Image Retrieval Using Linear Greyscale Granulometries

Marcos Cordeiro d'Ornellas* Niels J. Nes

ISIS - Intelligent Sensory Information Systems
University of Amsterdam, Faculty WINS
Kruislaan, 403 - 1098 SJ
Amsterdam, The Netherlands
ornellas@wins.uva.nl niels@wins.uva.nl

Keywords: greyscale granulometry, pattern spectrum, linear openings, image retrieval and image databases

Abstract

Opening distributions for image analysis constitute an extremely useful tool in morphological tasks. Efficient techniques have been proposed to compute granulometries in greyscale images based on linear openings. Greyscale granulometries using opening distributions are equivalent to a contour extraction problem. The present study addresses the development of a morphological approach based on particle size distributions for the analysis of greyscale images using linear openings and their use as an input to build queries on a image database. From the experimental results, we show that the pattern spectra derived from the images can be used in texture based image retrieval.

1 Introduction

The concept of granulometry has been used to characterize size distributions and shapes on binary and greyscale images as suggested by Pitas and Venetsanopoulos [8], Maragos [7], and Haralick et all. [6]. Granulometries using linear openings have been extended to greyscale images by Vincent [9]. The resulting filter satisfies the three required properties of an opening (idempotence, increasingness and anti-extensivity). The specific approach that handle with granulometries is based on the fact that a constant number of particles and constant amount of area, at each scale level of the structuring element are used to obtain particle distributions. The result of the opening is constructed from a maximum of connected openings, where each connected opening works on a regional maxima in the image. We have descended down through the threshold sets of the image that contain its middle regional maxima, removing those threshold sets that do not satisfy the given criterion.

The process of choosing a criterion to perform image database retrievals will drive our results. Regardless of the fact that this approach has some simplifications of size distributions, it improves classifications produced by raw distributions. In this paper we use the pattern spectra derived from the images using granulometries. Based on these representations we can query the database to retrieve all similar spectra, where similarity is defined using an inverse distance metric.

The layout of the rest of this paper is as follows. Section 2 explains the Granulometric Segmentation. Then in the section 3 greyscale granulometries and pattern spectra are presented. Section 4 explains the database model and queries. In section 5 we comment something about our testsuite and show the evaluation and results of our queries based on this image data set. We will conclude with section 6 about further research.

2 Granulometric Segmentation

Granulometries are an important characteristic of many types of images. Some applications include industrial and biomedical surface inspection, ground classification and segmentation of satellite or aerial imagery, and document analysis. A major problem in the application of this approach to real problems is that distribution analysis of raw materials in the real world are usually not uniform due to changes in orientation, scale, or other visual appearance. Nonuniform illumination may also cause problems for distribution analysis. Segmentation is also difficult because we usually do not know a priori what types of size distribution exist in an image, how many different sizes there are, and which regions in the image have similar sizes.

As presented by Dougherty [4], granulometries were originally formulated for binary images. They are used to characterize size and shape information

*Formerly at Universidade Federal de Santa Maria, Departamento de Eletrônica e Computação, Santa Maria-RS, Brazil. Supported by CAPES Foundation under grant BEX 2780/95-0.

following the methodology in which they are sieved through sieves of various sizes and shapes. Accordingly, the sieving process depends on its size and shape relative to the mesh of the sieve. The sieving model serve as a means to approach the removal of some image structure and can be developed further to obtain image signatures based on the rate of sieving as proposed by Breen and Jones [2]. This approach can be used to build queries in an image database according to a defined criteria. The following definitions are based on the work of Maragos [7], Dougherty [5] [4], and Vincent [10], as stated below:

Definition 2.1 (Granulometry) *A granulometry can be interpreted as a collection of binary image operators* $\{\Psi_t\}, t > 0$*, such that* Ψ_t *is antiextensive for all t,* Ψ_t *is increasing for all t, and* $\Psi_t\Psi_s = \Psi_s\Psi_t = \Psi_{max\{t,s\}}$.

Definition 2.2 (Euclidean Granulometry) *If a granulometry* $\{\Psi_t\}$ *is translation invariant and the equation* $\Psi_t(A) = t\Psi_1(t^{-1}A)$ *is satisfied for any* $t > 0$ *and for any binary Euclidean image* A*, it is called a Euclidean granulometry.*

Vincent and Dougherty [10] observed that the most important example of an Euclidean granulometry is a finite union of openings, each by a parametrized convex, compact primitive:

$$\Psi_t(A) = (A \circ tB_1) \cup (A \circ tB_2) \cup \ldots \cup (A \circ tB_n) \quad (1)$$

The set of primitives $B = \{B_1, B_2, \ldots, B_n\}$ is called the *generator* of the granulometry and the invariant class of Ψ_t is composed of all binary images that can be formed as unions of translates of scalar multiples tB_i of B_i where $t \geq 1$.

The fundamental type of granulometry for Euclidean Images can be viewed as closed subsets of the Euclidean plane. It can be shown that if B is convex and $r > s > 0$, then rB is sB-open; that is, $rB \circ sB = rB$. Consequently, $A \circ rB$ is a subset of $A \circ sB$. Indeed, since rB is sB-open, filtering by both, in either order will lead to $A \circ rB$ as shown below:

$$(A \circ rB) \circ sB = (A \circ sB) \circ rB = A \circ rB \quad (2)$$

If we consider $t > 0$ as a variable, the family $\{A \circ tB\}$ of opened images, B convex, is called a granulometry. if $\Omega(t)$ is the area of $A \circ tB$, with $\Omega(0)$ being the area of A itself, then $\Omega(t)$ is a decreasing function of t, known as a size distribution. Under the assumption that A is bounded, $\Omega(t) = 0$ for sufficiently large t.

One can now define the *normalized size distribution*. It can be shown that $\Psi(t)$ increases from 0 to 1 and is continuous from the left.

Definition 2.3 (Normalized Size Distribution) *The distribution:*

$$\Psi(t) = 1 - \frac{\Omega(t)}{\Omega(0)} \quad (3)$$

is a probability distribution function known as the granulometric size distribution of A with respect to the generator B, $\Omega(t)$ *being the area of* $A \circ tB$*, and* $\Omega(0)$ *the area of* A *itself.*

Definition 2.4 (Granulometric Size Distribution) *Lets consider a sequence* $B_1, B_2, \ldots$ *of structuring elements of increasing size, where* B_{k+1} *is* B_k*-open for all k. Owing to the latter requirement, if A is any image, then* $A \circ B_{k+1}$ *is a subimage of* $A \circ B_k$*. Consequently, opening in turn by the structuring elements yields a decreasing sequence of images:*

$$A \circ B_1 \supseteq A \circ B_2 \supseteq A \circ B_3 \ldots \quad (4)$$

For each k, let $\Omega(k)$ *be the number of pixels of* $A \circ B_k$*. Then* $\Omega(k)$ *is a decreasing family of openings defined by k. Under assumptions that* B_1 *consists of a single pixel and that A is finite,* $\Omega(1)$ *gives the original pixel count in A and* $\Omega(k) = 0$ *for a sufficiently large k. Applying the normalization presented on the definition above with k in place of t and* 1 *in place of* 0 *yields a normalized size distribution* $\Psi(k)$*. It is a discrete probability distribution function and possesses a discrete derivative*

$$\Psi'(k) = d\Psi(k) = \Psi(k+1) - \Psi(k) \quad (5)$$

which is a discrete density. The density is called a granulometric size distribution or pattern spectrum.

3 Greyscale Granulometries

Binary and greyscale granulometries openings share the same definitions in terms of erosion and dilation. While a binary opening of a set A by structuring element B is given by the union of all translates of B that are subsets of A, a greyscale opening of a function f by a structuring element (function) g is given by the supremum of all greyscale translates of g that lie beneath f.

3.1 Linear Granulometries

In general, an opening operation by a structuring element of a certain size removes all features from an image that are smaller than the size and geometry of the structuring element.

A horizontal line structuring element is used to preserve some characteristics in the images. In this way, a single structuring element can be used to generate particle distributions, simplifying the final analysis. Another reason for the use of a single element is computational efficiency, as the employment of a set of structuring elements is computationally more costly.

According to the linear greyscale granulometry approach proposed by Vincent and denoting by $NL(p)$ and $NR(p)$ respectively the left and the right neighbors of a pixel p, we are now in a position to analyse the effect of an opening by a linear segment $L_n, n \geq 0$ on a greyscale image I and define the horizontal line segment and the horizontal maximum as follows:

Definition 3.1 (Horizontal Line Segment) *A horizontal line segment S, of length $l(S)$, can be interpreted as a set of pixels $\{p_0, p_1, \ldots, p_{n-1}\}$ such that for $0 < i < n$, $p_i = N_r(p_{i-1})$.*

Definition 3.2 (Horizontal Maximum) *A horizontal maximum M of length $l(M) = n$ in a greyscale image I is a horizontal line segment $\{p_0, p_1, \ldots, p_{n-1}\}$ such that:*

$$\forall i, 0 < i < n, I(p_i) = I(p_1) \tag{6}$$

and,

$$I(NL(p_0)) < I(p_0), I(NR(p_{n-1})) < I(p_0). \tag{7}$$

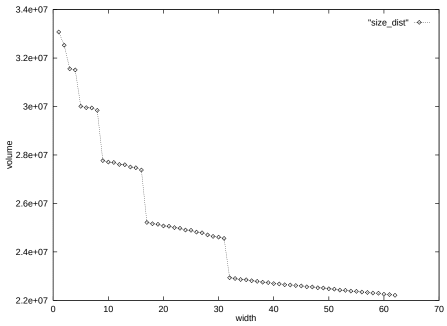
Furthermore, the effect of an opening of size n on the pixels of M can be quantified : the value of each pixel $p \in M$ is decreased from $I(p)$ to $MAX\{I(NL(p_0)), I(NR(p_{n-1}))\}$. In other words, the contribution of maximum M to the n^{th} layer of the horizontal pattern spectrum $PS_h(I)$ is:

$$n \times [I(p) - MAX\{I(NL(p_0)), I(NR(p_{n-1}))\}]. \tag{8}$$

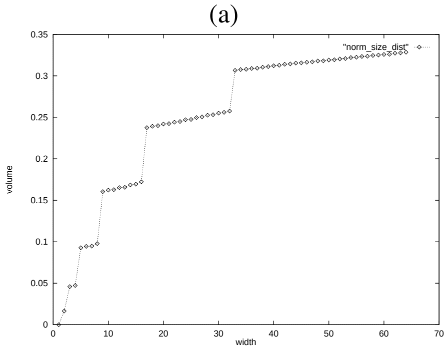
The effect of a horizontal opening of size n on M is that a new *plateau* of pixels is created at altitude $max\{I(NL(p_0)), I(NR(p_{n-1}))\}$. This plateau P contains M, and may be itself a maximum of $I \circ L_n$. According to this criterion and based on the definitions proposed, we have the following algorithm:

```
for (each maximum M of this line) {
    adds contribution of this maximum to l(M)^th layer of pattern spectrum;
    do {
        let P be the plateau of pixels formed by opening of size l(M) of M;
        if (P is itself a maximum of I ∘ L_l(M))
            computes its contribution to layer l(P) of pattern spectrum;
    } While (P is no longer a maximum)
    Mark the maximal region around M as already processed;
}
```

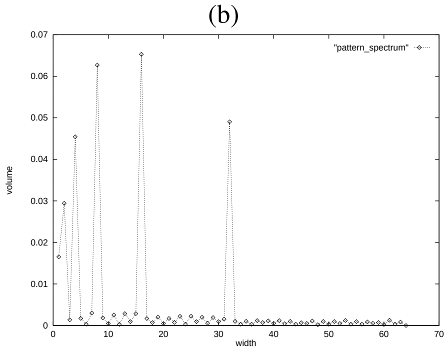
In accordance with the algorithm proposed, the distributions are generated by opening each binary image with a succession of horizontal linear structuring elements of increasing size. This is obtained in steps of 1 pixel, starting at length 0 (the original image), to a maximum of 64 pixels as we can see in figure 1:



(a)



(b)



(c)

Figure 1: Size Distribution(a),Normalized Size Distribution(b), and Pattern Spectrum(c) from image Rock.0019.

4 Image Database Queries

In this section we will explain how we use pattern spectra to retrieve images from an image database. We will introduce the data model and the queries involved.

4.1 Image Database Model

The database model needed for the image retrieval is defined by the tuple (image, pattern spectrum). For each image we derive its pattern spectrum using linear greyscale granulometries.

Searching images in a database can be done in various ways. Users of a image database could add keywords to a database, so the querying for these images could be done based on these keywords. The proposed solution is to use the image content directly. Two major problems with this approach exist: first, which content of the image should be used and second, how to express queries over the image content. Current solutions are focused on query by image example. These approaches search the image database for images with similar content based on an example image. The content is usually abstracted to some (long) vector of feature values. The query by image content used is based on a similarity measure (sm). These measures indicate the similarity between two vectors, i.e., between two images, by using the euclidean distance. Formally:

$$sm(ps_1, ps_2) = 1 - \sqrt{(ps_1 - ps_2)^T(ps_1 - ps_2)} \quad (9)$$

The only image content we use is the texture which we reduce to a pattern spectrum using the granulometries.

4.2 The Pattern Spectrum Queries

To retrieve images by example we query the database for similar pattern spectra. So given an image we calculate its pattern spectrum, ps. Our algorithm should find all spectra (and related images) which are similar according to the given measure. A sequential algorithm can solve this problem in linear complexity in the number of pattern spectra. Using an index structure on the spectra we could improve this substantially. Examples of those index structures are K-D and SS-trees, signature files and R-trees.

The image retrieval algorithms, granulometries and pattern spectra calculations are implemented in Monet[1] a novel main memory database. These algorithms are built using a special metric function which selects all objects which are within a certain distance for a given object. The M-select function needs a similarity relationship which defines a proper metric. Our measure is the proper L^2 or euclidean metric.

5 Evaluation

5.1 Test Images

To test our algorithm and evaluate our results, we had obtained the testsuite from the Queensland Node of The Cooperative Research Centre for Sensor Signal and Information Processing - Australia.[1].

The sample test data used in this evaluation are taken from 5 classes of natural textures, namely rock, grass, misc, asphalt, and concrete. These images are classified according to its contents, lighting and perspective as presented in table 1. Although the test images do not cover the full range of natural textures, the analyzed image data are fairly typical and diverse and are considered adequate for the purposes of this initial investigation. The algorithms developed in Monet were intended to generate pattern spectra for all images and to build queries based on these spectra.

[1]These test images are available at http://www.cssip.elec.uq.edu.au/$tilde$guy/meastex/meastex.html or at the same ftp server.

5.2 Experimental Results

Table 1 shows the results obtained from images belonging to the testsuite described above. Our aim is to classify *rock* images according to the similarity with **Rock.0019**. It should be noted from the table that there are no images belonging to the *asphalt* class in the first (20) twenty images and just a few belong to the other classes. Most of the images belong to the *rock* class [2]. Since the results are based on the similarity measure, some images from *misc* class are supposed to belong to the *rock* class. The performance presented based on the work of Vincent [9] and Breen and Jones [2] with this set of images may also indicate some of the limitations of the similarity measure used. Chauduri and Sharkar [3] proposed a texture segmentation method using fractal dimension motivated by the observation that the fractal dimension is relatively insensitive to an image scaling, and shows a strong correlation with human judgement of surface roughness. They also shown that natural textures have a linear log power spectrum, and that the processing in the human visual system is well suited to characterize such textures. A fractal dimension is then an approximate pattern spectra estimation. The additional task of developing algorithms that exploit this concept as well as of extending the aproaches mentioned to color texture images is part of further work.

According to figure 2, it is clear that the images are classified according to the similarity of their textures. This figure combines all the pattern spectra from the first (5) five images. It is easy to see that the differences among these pattern spectra are minimal. Figure 2(b) and (c) show the effects of unequal illumination. These effects can be reduced to insignificant amounts either by providing artificial lighting when taking pictures of the surfaces or by preprocessing.

6 Conclusions

This work represents an investigation into the utility of a single class of horizontal linear structuring elements as the basis for the morphological measures. Our preliminary results were produced using linear greyscale granulometries. They showed that our queries, based on the euclidean metric L^2 presented, were capable to distinguish one image class (rock) among the other classes based on the pattern spectra.

Although the use of closing distributions is not addressed in this study, future developments will explore their role in classification, especially in terms of their ability to detect spatial relationships between particles. This study were focused exclusively on opening distributions and their sufficiency in achieving the task of classification according to the similarity measure to build queries on an image database.

[2]There are (25) twenty-five rock images in the testsuite used.

	Image Name	Content	Lighting	Perspective	Similarity
01	Rock.0019	fine gravel	daylight direct	frontal pane	1.000000
02	Rock.0018	gravel	daylight direct	oblique	0.999845
03	Rock.0016	gravel	daylight direct	oblique	0.999840
04	Rock.0015	gravel	daylight direct	oblique	0.999820
05	Rock.0020	stone	daylight direct	oblique	0.999776
06	Rock.0005	gravel	daylight direct	frontal pane	0.999744
07	Rock.0017	gravel	daylight direct	oblique	0.999737
08	Rock.0022	bedding sand	daylight direct	frontal pane	0.999718
09	Rock.0004	gravel	daylight direct	frontal pane	0.999712
10	Misc.0000	bark mulch	daylight direct	frontal pane	0.999541
11	Concrete.0000	concrete (broomed)	daylight direct	frontal pane	0.999531
12	Rock.0000	sandstone block	daylight direct	frontal pane	0.999403
13	Rock.0008	fine gravel	daylight direct	frontal pane	0.999397
14	Concrete.0011	sprayed concrete	flash	frontal pane	0.999347
15	Misc.0009	bark mulch	daylight direct	frontal pane	0.999301
16	Misc.0004	office partition	daylight indirect	frontal pane	0.999297
17	Rock.0003	sandstone block	daylight indirect	frontal pane	0.999297
18	Misc.0001	bark mulch	daylight direct	frontal pane	0.999272
19	Misc.0005	office partition	flash	frontal pane	0.999230
20	Grass.0017	grass	daylight direct	frontal pane	0.999127
⋮	⋮	⋮	⋮	⋮	⋮
68	Misc.0002	corrugated iron	daylight indirect	frontal pane	0.988305
69	Concrete.0008	concrete wall	flash	frontal pane	0.987468

Table 1: Testsuite class information and similarity results

References

[1] P. A. Boncz and M. L. Kersten. Monet: An impressionist sketch of an advanced database system. In *Proc. IEEE BIWIT workshop, San Sebastian (Spain)*, july 1995.

[2] E. J. Breen and R. Jones. Attribute openings, thinnings, and granulometries. *Computer Vision and Image Understanding*, 64(3):377–389, 1995.

[3] B. B. Chaudhuri and B. U. Shankar. Texture segmentation using fractal dimension. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(1):72–77, 1995.

[4] E. R. Dougherty. Euclidean grayscale granulometries: Representation and umbra inducement. *Journal of Mathematical Imaging and Vision*, 1(1):7–21, 1992.

[5] E. R. Dougherty. *An Introduction to Morphological Image Processing*. SPIE Optical Engineering Press - Tutorial Texts in Optical Engineering - Vol. TT9, Belingham, 1992.

[6] R. M. Haralick, P. L. Katz, and E. R. Dougherty. Model-based morphology: The opening spectrum. *Graphical Models and Image Processing*, 57:1–12, 1995.

[7] P. Maragos. Pattern spectrum and multiscale shape representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 11:701–716, 1989.

[8] I. Pitas and A. N. Venetsanopoulos. Morphological shape decomposition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12:38–45, 1990.

[9] L. Vincent. Morphological area openings and closings for grey-scale images. In Y.-L. O, A. Toet, D. Foster, H. J. A. M. Heijmans, and P. Meer, editors, *Proceedings of the Workshop "Shape in Picture", 7–11 September 1992, Driebergen, The Netherlands*, pages 197–208, Berlin, 1994. Springer.

[10] L. Vincent and E. R. Dougherty. Morphological segmentation for textures and particles. In E. R. Dougherty, editor, *Digital Image Processing Methods*, pages 43–102. Marcel Dekker, New York, 1994.

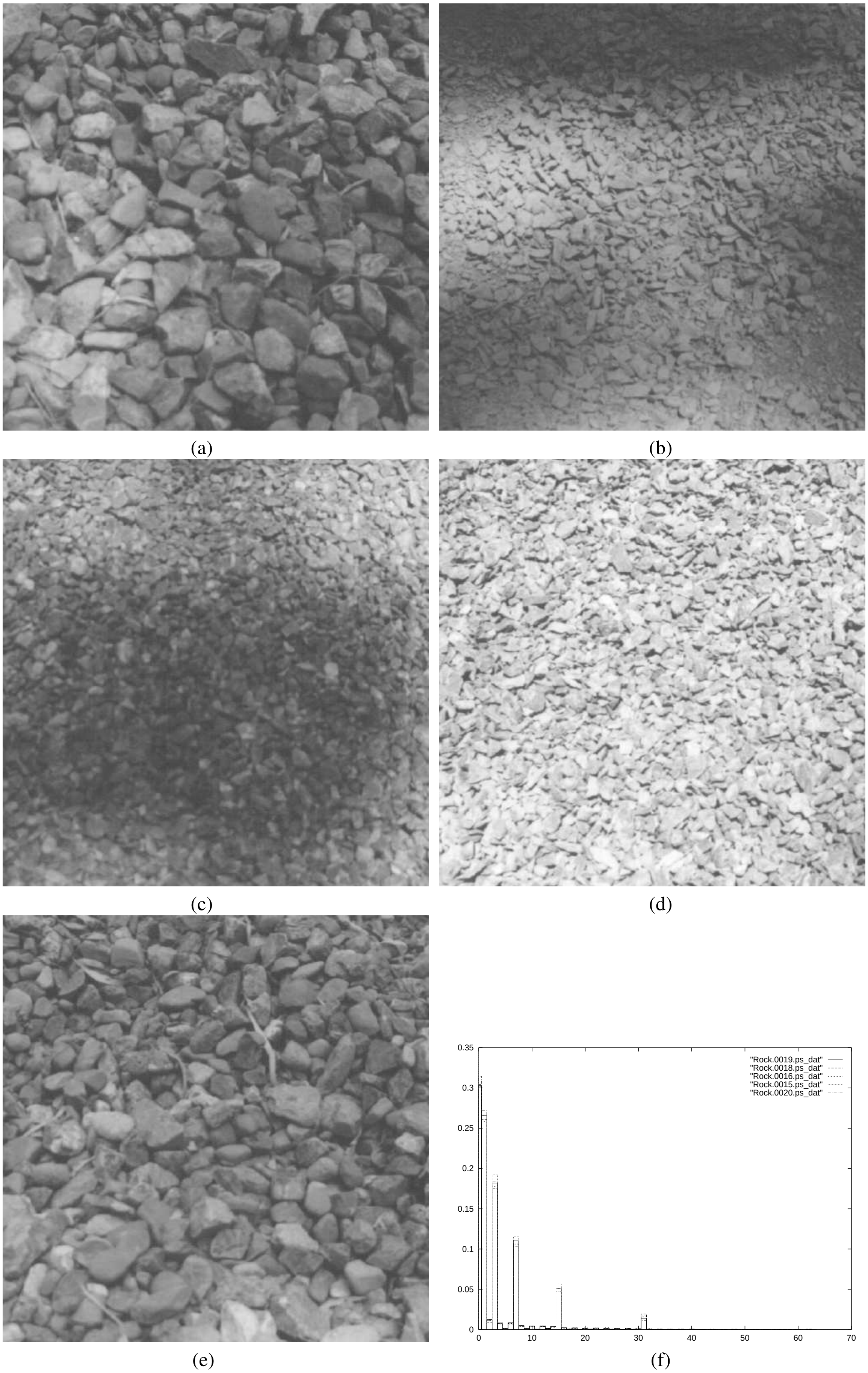


Figure 2: Rock0019(a), Rock.0018(b), Rock.0016(c), Rock.0015(d), Rock.0020(e), and Pattern spectrum(f).