4.2. Finally, in Section 4.3 we report the experimental results, followed by the conclusion in Section 4.4.

4.2 Proposed Method

In this section, we describe the multiscale method, namely MFD-PM, which is based on the following three steps: (1) a multiscale image representation constructed from the anisotropic diffusion, (2) the cartoon-texture image decomposition and, (3) the use of the Bouligand-Minkowski fractal dimension on each of these images. A schematic diagram of our method is shown in Figure 14. In the next sections, we explain the steps of our method.

Figure 14 – Schematic representation of our proposal. The dotted-line frames correspond to the images obtained by anisotropic diffusion over the scale space, and t stands for the different scales. The image decomposition is applied to each image of the dataset resulting in two component images: cartoon and texture. Then, the fractal dimension is estimated from each image, and a feature vector is concatenated with the mean and standard deviation of the fractal.

4.2.1 Multiscale Texture Analysis

In texture analysis, we assume that the texture scale representation is related to the analysis of intensity changes in different levels. Despite its importance, there is not acceptable

solution to the scale-selection problem (YITZHAKY; PELI, 2003; LINDBERG, 2008). Thus, it would be needed to measure all meaningful structures appearing in an image, represented by different types of derivatives and different scales (WITKIN, 1983).

Considering this assumption, instead of describing images on a single scale, we addressed an image as a multiscale space. Thus, the multiscale paradigm has been successfully used for representing images at multiple scales, also known as scale-space theory. The underlying idea is that images can be processed considering a finite number of scales, according to which the original image is derived into a set of new images (LINDBERG, 2008). Different multiscale paradigms have been proposed in the literature, including quad-tree, pyramid, wavelets, linear diffusion, non-linear diffusion, and total variation scale-space. A brief overview of each paradigm is given in (SALDEN; ROMENY; VIERGEVER, 2001).

The most classical linear and non-linear scale spaces are modeled by diffusion-type partial differential equations (PDE). The most used way to produce a scale space is by continuously smoothing an image $I(x; y) : \mathbb{R}^2 \rightarrow \mathbb{R}^+$ with a Gaussian filter, which is referred to as Gaussian scale space. The idea is to filter an image $I(x; y)$ with isotropic variance t , so that $I(x; y; t) = I(x; y) * G_t$, where $I * G_t$ represents the convolution of the image with the Gaussian kernel G_t . A detailed description of the axioms of the Gaussian scale space can be found in (WEICKERT, 1999) and (DUITS et al., 2004). The PDE for the linear diffusion is $\partial_t I = DI = \text{div}(-\nabla I)$, where D denotes the Laplace operator $\partial_x^2 + \partial_y^2$ and ∇ is the gradient operator $(\partial_x; \partial_y)^T$, which yields the solution after a time N . In order to get the physical interpretation, we have that $\partial_t I$ expresses the energy or the heat variation at every position in the image. In fact, diffusion is a generalization of the Gaussian smoothing method. Other examples of linear filtering are Canny (CANNY, 1983) and Marr-Hildreth edge detectors (MARR; HILDRETH, 1980).

Also relevant is the work of Perona and Malik (PERONA; MALIK, 1990), who introduced the anisotropic diffusion inspired by the works of Witkin (WITKIN, 1983) and Koenderink (KOENDERINK, 1984), featuring a coarse-to-fine procedure for scale-space description and edge detection. The nonlinear diffusion is a smoothing technique that is sensitive to discontinuities in the image, making use of a low-pass filtering in homogeneous regions, which results in the preserving of the regions where transitions occur.

The continuous anisotropic diffusion is given by:

$$\frac{\partial I_t(x; y; t)}{\partial t} = \text{div}[\alpha(x; y) \nabla I_t(x; y)] \quad (4.1)$$

where $I_t(x; y)$ corresponds to the image at time t , ∇I_t the gradient of the image, div is the divergence operator, and α the diffusion coefficient. The main idea is to choose α adaptively according to the edges of the image. The continuous anisotropic diffusion in Eq. 4.1 can be

discretely implemented as:

$$I_{t+1}(x; y) = I_t(x; y) + \frac{1}{\lambda} [c_N: -\nabla_N I + c_S: -\nabla_S I + c_E: -\nabla_E I + c_W: -\nabla_W I]_t(x; y) \quad (4.2)$$

where λ controls the numerical stability, $-\nabla$ is the gradient magnitude, c is the conduction coefficient, N; S; E and W are the mnemonic subscripts for North, South, East and West. In the anisotropic diffusion equation, $c_t(x; y)$ is considered as a function of the gradient, such as $c_t(x; y) = g(-\nabla_t(x; y))$, and can be rewritten as:

$$I_{t+1}(x; y) = I_t(x; y) + \frac{1}{x_{(x; y)}} \sum_{r \in x_{(x; y)}} \hat{A}_{(x; y); r} g(-\nabla_{(x; y); r}) - \nabla_{(x; y); r} \quad (4.3)$$

where I_t is the cartoon approximation, t denotes the number of iterations, $(x; y)$ is the spatial position of each pixel, $x_{(x; y)}$ represents the number of neighbors, and $g(-\nabla)$ is the conduction function. The magnitude of the gradient is calculated by approximating its norm in a particular direction as follows:

$$-\nabla_r(x; y) = I_r - I_t(x; y); r \in x_{(x; y)} \quad (4.4)$$

The function $g(-\nabla)$ has to be a non-negative, monotonically decreasing function with $g(0) \sim 1$ and $\lim_{-\nabla \rightarrow \infty} g(-\nabla) = 0$. Thus, the anisotropic diffusion equation filters the inner region with lower gradient and stops the diffusion process at the inter-region edges with higher gradients in the image.

Perona and Malik proposed two diffusion functions:

$$g(|-\nabla|^2) = e^{-\frac{|-\nabla|^2}{K^2}} \quad \text{and} \quad g(|-\nabla|^2) = \frac{1}{1 + |-\nabla|^2 K^2} \quad (4.5)$$

Where the parameter K controls the heat conduction, also known as contrast parameter. If K is too large, the diffusion process will over smooth the image. In contrast, if K is too small, the diffusion process will stop the smoothing in early iterations. The first equation favors high-contrast edges over low-contrast ones, while the latter favors wide regions over smaller ones.

Many other nonlinear methods, based on Perona and Malik, have been presented thereafter (GUIDOTTI, 2009). In addition, PM model has been used for several image processing applications, such as edge-detection (ALVAREZ; LIONS; MOREL, 1992), image restoration (SAPIRO; RINGACH, 1996; TSCHUMPERL; DERICHE, 2005; CHAO; TSAI, 2006), image smoothing (TORKAMANI-AZAR; TAIT, 1996; TSUJI et al.,) and image segmentation (NIESSEN et al., 1997; BAKALEXIS; BOUTALIS; MERTZIOS, 2002).

In image decomposition, an image can be modeled as the sum of two meaningful components: the cartoon component and the texture component. The cartoon component stands

for the piecewise-smooth part consisting of the geometrical information of the image, while the texture component is the oscillating part. To extract the cartoon component, we employ anisotropic diffusion, while the texture component is calculated by the pixel-by-pixel subtraction of the original image and cartoon. Figure 15 illustrates this procedure at different levels of the multiscale analysis for an image example and its decomposition in cartoon and texture components.

Figure 15 – Example of a multiscale representation of a textured image with derivatives of different scales defined by $t_1; \dots; t_f$. Image decomposition of (a) Input image, into two components: cartoon and texture. The first row shows the cartoon or geometric regions, while the second row shows the oscillatory part, namely, texture component.

4.2.2 Fractal Dimension of Multiscale Image Analysis

Although the original Bouligand-Minkowski method achieves promising results on image description, it does not capture the richness of the patterns present in image surfaces, we considered that this is because it has been used solely over one single image component. Differently, to estimate the fractal dimension of an image using the Bouligand-Minkowski method, we first create a multiscale image representation. This representation produces derivatives at each scale

t (see Figure 15) by means of the anisotropic diffusion of Perona and Malik. By handling the multiscale nature of the images, we were able to perform a feature extraction step to reveal patterns that single-scale analysis do not deal with. The anisotropic diffusion works by enhancing the richness of image details at different scales, while preserving important structures in image analysis, including edges and T-junctions.

For the characterization of the cartoon and texture components, defined as the total magnitude of the vertical and horizontal discrete gradients of an image, we are sampling the continuous scale dimension with n scales, $S = t_1; \dots; t_f$, which initializes at time $t = 0$, and evolves according to the partial differential equation that describes the diffusion process applied to the image. The process stops when t yields the solution obtained by the convolution of $t_{i+1} = t + Dt$, where $t_0 < t_1$. Hence, a set of derivative images $I_{t_1}; \dots; I_{t_f}$ is sampled from the scale space. Applying the anisotropic diffusion on them, as explained in Section 4.2.1, we obtain n texture images $T = \{T_{t_0}; T_{t_0+Dt}; \dots; T_{t_f}\}$, as well as n cartoon images $C = \{C_{t_1}; C_{t_0+Dt}; \dots; C_{t_f}\}$. After the multiscale representation, we estimate the fractal of Boulingand-Minkowski.

The Boulingand-Minkowski method estimates the fractal dimension based on the size of the influence area $|S_r|$ created by the dilation of S by a radius r . Thus, varying the radius r , the fractal dimension of surface S is given by:

$$D = 3 - \lim_{r \rightarrow 0} \frac{\log V(r)}{\log r} \quad (4.6)$$

where $V(r)$ is the influential volume obtained through the dilation process of each point of S using a sphere of radius r :

$$V(r) = |\{s' \in \mathbb{R}^3 \mid \exists s \in S: |s - s'| \leq r\}| \quad (4.7)$$

For this reason, the volumetric fractal method achieves invariance to rotation and translation and has shown promising results.

4.2.3 Feature Vector

In order to improve the discrimination power of our method, we use the entire curve $V(r)$ instead of using only the fractal dimension:

$$J_C = [V_{t_0}^C; V_{t_0+Dt}^C; \dots; V_{t_f}^C] \quad \text{and} \quad J_T = [V_{t_0}^T; V_{t_0+Dt}^T; \dots; V_{t_f}^T] \quad (4.8)$$

where J_C and J_T are the multiscale vectors computed from each of the components at all the scales of the derivative images.

After calculating the fractal dimension of the component images C and T for each scale, we take the average m and standard deviation s of these descriptors. This way, we are able to

reduce the dimensionality of the feature vectors, as given by:

$$m_C = \frac{1}{n} \sum_{i=0}^n V_{(t_0+i \cdot Dt)}^C \quad \text{and} \quad s_C = \frac{1}{n-1} \sum_{i=0}^n (V_{(t_0+i \cdot Dt)}^C - m_C)^2 \quad (4.9)$$

$$m_T = \frac{1}{n} \sum_{i=0}^n V_{(t_0+i \cdot Dt)}^T \quad \text{and} \quad s_T = \frac{1}{n-1} \sum_{i=0}^n (V_{(t_0+i \cdot Dt)}^T - m_T)^2 \quad (4.10)$$

With this procedure, we end up with the feature vector from the cartoon component $X_C = [m_C; s_C]$, and from the textural part $X_T = [m_T; s_T]$. The feature vectors are therefore obtained by using the fractal dimension of the scale space. Considering that we have two components, the final feature vector is composed by the concatenation of C and T, according to Equation 4.11.

$$J = [X_C; X_T] \quad (4.11)$$

4.2.4 Computational Complexity

Multiscale methods typically involve a computational cost higher than the feature description at a single scale. In the proposed method, the multiscale representation is performed with anisotropic diffusion over an image of size $N = W \cdot H$ pixels with a cost of $O(N)$. The fractal dimension step, then, is performed according to a dilation process that calculates the Euclidean distance between each point of the 3D space and the surface. The cost here follows that of linear time algorithms (SAITO; TORIWAKI, 1994; MEIJSTER; ROERDINK; HESSELINK, 2000), leading us to a cost of $O(2 \cdot N)$, i.e., N steps to calculate the anisotropic diffusion and other N steps to calculate the fractal dimension.

Since the input image is represented in T scales, each decomposed into 2 components, up to here, we have a total computational complexity of $O(2 \cdot T \cdot 2 \cdot N)$, that is, $2 \cdot T$ times the computational cost of the feature description step. Usually, the number of iterations is small – e.g., in this work the maximum number of iterations t is 200, with steps of 10. Thus, we can ignore the term $2 \cdot T$, since $N \gg T$ in image applications. Finally, the computational complexity of our multiscale method is $O(2 \cdot N)$.

4.3 Experimental Results

In order to evaluate our method, we performed experiments on four image datasets: Brodatz (BRODATZ, 1966), Vistex (SINGH; SHARMA, 2001), Outex (OJALA et al., 2002) and USPTex (BACKES; CASANOVA; BRUNO, 2012). The first two datasets were described in Chapter 2 and Chapter 3, respectively.

The Outex dataset (OJALA et al., 2002), in contrast to Vistex, is a challenging benchmark because it provides a larger set of textures acquired under controlled conditions, including the

illumination sources, the imaging geometry, and the characteristics of the equipment. Each texture sample is taken under three different illumination sources, nine rotation angles, and six spatial resolutions, totalizing 162 different images for each texture class. We can see that the illumination conditions increase the intra-class variability, making the classification task more difficult.

Figure 16 – Three classes of 68 texture surfaces of the Outex dataset. Each class has 20 samples of 128×128 pixels and 256 gray levels.

The USPTex dataset ([BACKES; CASANOVA; BRUNO, 2012](#)) contains 191 classes of natural textures taken under uncontrolled conditions. The images were captured with a size of 512×384 pixels. Each texture image was split into twelve non-overlapped sub-images with 128×128 pixels, available as gray levels. The image set consists of different natural surfaces including roads, clouds, vegetation, walls, gravel, seeds, and fabric. Some examples are shown in Figure 17. The variations in the viewpoint and illumination conditions directly affect the textured surface.

To evaluate the proposed method, we have performed two experiments: i) parameter evaluation and ii) comparison with the state of the art. The first experiment evaluates the influence of each parameter in the task of texture recognition; it is important to understand the proposed method. The second one compares its performance with the state of the art in four datasets. In our experiments, Linear Discriminant Analysis (LDA) ([TIMM, 2002](#); [FUKUNAGA, 1990](#)) in a 10-fold cross-validation was used to evaluate the classification performance. We described the LDA in Chapter 2, Section 2.4. To produce a single statistic, the results of the 10 processes are averaged.

Figure 17 – Four classes of 191 texture surfaces of the Usptex dataset. Each class has 12 samples of 128×128 pixels and 256 gray levels.

4.3.1 Parameter Evaluation

This section evaluates the four parameters of the proposed method: the initial scale t_0 , the incremental scale Dt , the final scale t_f , and the maximum radius r of the fractal dimension. The initial scale t_0 evaluated for each dataset is shown in the first plots of Figures 18 and 19. The plots provide the success rate of the cartoon, texture, and the concatenation of both components for t_0 varying from 10 to 80. We can observe that the highest success rate was obtained when $t_0 = 10$ for all datasets and the success rate decreases as t_0 increases. It indicates that the first scales are important in the texture recognition task.

The results also demonstrate that the concatenation of cartoon and texture components significantly improves the success rate for all datasets. These results suggest that homogeneous and heterogeneous regions of the image (cartoon and texture) are important to its description.

The success rates for different values of Dt in the four datasets are shown in the second plot of Figures 18 and 19. From the plots, we can observe that high values of Dt provided the highest success rates. As expected, the proposed method exploits a better range of scales with high values of Dt , which improves the texture description and consequently the success rate. For Brodatz, Vistex, Outex and Usptex datasets, the best result is achieved for $Dt = 50; 30; 80; 60$, respectively.

Figure 18 – Success rates for the Brodatz and Vistex datasets. Rows correspond to a specific dataset, while columns represent the evaluated parameters scales t_0 , Δt , t_f , and radius of the fractal dimension.

The results for different values of t_f are shown in the third plot of Figures 18 and 19 as function of x such that $t_f = t_0 + x * Dt$. Thus, x represents the number of scales used in the proposed method. For the Brodatz, Vistex, Outex and Usptex datasets, the maximum success is achieved for $x = 3; 5; 7$, and 3 , respectively. Given these results, we observe that few scales are required to obtain high success rates.

Finally, the fourth plot of Figures 18 and 19 evaluates the maximum radius of the fractal dimension. We can see that the success rate increases as the radius increases, stabilizing after a certain radius. Radius $r = 9; 6; 9$, and 7 provided the highest success rates for the Brodatz, Vistex, Outex and Usptex, respectively. The plots are important to point out the best parameters and to understand the behavior our method in texture recognition.

4.3.2 Comparison with other Methods

In this section, we compare the proposed method with the following traditional texture methods: Fourier descriptors (AZENCOTT; WANG; YOUNES, 1997), co-occurrence matrices (PALM, 2004; HARALICK; SHANMUGAM; DINSTEIN, 1973), Gabor filter (BIANCONI; FERNÁNDEZ, 2007; JAIN; FARROKHNI, 1991; GABOR, 1946), uniform rotation-invariant local binary patterns (OJALA; PIETIKÄINEN; MÄENPÄÄ, 2002). Recently, fractal methods have been also used in the comparisons, namely Multifractal spectrum (XU; JI; FERMÜLLER, 2009) and multiresolution fractal (FLORINDO; BRUNO, 2013). For each method, the traditional implementation was considered with a parameter configuration that yields the best results.

The comparative results for the Brodatz, Vistex, Outex and Usptex are shown in Table 5 (the best results are in bold). For each method, we show the number of features (dimensionality) and, the success rate and standard deviation in parenthesis. On the Brodatz, the local binary patterns, multiresolution fractal, and the proposed method have obtained the three highest success rates, respectively.

On the other three datasets, the proposed method achieved the highest success rate. Our method provided a success rate of 96:06% against 93:09% obtained by the multiresolution fractal on the Vistex dataset. On the Outex dataset, the proposed method achieved 86:54% and the co-occurrence matrices achieved 85:74%. Finally, on the Usptex dataset, the success rate was improved from 85:86% for the local binary patterns to 89:14% for the proposed method. These results corroborate the robustness in texture description of the proposed method since these datasets present several challenges, such as a high number of classes, viewpoint and scale changes.

We can also observe that using only the texture component, the results are already comparable to those of the literature. This component provided 92:59%; 82:06%; and 79:54% on the Vistex, Outex and Usptex datasets, respectively. Despite the promising results, the concatenation of cartoon and texture components achieved superior results on all the datasets,

indicating the importance of both components in texture recognition.

Method/Dataset	Brodatz		Vistex		Usptex		Outex	
	#	% ($\pm$ std)	#	% ($\pm$ std)	#	% ($\pm$ std)	#	% ($\pm$ std)
Fourier descriptors	101	80.81 ($\pm$ 2:37)	101	77.78 ($\pm$ 4:67)	101	81.76 ($\pm$ 2:68)	101	61.52 ($\pm$ 2:84)
Co-occurrence matrices	40	96.49 ($\pm$ 1:72)	40	76.74 ($\pm$ 4:91)	40	85.74 ($\pm$ 2:46)	40	85.86 ($\pm$ 2:25)
Gabor filters	48	91.88 ($\pm$ 2:06)	48	89.58 ($\pm$ 2:61)	48	78.31 ($\pm$ 2:91)	48	83.07 ($\pm$ 1:70)
Local binary pattern	54	98.11 ($\pm$ 1:31)	54	92.71 ($\pm$ 2:43)	54	83.38 ($\pm$ 2:09)	54	86.78 ($\pm$ 2:24)
Multifractal spectrum	78	89.01 ($\pm$ 2:03)	78	86.46 ($\pm$ 3:48)	78	75.51 ($\pm$ 3:14)	78	69.07 ($\pm$ 2:51)
Multiresolution fractal	FS	98.05 ($\pm$ 0:97)	FS	93.09 ($\pm$ 2:64)	FS	79.26 ($\pm$ 2:07)	FS	78.62 ($\pm$ 2:36)
Wavelet-fractal	PCA	91.56 ($\pm$ 0:01)	PCA	95.83 ($\pm$ 0:02)	PCA	85.56 ($\pm$ 0:02)	*	*
Cartoon component	69	93.51 ($\pm$ 1:63)	31	86.57 ($\pm$ 2:56)	69	80.00 ($\pm$ 4:38)	42	70.07 ($\pm$ 2:68)
Texture component	69	95.41 ($\pm$ 2:18)	31	92.59 ($\pm$ 2:78)	69	82.06 ($\pm$ 2:48)	42	79.54 ($\pm$ 3:21)
Cartoon and Texture (MFD-PM)	138	96.67 ($\pm$ 1:99)	62	96.06 ($\pm$ 3:06)	138	86.54 ($\pm$ 1:34)	84	89.14 ($\pm$ 1:85)

Table 5 – Success rate on the four datasets. # represents the dimension of descriptors, while the best success rate of each dataset is in bold. * symbol means that the author did not perform his method in the dataset. PCA and FS mean that the author performed dimensionality reduction by principal component analysis or feature selection.

4.4 Remarks of the Chapter

In this chapter, we have proposed a new method based on the anisotropic diffusion for texture classification. We considered a multiscale representation of a finite number of scales, estimating the fractal dimension of each of them. By using image decomposition, we split each image into a geometric component and into a textural component. The feature vector is then created by combining the multiscale fractal dimension from both components. After that, we use mean and standard deviation of the features since the multiscale step increases the dimensionality of the vector. The experiments were able to support the hypothesis of our method by improving the texture discrimination obtained from multiple scales of fractal dimension. In conclusion, we have demonstrated how the fractal dimension in multiple scales can be improved by extracting information at different levels of the image, instead of at a single scale only. Although traditional methods of texture analysis — e.g. Gabor filters, local binary patterns, and co-occurrence matrices — have provided satisfactory results, the method proposed here has proved to be superior for characterizing textures on the Vistex, Outex and Usptex datasets. On the Brodatz album, our method achieved the third higher performance, being slightly inferior to the local binary pattern method and to the multiresolution fractal descriptor (FLORINDO; BRUNO, 2013). It is worth saying that the multiresolution fractal used feature selection. Experiments on the others datasets indicate that our method significantly improved the classification rate with regard to the original fractal dimension of Bouligand-Minkowski method. As future work, we believe that our methodology can be extended by using other multiscale paradigms.

RECOGNITION OF SOYBEAN FOLIAR DISEASES VIA MULTISCALE FRACTAL DESCRIPTORS

5.1 Introduction

Soybean is one of the most important crops due to its beneficial effects on human health, to its role as a major nutrition source, and to its economic importance. It has been widely used in food and industrial applications because of its high protein and oil concentrations ([KUMAR et al., 2010](#)). Soybean occupies very large crops in which the monocropping and conservation tillage are commonly used. Such cultivation systems, however, have favored the occurrence of a large number of diseases ([CARMONA et al., 2015](#)) causing major economic losses. The solution is to apply preventive agrochemicals; but, because the identification of where the infestation took place is time-consuming, the usual practice is to use agrochemicals over the entire crop instead of only over specific subareas. This is an expensive practice that spreads unnecessary chemicals over terrain and air.

Accordingly, a more precise detection of the disease spots in the crop is an important step to decrease economic losses, to prevent the spread of diseases, and to reduce environmental pollution. Despite its importance, it is usually conducted visually by an expert ([MOSHOU et al., 2004](#)), an imprecise and time-consuming process, especially when carried out over large-scale farms. Alternatively, disease detection techniques based on chemical reactivities are available, such as the ELISA (enzyme-linked immunosorbent assay) method and the PCR (polymerase chain reaction) method ([SAPONARI; MANJUNATH; YOKOMI, 2008](#); [YVON et al., 2009](#); [GUTIÉRREZ-AGUIRRE et al., 2009](#)), however, they are expensive processes. Consequently, there is a demand for rapid and cheaper detection methods.

In this context, one active line of research is the use of image processing techniques.

The idea is to have the computer analyze images of soybean leaves (and of other cultures) to detect diseases by means of pattern recognition methods. (GUI *et al.*, 2015), for example, proposed a method for soybean disease detection based on salient regions and k-means clustering. (SHRIVASTAVA; HOODA, 2014) proposed a method for detecting brown spot and frog eye, two common soybean diseases; they used shape features and k-nearest neighbors classification. (MA *et al.*, 2014) proposed a technique for detecting insect-damaged vegetable soybean using hyperspectral imaging. A study to discriminate soybean leaflet shape using neural networks was proposed in the work of (OIDE; NINOMIYA, 2000). (YAO *et al.*, 2012) used hyperspectral images to study the damage caused by the herbicide glyphosate on soybean plants. (CUI *et al.*, 2010) reported image processing techniques for quantitatively detecting rust severity from soybean multi-spectral images.

Besides soybean, other cultures have been studied in the literature, such as the work performed by (RUMPF *et al.*, 2010), which presents an automatic system for classification of foliar sugar beet diseases based on Support Vector Machines and spectral vegetation indices. (MOSHOU *et al.*, 2004) investigated the automatic recognition of yellow rust in wheat using reflectance measurements and neural networks. (LIU; WU; HUANG, 2010) applied techniques neural network and principal components analysis for classifying fungal infection levels in rice panicles. Imaging techniques are also applied in the recognition of plant species (GONCALVES; BRUNO, 2013a). A review of techniques for detecting plant diseases can be found in the work of (SANKARAN *et al.*, 2010); a survey on methods that use digital image processing techniques to detect plant diseases is presented in the work of (BARBEDO, 2013).

In this study, we propose a computer vision system to identify soybean foliar diseases. Our proposal is based on a multiscale texture descriptor based on non-linear diffusion of Perona and Malik (PERONA; MALIK, 1990). Many recent texture-analysis methods are developed to extract measures on a single scale. In contrast, we assume that an image texture reveals different local structures according to the scale of observation, so that the scale concept of multiscale representation is of crucial importance (MACHADO *et al.*, 2016a). Subsequently, we estimate the Bouligand-Minkowski fractal dimension of each component and propose to combine the features to perform the texture classification (see the proposed method in Chapter 4). Experiments results indicate that our approach can successfully identify soybean leaf diseases and to be used a front-end application to non-experts or agronomists. In addition, our method is compared with the state-of-the-art texture methods, such as Fourier descriptors, co-occurrence matrices, Gabor filters and, local binary patterns. The results show the superiority of the proposed method for recognition of soybean leaf disease by using image analysis.

For classification purposes - considering classes disease and no disease, we use the supervised machine learning technique Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA). We evaluate our classification using classic ten-fold cross validation and metric correct classification rate (CCR). Therefore, we contribute by (i) introducing a systematic method

for computational identification of disease in soybean leaves; (ii) conducting an experiment over soybean that is unprecedented in its control, methodology, and scale; (iii) empirically comparing the main texture methods found in the literature, providing guidance for future works on image-based classification.

5.2 A Multiscale Fractal Approach to Recognition of Soybean Foliar Diseases

In this section, we introduce a computer vision system to soybean foliar diseases. In our system, we first take the assumption that an image leaf can present different structures according to the scale of analysis. Since leaf images exhibit fractal-like structures, the scale concept of multiscale representation is important in image analysis. Here, we propose a multiscale fractal descriptor using the non-linear diffusion of Perona and Malik ([PERONA; MALIK, 1990](#)). The gray levels of an image correspond to the energy diffusion at different levels that are represented in new derivative images. Inspired by the work of Yves Meyer ([MEYER, 2001](#)), we then split each new derivative into a geometrical and oscillatory part, named cartoon and texture, respectively.

A schematic diagram of our method is shown in Figure [20](#). It illustrates the methodology that consists of six steps to each leaf image: (1) cleaning, (2) texture sample picking, (3) set of texture samples, (4) grayscale image dataset, (5) multiscale fractal description and, finally, (6) leaf disease classification.

Image leaves are taken by using a macroscopy device, providing a digital image. After the image acquisition step, leaves are cleaned and dried up (see Step 1). In the second step, for each leaf, texture windows are taken in order to compose the dataset. In this task, a large number of small windows are extracted from the leaf images. In this case, an expert or an agronomist was responsible for assessing the representativeness of sample for statistical analysis. The result is a set of texture samples, see Step 3 of Figure [20](#). Subsequently, images were converted to grayscale, since our multiscale method description assumes that the spatial relation of the image $I(x; y)$, while the gray intensities, in the z-axis, is the scale of the textured surface. In Step 5, the main goal is first to represent the same image in different scales. At each scale, we then split each new derivative into a cartoon and texture, respectively. Bouligand-Minkowski fractal dimension is then applied into each derivative and the feature vector is created by combining the average and the standard deviation of fractal descriptors. Finally, in Step 6, SVM and LDA supervised classification are performed.

5.3 Material and Methods

These next sections cover the material and methods adopted in this study.

Figure 20 – The proposed computer vision system to identify soybean foliar diseases.

5.3.1 Experimental Design

The plant experiment was done in four fields of the Phytopathology Department of the Federal University of Grande Dourados (UFGD), Brazil. The crop evaluated was soybean [*Glycine max* (L.) Merr.], of cultivar BMX Potencia RR[®] (BRASMAX).

The density of the soybean fields was of about 300,000 plants ha⁻¹. For all fields, 320 kg ha⁻¹ of N-P-K (02-23-23) were applied in-furrow immediately before sowing. No N-fertilizer was applied in any field. The experimental design was a completely randomized block with four replicates. Each plot had 50 rows, spaced by 0.5 m, with 50 m (width) × 25 m (length) (1250 m²). Plots were separated by at least 10 m, where small terraces of approximately 5 m width were built to prevent contamination by superficial run-off containing bacteria or fertilizer, caused by heavy rains that commonly occur in the summer season. We did not use herbicides in three fields out of four. For one field, herbicides were used in order to have samples with no disease, while insects were controlled with biological and chemical insecticides.

In Dourados (22° 22' S and 54° 80' W) the fields are at an altitude of 600 m and the soil is classified as Latossolo Vermelho Distrófico (Brazilian classification) (Typic Haplustox, Soil Taxonomy, USDA). The climate is classified as tropical with dry winter and wet summer.

5.3.2 Image Sampling

Plant leaves were randomly collected in three different stages: V4 - fourth trifoliate, V5 - fifth trifoliate and R1 - blooming stage. At the V4 and V5 stages, nine plants were randomly collected per plot for evaluation of leaf diseases, especially those related to fungi. At the R1 stage, another nine plants were collected for evaluation. Sampled material was split in the trifoliates of the growing stage. For this region of Brazil, three classes of diseases are commonly found: anthracnose, mildew and soybean rust. Soybean rust is caused by the fungus *Phakopsora pachyrhizi* Sydow & Sydow. During collection, a unique group of leaves was created and classified according to the types of color lesions: Rust TAN and Rust RB. TAN lesions are tan in color and, RB referred to reddish-brown lesion color (BONDE et al., 2006). The RB lesion type is considered a resistant lesion type when compared with a fully susceptible TAN lesion (MILES et al., 2007). Furthermore, RB lesions are not sparsely sporulating uredinia.

After sampling the crops, the collected leaves went through a digital macroscope image acquisition, Nikon SMZ745. The idea consists of three main parts (see Figure 21): (1) Image acquisition of soybean leaves, (2) Sampling of the leaves and (3) Set of texture samples. At the end, 4 classes of soybean leaves were created from 340 images.

For each leaf of the plant stage, nine leaves were collected. From each leaf, windows with size of 200 x 200 pixels from specific spots, detected by specialists as diseases, were cropped. We selected 360 windows of each disease (Mildew, Rust and Anthracnose), totalizing 1080 images. Another 360 were collected from the healthy plants. Therefore, the image dataset is composed of

Figure 21 – Image acquisition procedure adopted in this study. Four classes compose our image dataset.

1440 samples divided into four classes, three of them attacked by fungi and one with no disease.

5.4 Experiments and Discussion

In this section, we describe experiments and results obtained by the proposed approach that uses the multiscale fractal descriptor. In the classification step, we have used two kernels of SVM, Linear and Radial Basis Function (RBF), and LDA classifiers using stratified 10-fold cross validation, since these algorithms are well-accepted in machine learning and artificial intelligence. In the stratified 10-fold cross validation, the images of the dataset are partitioned into 10 folds ensuring that each fold has the same proportion of each class. Then one fold is used for testing while the remaining folds are used for training the SVM classifier. The process is repeated 10 times using each fold exactly once for testing. Finally, the correct classification rate (CCR) is given by the average of the 10 rounds.

The idea of the first experiment is to classify images by using the Bouligand–Minkowski fractal dimension with no scales. The total number of descriptors depends on the maximum radius assumed. Table 6 shows the correct classification rates for a number of dilation radii and the number of fractal descriptors generated for the SoyBean dataset. Although in most cases a larger radius number is required with SVM classifier, a reduced number of descriptors using LDA were enough to obtain the success rates reported here, for $r = 10$. This analysis was performed to identify radii values providing the best performance with a minimum number of descriptors.

Table 7 summarizes the best CCR for each descriptor and its respective number of dimensions. Traditional texture descriptor methods, such as Fourier descriptors, co-occurrence matrices and Gabor filter, ill-performed with 77.36% (± 4.53), 76.80% (± 3.54) and 77.63% (± 4.03), respectively. The traditional method in the literature, the local binary patterns achieved 88.68% (± 2.89), while fractal descriptors achieved 79.58% (± 3.48) and the proposed method, multiscale fractal dimension, achieved 92.43% (± 1.02) using scale $t = 8$. Although the dimensionality of our method is higher, with 108 features, the method increased the CCR in 12.85% compared with the traditional fractal dimension of Bouligand–Minkowski.

Dilation radius	#	SVM-RBF (%)	SVM-Linear (%)	LDA (%)
1	1	41.87 ($\pm$ 3:70)	44.37 ($\pm$ 3:47)	43.12 ($\pm$ 3:99)
2	4	50.76 ($\pm$ 3:02)	48.05 ($\pm$ 3:22)	55.76 ($\pm$ 3:85)
3	8	63.54 ($\pm$ 3:31)	57.50 ($\pm$ 3:95)	70.69 ($\pm$ 4:35)
4	14	71.52 ($\pm$ 3:54)	62.77 ($\pm$ 3:63)	76.59 ($\pm$ 3:04)
5	22	76.25 ($\pm$ 3:33)	67.22 ($\pm$ 4:55)	78.89 ($\pm$ 4:55)
6	31	76.94 ($\pm$ 3:13)	67.25 ($\pm$ 5:08)	80.62 ($\pm$ 3:74)
7	42	78.19 ($\pm$ 3:27)	68.95 ($\pm$ 5:13)	82.01 ($\pm$ 3:23)
8	54	77.84 ($\pm$ 3:26)	70.83 ($\pm$ 4:68)	83.47 ($\pm$ 3:12)
9	69	78.54 ($\pm$ 3:40)	70.27 ($\pm$ 4:32)	84.30 ($\pm$ 3:16)
10	85	79.58 ($\pm$ 3:48)	70.90 ($\pm$ 4:79)	84.51 ($\pm$ 2:84)
11	102	80.13 ($\pm$ 2:85)	72.63 ($\pm$ 4:91)	84.50 ($\pm$ 2:95)
12	121	81.18 ($\pm$ 2:64)	72.98 ($\pm$ 5:06)	84.01 ($\pm$ 2:82)
13	142	81.31 ($\pm$ 2:58)	74.44 ($\pm$ 5:28)	84.51 ($\pm$ 3:09)
14	165	82.29 ($\pm$ 2:47)	74.72 ($\pm$ 4:56)	84.44 ($\pm$ 2:78)
15	189	82.70 ($\pm$ 2:50)	75.06 ($\pm$ 4:19)	84.09 ($\pm$ 2:99)

Table 6 – The experimental results on the soybean dataset, ranging the radius from 1 to 15. # means the dimensionality of the feature vector.

Method	#	SVM-RBF (%)	SVM-Linear (%)	LDA (%)
Fourier descriptors	101	77.36 ($\pm$ 4:53)	72.08 ($\pm$ 3:15)	78.26 ($\pm$ 4:09)
Co-occurrence matrices	40	76.80 ($\pm$ 3:54)	67.70 ($\pm$ 2:25)	81.94 ($\pm$ 4:15)
Gabor filter	48	77.63 ($\pm$ 4:03)	74.09 ($\pm$ 3:40)	76.32 ($\pm$ 4:34)
Fractal dimension ($r = 10$)	85	79.58 ($\pm$ 3:48)	70.09 ($\pm$ 4:79)	84.51 ($\pm$ 2:84)
Local binary patterns	54	88.68 ($\pm$ 2:89)	86.87 ($\pm$ 2:37)	88.89 ($\pm$ 1:43)
Multiscale fractal descriptor	108	92.43 ($\pm$ 1:02)	90.97 ($\pm$ 1:09)	91.25 ($\pm$ 1:14)

Table 7 – Comparison of different texture methods on the soybean dataset. # means the dimensionality of the feature vector.

5.4.1 Computational cost

In this section, we show the computational time in seconds for the local descriptors. The experiments are performed on an Intel Core i5 1.3GHz with 4GB of RAM running OSX 10.9.5. The running time was calculated only for feature extraction methods, excluding the time spent on other parts such as image reading. The values correspond to the mean and standard deviation calculated for 1440 images of 200×200 pixels.

In our experiments, co-occurrence matrices method was the fastest, taking $0:0045(\pm 0:001)$ seconds per image, followed by local binary patterns, with $0:0075(\pm 0:001)$. As expected, fractal dimension and multi-scale fractal dimension performed with an average of $0:152(\pm 0:001)$ and $0:189(\pm 0:006)$ seconds per image, respectively. In general, all local descriptors perform in an acceptable running time.

5.5 Remarks of the Chapter

Soybean disease recognition is important to decrease economic losses in agriculture and reduce environmental pollution from agrochemicals. In this paper, we proposed a new approach using multiscale fractal descriptors for soybean disease recognition. Experiments were focused on the comparison of state-of-the-art texture methods. For this, an image dataset composed of healthy samples and three diseases was constructed to evaluate the approach.

Experimental results show that multiscale descriptors are efficient and effective in soybean disease recognition. These results showed that a multiscale fractal method provided the best result, followed by local binary patterns and fractal dimension.

Experimental results indicate that our method applied improves correct classification rate from 79.58%(± 3.48) to 92.43(± 1.02) when comparing fractal descriptors over grayscale images. Our method achieved a superior performance with an average improvement of 3.75% when compared with local binary patterns. Due to the good results, we believe that the proposed approach can be applied to other disease crop recognition, such as cotton and corn.

A COMPLEX NETWORK APPROACH FOR NANOPARTICLE AGGLOMERATION ANALYSIS

6.1 Introduction

Synthetic nanoparticles have been widely investigated because of their applicability, including drug delivery in medicine ([SALATA, 2004](#); [PAN et al., 2007](#); [SUGAHARA et al., 2009](#)), cancer treatment and diagnostic tools ([MICHALET et al., 2005](#); [SUGAHARA et al., 2009](#); [B. et al., 2011](#)), and industrial products, such as cosmetics ([NOHYNEK et al., 2007](#); [LORENZ et al., 2011](#)), semiconductor and photovoltaics ([HILLHOUSE; BEARD, 2009](#); [FRANZMAN et al., 2010](#); [EMIN et al., 2011](#)), and many others ([LUTHER, 2004](#)). They are designed to have special physical and chemical properties that reflect in their structural characteristics and interaction ([MASCIANGIOLI; ZHANG, 2003](#)). However, the development and use of new nanoparticles are still constrained by the lack of specialized tools to interpret experimental results, so to characterize such particles ([FRAIKIN et al., 2011](#); [DING; BUKKAPATNAM, 2015](#)). A particular line of investigation is the safety to human beings. This is because they are more chemically reactive and bioactive, penetrating organs and cells easily. Actually, toxicological studies ([HOET; BRÜSKE-HOHLFELD; SALATA, 2004](#); [SAYES et al., 2006](#); [LI et al., 2012](#)) have shown that some nanoparticles are harmful to humans.

To better understand the impact of real and synthetic nanoparticles, material scientists use analytical devices whose output are grayscale images of nanoparticles in a sample region. After the synthesis process and imaging of nanoparticles, an important task is to extract measurements from such images. Hasselhof and Kaegi ([HASSELLÖV; KAEGI, 2009](#)) described key visual characteristics that need to be assessed, including concentration, particle size distribution, particle shape, and agglomeration. Despite the importance of nanoparticle assessment, there is a

limited number of works on the characterization of nanoparticles by means of image analysis.

Fisker et al. (FISKER et al., 2000) developed an automatic method to estimate the particle size distribution based on a deformable ellipse model applied to ferromagnetic (α - $\text{Fe}_{1-x}\text{C}_x$) and hematite (α - Fe_2O_3) nanoparticles. In the work of Park et al. (PARK et al., 2012), the authors propose a semi-automatic method to shape analysis of particles. In the work (PARK et al., 2012), Park et al. used six images of Transmission Electron Microscopy (TEM) to characterize the shape of gold nanoparticles by representing boundary corners into a parametric curve. Although the authors created a rotation invariant approach, the reconstruction depends on the corners that the algorithm detects. This idea is sensitive to the edges detected by Canny's algorithm (CANNY, 1986). Furthermore, since the border detection fails for a number of cases, they reconstruct the particles with incomplete boundaries using functional-PCA (FPCA) (JONES, 1992) and the gravity center of each shape. Since the dimensionality is very high, the authors used the curve representation to reduce the number of features with a multidimensional projection method, named Isomap (TENENBAUM; SILVA; LANGFORD, 2000). Finally, they classified the shapes using a graph-based semi-supervised clustering for complete particles and k-nearest neighbors over incomplete boundary information. Although this approach presented good accuracy for nanoparticle shape recognition, they did not focus on analyzing the groups and interaction of particles. Vural and Oktay (VURAL; OKTAY, 2014) proposed a method to segment Fe_3O_4 nanoparticles in TEM images by using Hough transform (DUDA; HART, 1972). Similarly, a number of other works (MUNEESAWANG; SIRISATHITKUL, 2015; MUNEESAWANG; SIRISATHITKUL; SIRISATHITKUL, 2015) used a multi-level image segmentation for measuring the size distribution of nanoparticles in TEM images. However, these works disregarded the agglomeration of particles.

We can find a rich literature with similar nanoparticle problems in biomedical imaging, such as detection and counting of cells (M., 2010; BUGGENTHIN et al., 2013; SCHMITZ et al., 2014; LIAO et al., 2016), morphological cell classification (CARPENTER et al., 2006; CHEN et al., 2012), and cell tracking (PERNER, 2015; ZHANG et al., 2015). Unlike conventional cell image analysis, agglomeration and interaction analysis of nanoparticles are still a visual counting task. Such task not only demands an extensive work, but it is time-consuming. Therefore, modeling the relationship of nanoparticles in images has emerged as an interesting line of research to characterize their interaction and agglomeration. In this scenario, complex networks define a promising model to draw the relationships observed in nanoparticle images, fostering the comprehension of complex phenomena, most notably interaction and agglomeration.

Complex networks have become an important topic in science due to their ability to model a large number of complex systems such as interaction in society (NEWMAN; PARK, 2003; EUSTACE; WANG; CUI, 2015), processes in biology as protein interaction (BARABASI, 2004), financial markets (PERON; COSTA; RODRIGUES, 2012), computer vision (CHALUMEAU et al., 2008; GONCALVES; MACHADO; BRUNO, 2015), and physics (AMARAL; OTTINO,

2004). In computer science, complex networks have been used to understand the topology and dynamics of the Internet (FALOUTSOS; FALOUTSOS; FALOUTSOS, 1999; TYLER; WILKINSON; HUBERMAN, 2003), characterization of social networks (LEWIS et al., 2008; LEE et al., 2010; KIM et al., 2015), text summarization (ANTIQUERA et al., 2009), aspects of scientific co-authorship (NEWMAN, 2004), and citation networks (PORTER; RAFOLS, 2009).

Benefiting from the potential of complex networks, we propose a new approach to analyzing nanoparticle agglomeration. As far as we know, this work is the first to report the use of complex networks on nanoparticle images. In the proposed approach, similar to (FISKER et al., 2000), each particle of a nanoscale image is initially detected by using 2D-template matching, described in more details in (BRUNELLI, 2009). Then, each particle is mapped into a vertex of the complex network. Systematically, a network is built by connecting each pair of nodes by using a threshold for density estimation over a certain radius. For each nanoparticle, we calculate its density, according to which two particles are linked only if the distance between them is lesser than a radius and its density is higher than a given threshold. Then, we represent our complex network topology by calculating the spatial average degree, and the max degree for networks transformed by different values of radius and thresholds. We tested our approach on real-image particles taken with Scanning Tunneling Microscopy (STM), a technique that creates high-resolution images of nanoparticle settings.

This work was integrated to an expert system, named NanolmageAnalyzer, and it was deposited to software registration applied to the INPI – National Institute of Industrial Property. This chapter is organized as follows. Section 6.2 presents a brief review of the complex network theory. In Section 6.3, the proposed approach for nanoparticle characterization is described in detail. The experiments conducted and the discussions of the results are presented in Section 6.4. Finally, conclusions are given in Section 6.5.

6.2 Complex Networks

Complex networks (CN) have emerged as a highly-active research field in the first decade of the XXI century. It came as an intersection between graph theory and statistical measurements (COSTA et al., 2007), resulting in a truly multidisciplinary field, building on top of mathematics, computer science, and physics, leading to a large range of applications (COSTA et al., 2011). Complex networks are natural structures that represent many real-world systems; its popularity comes from the fact that it is able to model a large range of phenomena. As illustration, we can cite three main developments that have contributed for complex networks research (COSTA et al., 2007): (i) investigation of the random network model (ERDOS; RÉNYI, 1959; ERDOS; RENYI, 1960); (ii) investigation of small-world networks (WATTS; STROGATZ, 1998); and (iii) investigation of scale-free networks (BARABÁSI; ALBERT, 1999). Recently, works have focused on the statistical analysis of such networks (BOCCALETTI et al., 2006; COSTA et al.,

2007; DOROGOVTSSEV; MENDES, 2013; NEWMAN, 2003), in order to characterize them.

In general, works using complex networks have two steps: (i) model the problem as a network; and (ii) extract topological measures to characterize its structure. As complex networks are represented by graphs, every discrete structure such as lists, trees, networks and images can be suitably modeled. In this context, the main step is to define the best approach to represent the given problem as a set of vertices and connections, so that its complex behavior can be measured as a CN.

Complex Networks Representation and Measures

Complex networks are represented by graphs. An undirected weighted graph $G = \{V; E\}$ is defined wherein $V = \{v_1; \dots; v_n\}$ is a set of n vertices and $E = \{e_{v_i; v_j}\}$ is a set of edges connecting two vertices; $e_{v_i; v_j}$ represents the weight of the connection between the vertices v_i and v_j .

Considering a network that fits in one of the CN models (random-network, small-world of scale-free), its structure can be deeply analyzed. In these circumstances, there are many measures that can be extracted from a CN to characterize it. The reader may refer to the work of Costa et al. (COSTA et al., 2007) for a review of different classes of measures. We focused in two simple and important characteristics extracted from each vertex, the degree and the strength. The degree of a vertex v_i is the number of its connections:

$$k(v_i) = \sum_{v_j \in V} \begin{cases} 1, & \text{if } e_{v_i; v_j} \in E \\ 0, & \text{otherwise} \end{cases} \quad (6.1)$$

The vertex strength is the sum of the weights of its connections:

$$s(v_i) = \sum_{v_j \in V} \begin{cases} e_{v_i; v_j}, & \text{if } e_{v_i; v_j} \in E \\ 0, & \text{otherwise} \end{cases} \quad (6.2)$$

The vertex degree and strength describe the interaction with neighboring vertices and can be used to analyze the network structure. Globally, it is possible to characterize the behavior of the vertices of the network using the mean degree:

$$m_k = \frac{1}{|V|} \sum_{v_i \in V} k(v_i) \quad (6.3)$$

and the mean strength:

$$m_s = \frac{1}{|V|} \sum_{v_i \in V} s(v_i) \quad (6.4)$$

In this work, we analyze the degree and the strength of the vertices to detect regions with strong connections, which are evidence of vertex agglomerates. In the context of our application,

these regions present nanoparticle agglomeration, which is the focus of interest. The following section describes how we apply these CN concepts to the detection and characterization of nanoparticle agglomerations.

6.3 Proposed Methodology for Detection, and Agglomeration Analysis

In this section, we describe our approach for detection and characterization of nanoparticle agglomerations. For this purpose, we use template matching to detect the positions of nanoparticles in nanoscale images. Subsequently, we build a CN with their relative positions. Finally, the degree and strength of the resulting network are used as features to support analysis.

6.3.1 Modeling Complex Networks for Nanoparticle Agglomeration Analysis

The CN is built after the spatial positions of the nanoparticles in the image. The network is built considering each nanoparticle as a vertex. To build the set E , the weight of the connections is defined according to the Euclidean distance – shortly referred to as a function $\text{dist} : V \times V \rightarrow \mathbb{R}$. In order to connect only close vertices, a radius $r \in [0; 1]$ is considered. First, the vertex distance is normalized into the interval $[0; 1]$ dividing its Euclidean distance by the distance between the two more distant vertices. Thus, each pair of vertices is connected if its normalized Euclidean distance is less or equal to r :

$$e_{v_i;v_j} = \frac{\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\max(e_{v_i;v_j})} \quad (6.5)$$

$$e_{v_i;v_j} = \begin{cases} r - e_{v_i;v_j}, & \text{if } e_{v_i;v_j} \leq r \\ 0, & \text{otherwise} \end{cases}$$

where x_i and y_i are the spatial coordinates of the nanoparticles and $\max_{e_{v_i;v_j}}$ is the distance between the two most distant nanoparticles. It is important to notice that $r - e_{v_i;v_j}$ inverts the edge weight, which was originally the Euclidean distance. After this operation, the closer any two vertices are, the higher is their weight. This is performed considering the vertex strength, that is, stronger vertices represent high interplay among neighbors.

The resulting CN contains connections between vertices inside a given radius, according to the Euclidean distances. However, this representation does not consider the agglomeration level of the vertices, which is the main purpose of the problem. To finally model the network in a proper way, revealing the level of nanoparticle agglomeration, we propose another transformation on its topology. A new function is applied to calculate the density of the vertices, which represents their relation to their neighbors in terms of distance. This measure can be calculated using the CN information obtained so far. It becomes necessary to extract the degree and the strength of

the vertices (Equations 6.1 and 6.2). The neighborhood is defined by the radius r , so each vertex inside the distance defined by the radius value is analyzed. Given a resulting CN G^r built with a radius r , and the respective degree and strength of each vertex v_i , its density is defined by:

$$d(v_i) = \frac{\boxed{\text{Eq 6.1}}}{\boxed{\text{Eq 6.2}}} = \frac{s(v_i)}{k(v_i)} \quad \forall v_i \in V \quad (6.6)$$

$$d(v_i) = \frac{d(v_i)}{\max(d(v_i))}$$

where $\max(d(v_i))$ is the greatest density on the network, and the division is a normalization factor that keeps the density value between $[0; 1]$.

The density can also be defined as a mean of the vertex connections, as the degree is the number of connections and the strength is the sum of its weights. This measure, hence, characterizes vertices that have the same strength but different degrees. In other words, vertices with a larger number of close neighbors tend to have greater densities.

With the density, it is possible to perform another transformation to highlight the agglomerates of the network. We proceed by considering only the connections between vertices with density higher than a threshold t , discarding the other ones. In this context, a new CN G^{rt} is obtained by analyzing each edge $e_{v_i;v_j}$:

$$\forall e_{v_i;v_j} \in E = \begin{cases} e_{v_i;v_j}, & \text{if } d(v_i) \text{ and } d(v_j) \geq t \\ \emptyset, & \text{otherwise} \end{cases} \quad (6.7)$$

This final transformation results in a CN that better represents the agglomeration of the vertices, instead of the limited distance analysis of the first transformation. It means that the use of the density to define connections allows selecting vertices in regions of interest, i.e., high density. In the context of the current application, the network now presents connections between nanoparticles in the same agglomerate, or in other close agglomerates, according to the radius r and the density threshold t . In Figure 22, a real image of nanoparticles is analyzed and a CN is modeled using radius $r = 0.04$ and threshold $t = 0.5$. The color indicates the density ranging from black/red (low density) to white/yellow (high density).

6.3.2 Dynamic Analysis of Complex Networks

To analyze the CN structure, it is necessary to consider its dynamic aspects and behavior. As mentioned earlier, two parameters are necessary (radius r and threshold t) to model a CN given the position of each nanoparticle. However, the value chosen for r and t affect directly the network topology, resulting in networks with dense or sparse connections. This can be observed in Figure 23, where the difference between the networks due to alterations in r and t can be observed. This influence is useful to analyze the network in depth, considering the possible changes in its topology by varying the parameters. Moreover, a network characterization cannot

Figure 22 – Nanoparticle image modeled as a Complex Network according to the proposed approach. (a) Input image. (b) Density of each nanoparticle (colors) and connections of the resulting Complex Network. (c) Zoomed-in regions as indicated in (b).

be fully complete without considering the interplay between structural and dynamic aspects (BOCCALETTI *et al.*, 2006).

In this context, to perform a concise analysis, a set of radii $R = \{r_1; \dots; r_{nr}\}$ and a set of

Figure 23 – Complex Network topology changes by varying the parameters r and t .

thresholds $T = \{t_1; \dots; t_{nt}\}$ are combined to model the CNs. The resulting networks are evaluated individually, i.e., each topology provides different measures that, combined, result in a robust feature vector. Thus, the network growth is evaluated from its creation (little values) until its stabilization (high values). This kind of analysis allows a complex characterization of the nanomaterial, considering the global structure of the nanoparticles.

6.3.3 Feature Vector

Once the network is correctly modeled to represent the nanoparticles, its characterization can be performed. To evaluate the network structure, we extract four measures from the vertices: the mean degree (Equation 6.3), max degree ($k_{\max} = \max(k(v_i) \ \forall v_i \in V)$), mean strength (Equation 6.4) and max strength ($s_{\max} = \max(s(v_i) \ \forall v_i \in V)$). Each one of these measures are evaluated in depth in Section 6.4. According to the dynamic analysis presented in the previous section, the feature vector is composed by the concatenation of measures extracted from the combination of the radius set $R = \{r_1; \dots; r_{nr}\}$ and a threshold set $T = \{t_1; \dots; t_{nt}\}$:

$$j = [m_k^{1;t_1}; k_{\max}^{r_1;t_1}; \dots; m_k^{r_{nr};t_{nt}}; k_{\max}^{r_{nr};t_{nt}}] \quad (6.8)$$

The number of features depends on the number of radii, thresholds and the number of

measures extracted of each CN. In other words, the size of the feature vector can be described as $|j| = n_r * n_t * m$, where m is the number of measures.

6.4 Results and Discussion

In this section, the experiments performed to evaluate the proposed approach are described and discussed. We show results in real nanoparticle images by differentiating three different cases of agglomeration.

6.4.1 Image Dataset

To conduct the experiments reported in this work, we built a dataset of nanoparticle images with 10 samples labeled into 3 agglomeration cases: Case 1 – the image have few groups and nanoparticles are uniformly spread; Case 2 – the number of groups is larger related to the Case 1, facing a little of nanoparticle agglomeration; Case 3 – the image have a strong level of agglomeration and overlapping. Each image can be observed in Figure 24. We have used STM images of gold nanoparticle standard reference materials (NIST 8011, 8012 and 8013 – NIST[®], Gaithersburg, MD, U.S.). The gold particles were suspended in a solution of deionized (DI) water at a concentration of 250,000 particles/mL. In order to avoid dissolution of the gold nanoparticles, acid was not added.

6.4.2 Assessing the Quality of Parameters and Network Measures

In this section, we evaluate different feature spaces produced according to the two parameters – radius set R and threshold set T – and the set of CN measures for the characterization. Experiments were conducted using 10 images described in Section 6.4.1, measuring the separability of each feature computed, and also its combinations. In order to determine the quality of the feature spaces, a measure named silhouette coefficient (TAN; STEINBACH; KUMAR, 2005), which was originally proposed to evaluate results of clustering algorithms, is employed. Before measuring the feature space quality, features are set to the standard score (LARSEN; MARX, 2012). It is calculated by the feature value, minus the mean score, divided by the standard deviation of all features.

The silhouette coefficient measures the cohesion and separation between instances of clusters. Considering an instance i belonging to a cluster, its cohesion a_i is calculated as the average of the distances between i and all other instances belonging to the same cluster. The separation b_i is the smallest distance between i and all other instances belonging to the other clusters. The silhouette measure of a feature space is the average of the silhouette of all instances,

Figure 24 – Images for the three levels of nanoparticle agglomeration used in the experiments.

where n is the number of instances. Equation (6.9) formalizes the average silhouette.

$$S = \frac{1}{n} \sum_{i=1}^n \frac{(b_i - a_i)}{\max(a_i, b_i)} \quad (6.9)$$

The silhouette can range between $-1 \leq S \leq 1$, where larger values indicate better cohesion and separation between clusters. In our experiments, clusters are composed taking into account labeled instances, and the silhouette indicates whether images belonging to the same class are more similar between themselves than images belonging to other classes. Therefore, the best set of features is the one which yields the projection with the largest silhouette coefficient.

6.4.3 Evaluation of Parameters

As previously discussed, the parameters of the proposed approach are the radius set $R = \{r_1; \dots; r_{nr}\}$ and the threshold set $T = \{t_1; \dots; t_{nt}\}$. We defined the radius interval limits by analyzing the silhouette of mean degree (Equation 6.3) features from CNs built to each image, varying the radius between 0 and 0.06. In this experiment, we used $nt = 5$ thresholds in the interval $[0;1;0.9]$. The results can be observed in Figure 25, where the curve describes the silhouette coefficient as the radius r is incremented.

Figure 25 – Silhouette coefficient in function of the radius r , calculated from mean degree features of each sample of the agglomeration cases.

This result allows to detect and discard values from the radius interval that does not present relevant information about the CNs structure in terms of nanoparticle agglomeration, i.e. irrelevant measures for the characterization. We can observe that radius values in the range $0 < r < 0.015$ are not sufficient to connect nanoparticles/vertices in the CN, therefore, it is not possible to calculate the mean degree of the network, which explains the silhouette 0. We also discard previous values in $[0.015; 0.035]$ due to the inconstant results, although there is a peak in 0.0215. Analyzing other values, it is possible to notice that the best results are achieved in the range $[0.035; 0.048]$ in a stable region. Following, there is a loss of performance probably caused by CNs with dense connections which are not useful to discriminate agglomeration, and therefore do not present relevant information to the proposed approach. Based on this results, we define the radius interval by rounding the best values: $[r_1 = 0.03; r_{nr} = 0.05]$, i.e., the radius set $R = \{r_1; \dots; r_{nr}\}$ will be composed by nr equidistant values ranging from 0.03 to 0.05. We decided to not use the exact values found to avoid overfitting of the radius interval to our dataset, even with a drop in the performance of the results reported. Thus, the rounding in the interval limits helps to provide a more generalizing radius range.

To define the threshold interval, we removed the limits 0 and 1, and the range is defined by $[t_1 = 0.1; t_{nt} = 0.9]$, which covers most of the cases. Therefore, the threshold set $T = \{t_1; \dots; t_{nt}\}$ is composed by nt equidistant values ranging from 0.1 to 0.9.

Once the limits are defined, it is necessary to evaluate the number of radius (nr) and the number of thresholds (nt). First, nr is analyzed from 2 to 20 by the silhouette coefficient obtained

from the dataset using the mean degree feature and $nt = 5$, results can be observed in Figure 26. According to the curve, it is possible to notice that the silhouette value stabilizes after $nr = 6$, and higher values provide similar results between 0.84 and 0.86. This is expected considering that as nr is increased, subsequent radius values will be closer, which result in networks with very similar topologies, and therefore similar features. Considering that higher values to nr increase the number of features, the use of $nr = 6$ as the standard parameter is justified.

Figure 26 – Analyzing the number of radius (nr) and its influence on the silhouette coefficient. It was used the intervals previously defined and $nt = 5$.

Following the same idea of the previous experiment, we analyze the number of thresholds nt by varying it from 2 to 20, using the mean degree feature and $nr = 6$. As results in Figure 27 shows, the higher silhouette values are achieved with $2 < nt < 7$. It is an interesting result, which implies that higher values are not needed, therefore resulting in fewer features. Thus, we fixed $nt = 3$ as standard, which also provides the best result.

6.4.3.1 Evaluation of Complex Network Measures

To characterize the CN structure, 4 measures were evaluated: mean degree (Equation 6.3), max degree ($k_{\max} = \max(k(v_i) \ \forall v_i \in V)$), mean strength (Equation 6.4) and max strength ($s_{\max} = \max(s(v_i) \ \forall v_i \in V)$). We consider each possible combination between these measures, to definitely find the best one. For that, an experiment is conducted (using the parameters previously defined) where it is analyzed the resulting silhouette coefficient of the dataset considering each measure and its combinations. Each result can be observed in Table 8 along with the standard deviation of the silhouette value from each sample of the dataset.

Figure 27 – Analyzing the number of thresholds (nt) and its influence on the silhouette. It was used the intervals and the number of radius (nr = 6) previously defined.

Table 8 – Silhouette coefficient of complex network measures. Table shows the coefficient values combining measures for nr = 6 and nt = 3. In brackets the standard deviation computed from the silhouette of each image sample of the dataset.

m_k	$k_{\max}$	m_s	$s_{\max}$	no. of features	silhouette
X				18	0:88 ($\pm$ 0:11)
	X			18	0:15 ($\pm$ 0:13)
		X		18	0:89 ($\pm$ 0:07)
			X	18	0:24 ($\pm$ 0:35)
X	X			36	0:39 ($\pm$ 0:07)
X		X		36	0:91 ($\pm$ 0:07)
X			X	36	0:91 ($\pm$ 0:08)
	X	X		36	0:27 ($\pm$ 0:11)
	X		X	36	0:27 ($\pm$ 0:10)
		X	X	36	0:33 ($\pm$ 0:18)
X	X	X		54	0:41 ($\pm$ 0:07)
X	X		X	54	0:40 ($\pm$ 0:07)
X		X	X	54	0:92 ($\pm$ 0:07)
	X	X	X	54	0:28 ($\pm$ 0:12)
X	X	X	X	72	0:41 ($\pm$ 0:08)

According to these results, it is possible to notice that the max degree and max strength does not provide good discrimination if applied individually. However, the max strength proved to be useful if combined with the mean strength and mean degree, which results in the best result

achieved (0.92) using 54 features. The means, individually and combined, provide results close to the best (0.88, 0.89 and 0.91 combined), but on the other hand, they use fewer features (18 individually and 36 combined). The combination of all features proved to be not applicable for agglomeration analysis.

Concluding, we can argue that the use of CN to characterize nanoparticle agglomeration is a promising approach. The results observed by the silhouette coefficient indicates high separability of the three cases of agglomeration, considering that the largest coefficient values are above 0.9, with a low standard deviation (± 0.07). This also indicates that low variations occur between intraclass images, i.e. the CN measures are robust to variations inside the same agglomeration case.

6.5 Remarks of the Chapter

The analysis of nanoparticles agglomeration is important for the interpretation of experiments in engineered nanomaterials. In this work, we proposed a novel approach for nanoparticle agglomeration analysis based on complex networks. In particular, the proposed approach can be easily handled by a large number of particles and it is much faster and less subjective than commonly used manual techniques. Our experiments over synthetic images and over real gold nanoparticle images have demonstrated the effectiveness of the approach. The experiments showed the potential of applying the same approach to different nanoscale images. One limitation of our work is related to the overlapping of the nanoparticles, that is, when particle shapes are not well-defined by the chosen template. However, this limitation is understood as an initial step that can be improved in future works. The results support the idea that our approach can be used as a feasible step for nanoparticle analysis in material engineering, benefiting visual analysis for important industries, such as cancer treatment, cosmetics, pharmaceutical, photovoltaics and food engineering.

CONCLUSION

Texture description has always been a challenging task in image analysis and computer vision. Texture analysis methods have emerged as important tools for real-world applications, this is because they can learn patterns from objects or regions with annotated examples. Typically, such methods aim to measure raw image pixels into a discriminant data space. Despite the achievements, effective feature description is still a challenge in two aspects. In this work, we introduced novel methods for texture description applied over domains ranging from agriculture to nanomaterials. We have achieved promising results, as previously discussed, with the aim of demonstrating that texture, as found in natural settings (leaves and nanoparticles), is of great potential in image analysis and computer vision.

7.1 Summary of Contributions

In this thesis, we have explored and extended the limits of texture methods based on artificial crawlers, fractal surface analysis, and non-linear multiscale representation. The following contributions were made:

- An improved artificial crawler method applied to texture analysis, presented in Chapter 2. We propose a new rule of movement that not only moves artificial crawlers toward higher intensity pixels but also to lower ones. This strategy is able to capture more details because the agents explore the peaks as well as the valleys in the image. The proposed method was evaluated on material quality assessment, in the context of texture, silk fibroin scaffolds. Experiments on the most well-known benchmark demonstrate the superior performance of our method. We have shown that, despite their simplicity, agent-based methods are powerful in discriminating textures and can be applied to different real-world problems. Since agent-based methods are based on a set of rules related to neighboring pixels for the evolution process, they are sensitive to noisy data.

- A method for texture analysis based on the Bouligand-Minkowski fractal dimension of artificial crawlers, presented in Chapter 3. This proposal assumes that an image surface cannot be described only using a set of rules with agents interacting with the environment and each other. Since this swarm system alone does not achieve a powerful discrimination in terms of invariances, we developed a new method using the artificial crawlers, together with the fractal dimension geometry. We estimated the fractal dimension by the Bouligand-Minkowski method with the map of energy of the agents. We validate our method on two texture benchmarks. Experimental results revealed that our method leads to highly discriminative textural features when compared with traditional methods of the literature. The results indicate that our method can be used as a feasible step for texture classification.
- A multiscale texture descriptor based on non-linear diffusion of Perona and Malik, as proposed in Chapter 4 and extended to soybean leaf disease identification in Chapter 5. Non-linear diffusion equations were introduced to simulate the physical process of heat diffusion in images. We assume that an image texture presents different levels of energy, i.e. patterns, according to the scale of analysis. Thus, we represent iteratively the original image in a set of new images, where images are split into two components: oscillatory (texture) and geometrical (cartoon) patterns. Subsequently, we estimate the average and deviation of the Bouligand-Minkowski descriptors computed over the two components, combining both measures extracted in order to compose our feature vector. Experimental results on four well-known texture benchmarks reveal the superior performance when compared with traditional methods of the literature. The results demonstrate the strong potential of multiscale image representation in texture discrimination. However, our work addresses an important concern on the Perona-Malik equation, since it does not preserve the structures close to the boundaries, completely sharp and regularization is needed.
- Finally, a complex network approach for nanoparticle agglomeration analysis, presented in Chapter 6. In particular, instead of assuming that a nanoscale image is a textured surface, we have modeled the nanoparticles like vertices of a graph. Each detected particle of the image is mapped into a vertex of the complex network. Basically, a network is constructed by connecting each node according to a thresholding for density estimation over a certain radius. For each nanoparticle, we calculate its density, having two particles linked only if their distance are lesser than a radius and its density is higher than a given threshold. In addition, our proposal demonstrated to be effective to model and characterize particles as complex networks. Experiments in real images of synthetic gold nanoparticle have demonstrated the effectiveness of the approach. Thereby, overlapping also occurs when visual analysis has been performed. Experimental results indicate that our proposal can be a useful tool for particle studies, present nowadays in home products, such as toothpaste, dermatological creams, food industry, etc.

7.2 Future Work

The works presented in this thesis provide solutions for different problems with a direct impact in real-world applications. Nonetheless, new promising steps for future works emerge from our research, as described in the following:

- Improved multiscale image representation. We believe that a significant gain in performance of texture discrimination is still to be achieved from further development of a different multiscale method analysis. Future research could focus on improving multiscale image representation, since there is still no consensus on what is the best way to combine features and how to efficiently find such combinations.
- Fusing texture and color attributes. The effectiveness of color combined with texture description needs to be investigated. The idea is to exploit color attributes for improved image classification based on texture description.
- Robustness to noisy image data. Robustness to noisy image has not received the deal of attention from the computer vision community. We believe it is possible to improve the robustness of our texture analysis method to noisy training labels.

In conclusion, this work departed from the hypothesis that the use of texture information can improve systems that depend on image analysis. We tested this initial assumption over several domains using different proposed methods. Our results, as discussed in the previous chapters, demonstrated that, indeed, multiscale image representation has potential in enhancing the discriminatory power when the scale is taken into account. Future directions of the feature design are lead by advances in deep neural network construction, that has brought a significant breakthrough for feature description.

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