A General Morphological Framework for Perceptual Texture Discrimination based on Granulometries

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Abstract

Reviewing the works on texture discrimination in computer vision, we can distinguish two different approximations, a first one based on the mathematical modelization of textures, and a second one focused in finding measures which fit human perception models. Our work is centred in the second line, concretely, in the models based on texton theory. These works base texture discrimination on differences in density of textons attributes. We link this approach with a morphological tool, granulometry, as a helpful multi-scale analysis of image particles. The granulometric measurement provides a density function of a given feature, which depends on the family of algebraic openings selected. Thus in this paper we define different granulometries which allow us to measure the main texton features, such as, shape, size, orientation or contrast. Proposing a granulometric analysis as a general tool for texture discrimination accordingly with a perceptual theory. We finally present a practical application of measuring size density on radiographic images suffering from pneumoconiosis.

1 Introduction

First of all we present a brief review of works on texture discrimination. We draw our attention to those works which intend to be a general model for pre-attentive texture discrimination and whose results agree with human visual perception. In this sense we mainly start from works following texton theory based on differences in the density of textons [1] attributes.

Secondly we introduce a classical tool in Mathematical Morphology, the granulometry. The axioms given by Matheron [19], to formalize a granulometry, deal with a multi-scale image filtering analysis ([16, 7, 14]). The multi-scale approach has provided interesting results in various fields of computer vision. The granulometric measurement provides a density function of a given feature, which depends on the family of algebraic openings selected to perform the multi-scale analysis.

Consequently we define different granulometries which will allow us to measure the main features of image particles. We show some examples on natural images taken from [2]. And finally we present a texture perception problem on radiographic images where a classification based on the size of particles is required.

[1] Particles

2 Perceptual Texture Discrimination

Texture discrimination is an important area in Computer Vision. An important treatment of this topic is the one based on the use of mathematical models capable of describing and, normally, to synthesize a textured image, considering image texture as a particular result of that model [3]. In this sense Mathematical Morphology has provided outstanding models as the Boolean model or the Dead Leaves Functions models [9, 20].

The second approach uses image measurements based on perceptual considerations. Early works tried to define measures whose behaviour agreed with the perceptual description of a textural property [8, 24]. Among these methods we can find the statistical approach, oriented to statistical properties at the pixel level, and the structural approach aimed to extract structures or region features of images [6]. The psycho-physical studies performed by Julesz [10, 13, 12, 11] culminated in the well-known texton theory — which agrees with the Marr's Primal Sketch [17, 18]. Recently a general computational model based on perceptual considerations has been presented in [15]. This model intends to be consistent with physiological mechanisms of early vision and its results match psychophysical data. In all cases it is assumed that pre-attentive[2] texture

[2] Differences between attentive and pre-attentive vision

discrimination depends on differences in the density of textons, called blobs by Marr, as well as on their attributes — orientation, shape, size or contrast.

These blobs are regarded as image regions which are either brighter or darker than the background. These have been defined as the duals of edges in [26, 27], or the regions associated with a (at least one) local extremum point in [14].

Some works treat the problem of measuring the density of blobs attributes. H. Voorhees and T. Poggio [27] propose a general blob detection and a posterior attribute measurement for each detected blob. Once the measurements are made, we obtain the distributions of attributes which can be compared in order to discriminate.

Another important contribution comes from R. Vistnes [25] who proposes computing attribute distributions without isolating image substructures, or blobs, provided that the existence of such image structures is uncertain in a statistical sense. Thus he proposes to test statistically the hypothesis that a structure with a particular feature value exists in a image, then to estimate a feature histogram is made by combining different attributes values. In other words, to estimate histograms of edge orientation he would compute orientation detectors in several directions.

Out of this last point of wiew we propose some morphological tools to obtain approximations of blob attributes densities. Heretofore we will use the term particle, more common in morphological processing, in the same sense as blob or texton.

3 Granulometry

A granulometry is a generic method based on a sieving process used to calculate size distributions of particles of certain materials. Matheron's formalization [19] allowed its use in image analysis. He defined the axioms to be accomplished by a family of transformations to suit granulometry calculation:

Definition 3.1 *A family of parametric transformations $\{\phi_\lambda\}$ in $\lambda > 0$ allows calculating a granulometry if*

1. $\forall\lambda > 0,\ \phi_\lambda$ *is an algebraic opening,*
2. *Stability of the parameters is acccomplished*

$$\phi_\lambda \circ \phi_\mu = \phi_\mu \circ \phi_\lambda = \phi_{Sup(\mu,\lambda)}\ \ \forall\lambda,\mu \geq 0 \qquad (1)$$

where an algebraic opening is defined as:

Definition 3.2 *An algebraic opening is any mapping $\phi : \mathcal{F} \longrightarrow \mathcal{F}$ fulfilling the following axioms:*

(i) Antiextensivity

$$\phi(f) < f \qquad (2)$$

(ii) Preservation of order, or increase

$$f < g \Longrightarrow \phi(f) < \phi(g) \qquad (3)$$

(iii) Idempotence

$$\phi[\phi(f)] = \phi(f) \qquad (4)$$

Serra and Vincent's work [23] presents a non-exhaustive catalogue of openings. There are four main types of openings: morphological openings, trivial openings, connected openings and envelope openings. From these types and by cross-union of various types, we can define a large number of different algebraic openings.

Considering $f(x,y)$ and $g(x,y)$ as finite-support greytone image functions, defined in $\mathbb{Z}^2$ and ordered by the following relation

$$f < g \Leftrightarrow f(x,y) < g(x,y) \quad \forall(x,y) \qquad (5)$$

we can construct several families of transformations suitable to calculate a granulometry on an image.

In short, a granulometry is based essentially on a sieving process and provides a size distribution of particles. Nevertheless, we are working on abstract sieves, which not only provide information on size but also on other features of particles. One of the goals of this work was to link the granulometry to first order statistics[3] of textural features. So, we propose to interpretate what we measure on particles as texton attributes.

To calculate a granulometry we firstly have to describe the opening, normally depending on a parameter b — the structuring element if the opening is based on morphological transformations –, and the parameters that define the transformation family. This selection depends on the blob feature measured.

Once we have applied the transformations to the image, one must calculate the granulometric curve, we will name it $GC_f(p, b(p))$. This curve is a feature distribution function:

$$GC_f(p, b(p)) = \frac{1}{\eta} \cdot \frac{dM(\phi_p(f))}{dp} \quad p \geq 0 \qquad (6)$$

where M represents a measure, which can be any Lebesgue measure, and η corresponds to a normalization parameter, in such a way that

are fairly well explained by Julesz in [10]

[3]The term first order statistics of a feature are used by Julesz as a density of the feature on the image

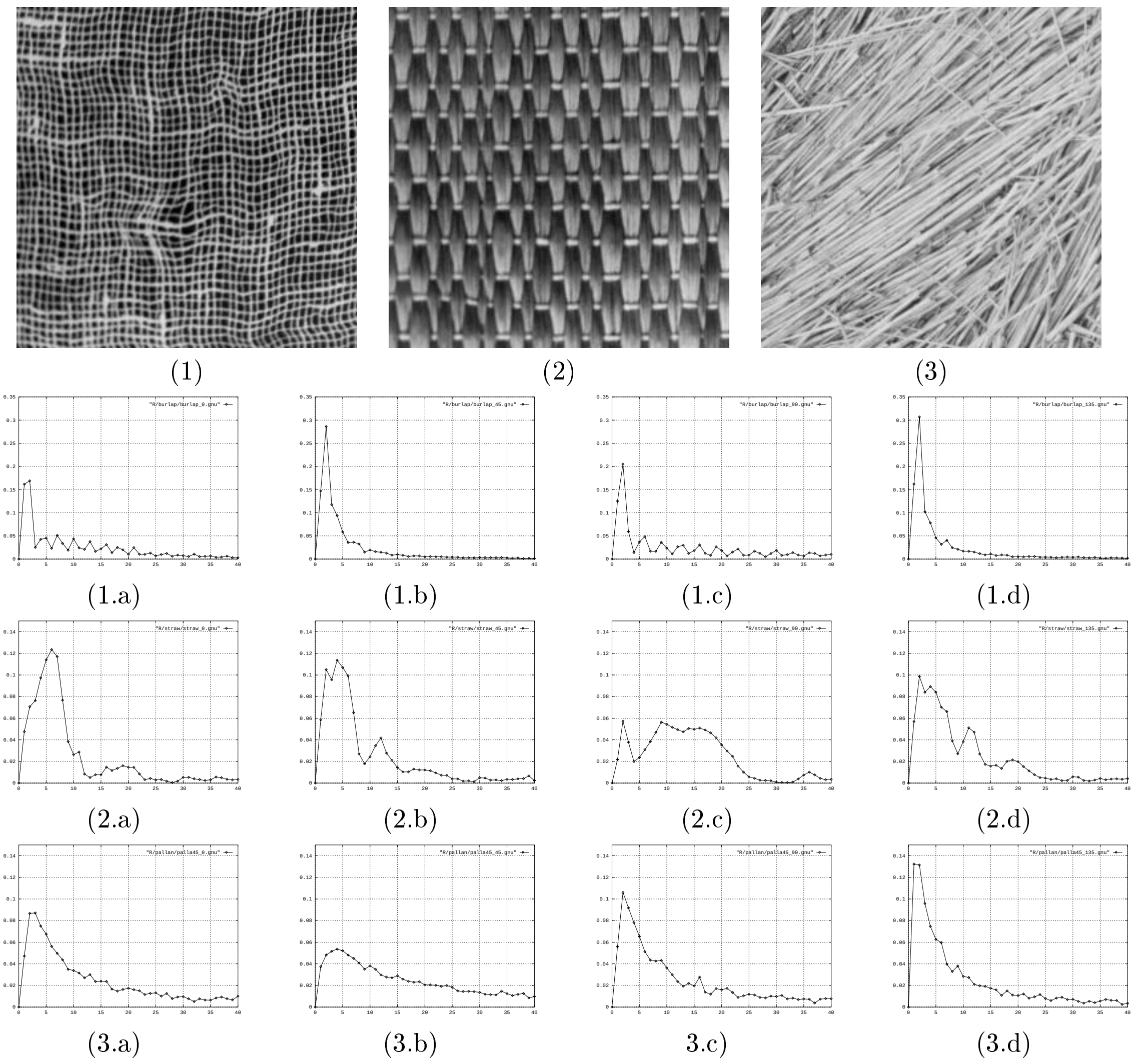


Figure 1: (1), (2) and (3) are the original images. (1.a), (1.b), (1.c) and (1.d) are the granulometric curves with a linear structuring element in a given direction $0°, 45°, 90°$ and $135°$, respectively.

$$\int_0^\infty GC_f(p,b)dp = 1 \qquad (7)$$

A discrete formulation of the expression above, assuming finite difference as a derivative approximation, is obtained by

$$GC_f(p,b) = \frac{1}{\eta} \cdot (M(f) - M(\phi_p(f))) \;\; p \geq 0 \qquad (8)$$

where $\eta = M(f) - M(\phi_{p_{max}}(f))$.

Once we have defined the granulometry, next, we will show how to aproximately design specific granulometries in order to calculate different textural features.

4 Size

By definition, a granulometry is a generic method to calculate size distribution of particles. By computing a granulometry on an image we obtain an approximation of the probability to see a particle of a given size in the image. It is not easy to define the meaning of size as Serra in [21] states. In our case we constrained the concept to individualized particles. Here particle size is very related to its shape, that is, given a particle shape one can easily find a good size descriptor for it.

If we know the a priori shape of particles, we can define a granulometry using a family of morfological openings with a structuring element accordingly with the particles shape. The structuring element $b(p)$ has an associated parameter p to define the size or scale of b.

In the event of not knowing the shape of the particle, we can use the inside longest straight distance between any two points. We can obtain this measure computing a granulometry by a family of algebraic openings defined as the supremum of morphological openings with linear structuring elements in the main directions, these are denoted by B_θ

$$\begin{aligned} \phi_p(f) &= \sup_\theta((f \ominus b(p)) \oplus b(p)) = \\ &= \sup_\theta((f \ominus pB_\theta) \oplus pB_\theta) \end{aligned} \tag{9}$$

In figure 3 we show some results of applying this algebraic opening[4] to a set of images with particles of various sizes.

5 Shape

Measuring or describing shape of particles is an important problem. P. Maragos studied it in depth in [16] and defined a shape-size descriptor called *pattern spectrum*. He also demonstrated the ability of the pattern spectrum to measure shape-size relation.

The pattern spectrum is given by

$$PS_f(r, g) = -\frac{dA((f \ominus rg) \oplus rg)}{dr} \quad r \geq 0 \tag{10}$$

hence we can directly relate it to a granulometric curve

$$PS_f(r, g) = -\eta \cdot GC_f(r, b(r)) \tag{11}$$

where $b(r) = r \cdot g$ and

$$M(f) = A(f) = \int_{\mathbf{R}^m} f(x)dx \tag{12}$$

Therefore the morphological opening has proved to be a good opening to describe shape. In this case $b(r)$ represents a structuring element of a given shape and scale r, it will determine the behaviour of the morphological opening with respect to the shape of the image particles.

As we have seen either PS as GS are functions depending on two parameters: scale r, and function $b(r)$. By fixing this last one we have a classical granulometric curve for a given structuring element, but varying both r and $b(r)$ we obtain the called *full pattern spectrum* in [16], as a *complete shape-size descriptor*.

In short, a set of granulometries can be a good complete descriptor of shape. We will apply these concepts to other specific granulometries in order to obtain *complete feature-size descriptors*.

6 Orientation

Defining the orientation of a given blob consists in determining how the blob lies in the field of view, we have to assume that it is an elongated blob[5]. Thus the orientation of the object is defined by the orientation of the *axis of elongation*. Usually it has been computed choosing the axis of least second moment [1]. To identify a particular line in an image we need to specify an angle and a distance from a x-y coordinate system.

Considering that we do not detect the blob, we will measure the distribution of orientation directly on the image — following the Vistnes's model. Using a granulometry we can compute the probability to find a particle of any size with an axis of elongation in a given orientation. It can be obtained by defining a family of morphological openings with a linear structuring element in a given direction θ, as B_θ defined in section 4.

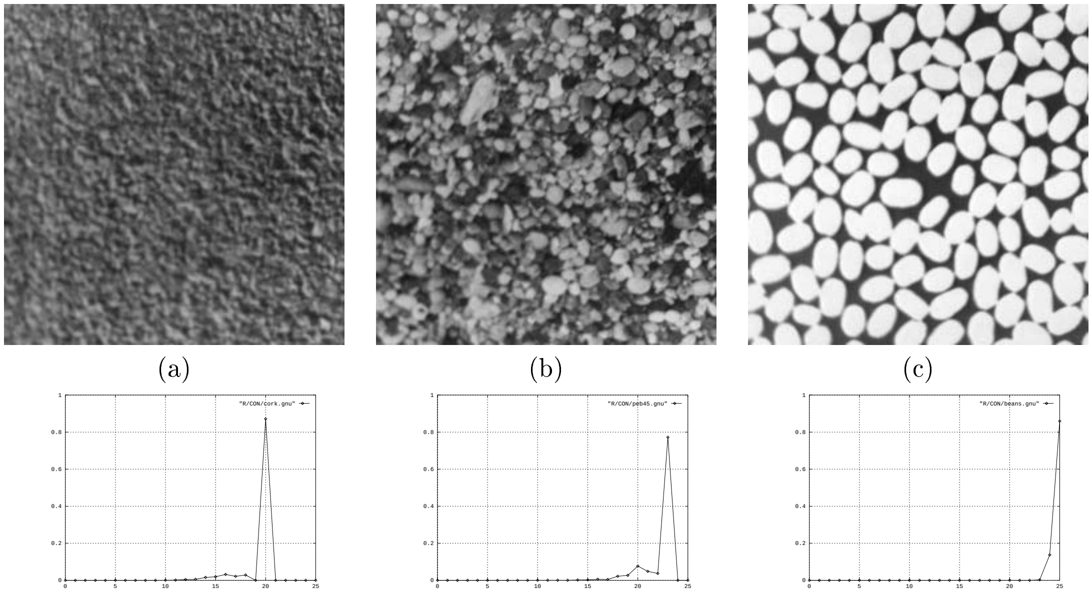
In the same way we need a x-y coordinate system to describe orientation, we will need more than one granulometric curve for a complete orientation description. Since each of them describe the orientation-size relation for a given direction, we define a *complete orientation-size descriptor* by grouping a set of granulometries, which provides the probability to find a particle in a given direction with regard to its scale or size. From this standpoint we show in figure 1 some images where a group of four granulometries has been measured, in order to give a full description of the predominant orientation of image particles. All of them present a global maximum at the first sizes, but the differences of their maximum values depend on the predominant orientation of image blobs. Therefore we can say that the smaller values of these maxima indicate which is the predominant orientation.

7 Contrast

In [27] has been demostrated that the constrast of a blob is a good blob attribute for texture discrimination. A review of the literature reveals that obtaining an approximation for the density of contrast values of blobs, without a previous blob detection, is a non trivial problem.

[4]Serra in [22] demonstrates that the supremum of a family of algebraic openings is also an algebraic opening

[5]Elongated blobs have been named *bars* by Marr



(a) (b) (c)

(d) (e) (f)

Figure 2: (a), (b) and (c) are the original images. (d), (e) and (f) are the three corrresponding granulometric curves.

The foregoing problem is illustraded by M. Grimaud in [5]. There, he presents an important reviewing of the classical primitives for contrast measurement as Rh-maxima or h-maxima, showing their main problems. He shows the weakness of the Rh-maxima in front of noise, and the non stability of parameters in a family of h-maxima transformations. Nevertheless, in the same work he offers a new measure, the dynamic of the extrema which allows to work in terms of contrast without regard to the size or shape of the substructures. It would be an interesting measure in order to construct a family of transformations, for granulometric purposes, based on a geodesic reconstruction of extrema with a dynamic value greater than a given h. However these transformation do not satisfy the increasing property, which is required to be suitable for a granulometry.

In view of these considerations we have not a good algebraic opening for contrast measuring. Even though, we show the granulometric curves obtained from applying a family of algebraic openings constructed by a geodesic reconstruction of image maxima which are greater than a h value (see figure 2). Consequently we obtain a density distribution of the intensity value of the image maxima. Which is a measurement at the pixel level, and does not supply us with enough information of the particles as image substructures.

8 Practical Application

We have calculated a series of granulometric measures on a set of chest radiographic images suffering from pneumoconiosis (See figure 3). This disease manifests itself as small opacities appearing on the radiographs and forming a certain textural pattern of bright blobs. The radiologist classifies the images according to a size criteria of the opacities — large, medium or small. They may classify a large number of images in a short time, thus this seems to be a preattentive perception problem.

Considering that an image has just one predominant size of opacities. On these images we have calculated the size density distribution. The algebraic opening applied in order to construct the granulometric curve is the supremum of linear structuring elements as defined in figure 10, with four predominant directions ($\theta = 0°, 45°, 90°, 135°$). The choice of this opening is due to their robustness at detecting the main diameter of the opacity, since the blobs are not perfectly rounded. The results show some granulometric curves in figure 3 where we can see a maximum, in the corresponding size interval.

9 Concluding Remarks

In this paper we have presented a general framework for texture discrimination based on the granulometric approach. We have shown some examples

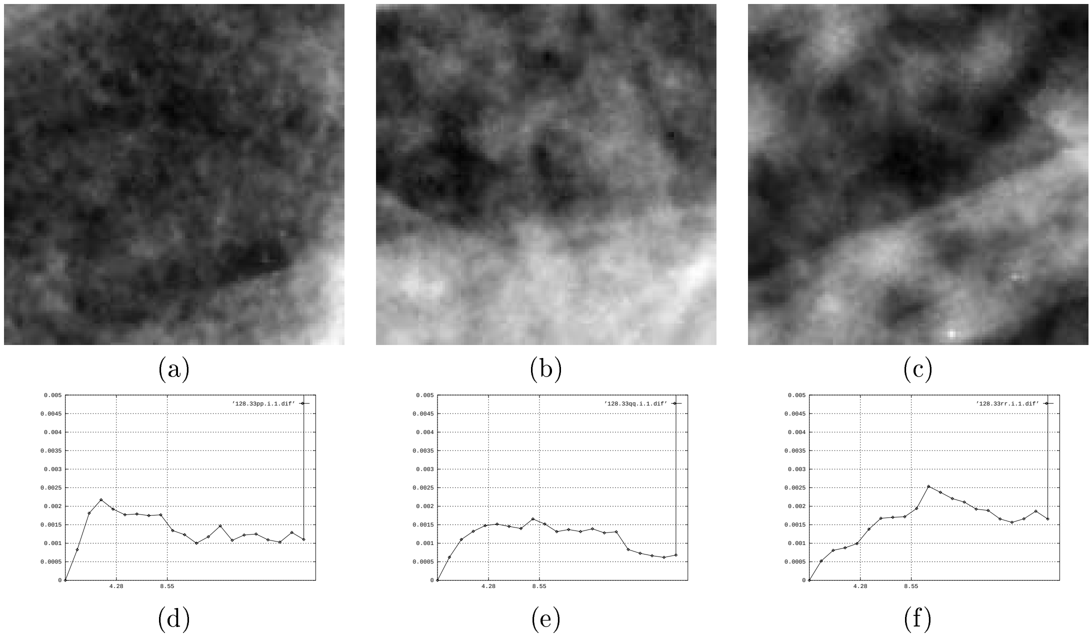


Figure 3: (a), (b) and (c) are radiographic images showing a textural pattern produced by rounded opacities of small, medium and large size, respectively. (d), (e) and (f) are the three corrresponding granulometric curves.

on how to construct granulometries. These enable us to estimate different attributes of local features, such as orientation, shape, size or contrast, in the framework of texton theory.

For this purpose we have extended the concept of *full pattern spectrum* [16], to an orientation-size descriptor. And we have used the classic granulometry as a tool to compute size density of particles. Finally we have exposed the problems in finding a good algebraic opening to measure the density of blobs contrast, whereas we have shown some works wich can help in defining such a transformation. For a complete framework we can introduce the concept of local granulometric size distributions exposed in [4] for segmentation purposes.

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