Chapter 6

Conclusion and future work

We pointed out in the introduction, when discussing about the versatility of wavelets as a tool in signal processing, that they can be adapted to many problems of different scientific disciplines and especially in our field, computer vision and image processing. In this work, we have shown that wavelets have this well-known flexibility permitting us to explore the solution for several general problems as segmentation and classification extending these solutions to several applications. Problems presented in this work are related to texture analysis, a large area of study in itself. We have began this dissertation on an introductory work aimed at the segmentation of a specific kind of images, and later we changed the approach to explore the topics of texture classification and synthesis. Besides, in all the problems we have proposed an image model as a starting point to study and justify how to process them.

The first part of this thesis has dealt with the classification of marble images that can be seen as structural textures. The elements defining these textures are grains that must be segmented. This segmentation of marble samples in their grains is used for specialists to classify them. This is a technique with good classification results but with a cumbersome stage of segmentation that makes infeasible perform it by hand. In this work we have automated this task, delivering to the professional this segmentation and morphological parameters of each grains useful in the classification stage.

If we analyze these marble images we realize that to delimit each grain is a difficult task due to noise in the image, macles, weak boundaries etc. Professionals use the information that arises from the observation of the samples through polarized light in order to decide where grains are. We also take advantage from this fact, and use the image formation model offered by the Johannsen's law, which relates the incident and transmitted light intensities through uniaxial crystals (marble). From a sequence, we can calculate two parameters (amplitude and phase) intrinsic of each grain that is used to aid segmentation.

Several methods have been evaluated to achieve the segmentation. In this sense, and due to the characteristics of grains that are closed regions, we conclude that watershed transform is the best solution for this problem. This transformation applied directly to the images gives an excessive over segmentation due basically to noise. Therefore a previous filtering stage is mandatory.

The filtering step was done initially with similar tools used in the segmentation, but once we started to study multiresolution schemes, this step was redefined and designed in terms of the wavelet transform. In this work we have proposed a new wavelet filtering approach whose results can be easily interpreted in terms of relevant elements of the image: noise, non-homogeneous illumination and contributions to crest and valleys. In this way, we can isolate the important information to our problem that are ridges, now free of disturbing elements, giving a good starting point for the segmentation step. The information obtained in the segmentation is now expressed as a graph to refine the results with the previous amplitude-phase information. This duality of the representation, as image or as a graph, permits to work with the best one according to each process.

The same idea of a partial reconstruction of a wavelet decomposition in order to extract only the necessary elements and the representation of the partial result as a graph can be easily extended to similar problems of image segmentation. As a future development we include some preliminary results on the segmentation of people in indoor scenes. In this case, segmentation is a starting point of a labeling process where any part (clothing) of the subject must be automatically described in natural language in pursuit of a global description of the subject.

Results show that our method achieves a correct segmentation for most grains in a variety of marble types, without any initial knowledge on their characteristics. Once the segmentation is done, the expert studies several parameters related to the morphology of each grain and the relation among the bulk of grains. With all this information and based on his knowledge and expertise he gives a source quarry for the sample.

The second part of this work has addressed a problem of color texture classification through multiresolution decomposition techniques. This is an important subject due to its implications in quality control, and image retrieval. Since our research is related to one real application, we approach this part as a general texture classification but then tend to center our attention on achieving practical solutions. The kind of images we face now are characterized by their high visual similarity, that is, a completely different problem with regard to most publications in this area.

We adopt a common strategy to study this problem with a decomposition stage and a feature extraction but adapting each step to our requirements. In this sense, our aim was to find an optimal combination of color representation, decomposition scheme plus base and number of levels, and discriminant features.

A conclusion that reveals our work and also reported for other authors is that the bases used in the decomposition do not play a significant role achieving similar percentages of success. However all the process can be tuned for a specific problem or set of images to slightly increase the classification rate.

Texture and color are two properties that coexist at the images and their interrelations can be more or less strong depending on the images. In this sense, we have proposed three image models in which this interrelation has different weight, and then some spatial-chromatic features are more important than others. These models refer to how texture is embedded into color and how texture in each channel relates to texture of the other ones.

In most papers related to texture classification, the feature extraction step yields a lot of information that must be reduced. This reduction should be performed by classic methods of dimensionality reduction without any knowledge about the data. In this work, we propose models in such a way that images following one of these models need a specific set of features to be characterized. This idea has been supported by actual results showing that selecting the right features achieves the smallest classification error.

Future research will address the estimation of other features with a high level of interrelation among channels and levels of the decomposition. Also, we will try mutual information as other measure of dependence between the images of the decomposition. Then, we will apply these results to a more elaborate paint recognition problem. In this case, we want to complete classification results with other inputs as chromatic (spectral) information to arrive to the determination of the components of these paints.

Finally, we essay to characterize texture through multidimensional probability density functions extracted from pixel neighborhoods. This description is used to classify and also to synthesize similar textures. We propose a way to classify textures according with this probability model based on similarity measures over these density functions. We compare the proposed 'metric' with standard distance values. Our synthesis starts with this model as a base and then has evolved to a multiresolution scheme. Results of the last part are still preliminary and a deal of further work is still necessary.

Appendix A

Detailed results

A.1 Tiles

The tile case was studied in-depth in order to plan the strategy in later classification studies. In this case a lot of decomposition schemes, bases and decomposition levels were analysed arriving to some conclusion in order to reduce the number of possible trials in other problems.

Tables represent the percentage of successful classification, % symbol has been elided for the sake of a better presentation of data. The proofs done in this section refers to three models of tile: A (Du, Duero), B (Es, Esla), C (Tb, Tiber); letters are the name used in the previous explanation (Sec. 4.4), names in parentheses are the label used in tables first, and the commercial name of these tiles.

Nomenclature used to label rows and columns of the next tables comprise: number of components of the feature vector (#f), type of set used in the classification (l: learning, t: test), transformation (W: multiresolution analysis, WP: wavelet packets, T: *à trous*, number of levels in the decomposition as the number that follows the transform or labeled as #l, functions used to obtain the features (L2: energy, EN: entropy), bases in the decomposition (D: Daubechies, B: B-spline), features are represented a prefix to the transform (F.a: without prefix, F.a+F.b: CN, F.a+F.b+F.c: CC). If a table is not divided in models it means that results are totals.

Table A.1: Classification ratios from simple features for models A, B and C.

		Du		Es		Tb		
Features	#f	l	t	l	t	l	t	total
mean and variance	6	100.0	94.4	90.0	79.4	100.0	87.5	87.1
mean	3	93.8	76.3	83.8	63.8	82.5	79.4	73.2
variance	3	98.8	90.0	90.0	72.5	73.8	70.0	77.5
energy of RGB	3	95.0	73.1	86.3	71.9	77.5	75.0	73.3

Table A.2: Classification of the tree models using multiresolution analysis (Mallats algorithm) with energy features without removing mean and variance.

		Du		Es		Tb		
Scheme	#f	l	t	l	t	l	t	total
W1L2D2	12	100.0	93.1	97.5	84.4	100.0	88.8	88.8
W1L2D4	12	100.0	94.4	97.5	83.8	97.5	88.1	88.8
W1L2D6	12	100.0	95.6	95.0	85.0	95.0	84.4	88.3
W1L2D8	12	100.0	95.0	97.5	82.5	95.0	86.3	87.9
W1L2D10	12	100.0	95.6	96.3	81.9	97.5	86.3	87.9
W1L2D12	12	100.0	95.6	95.0	80.6	91.3	86.3	87.5
W1L2D14	12	100.0	96.3	97.5	81.3	88.8	88.1	88.6
W1L2D16	12	100.0	95.0	96.3	81.9	85.0	90.0	89.0
W1L2D18	12	100.0	95.0	96.3	82.5	85.0	88.8	88.8
W1L2D20	12	100.0	95.0	93.8	83.1	86.3	86.3	88.1
W2L2D2	21	100.0	93.8	97.5	82.5	98.8	89.4	88.6
W2L2D4	21	100.0	95.6	97.5	82.5	96.3	85.6	87.9
W2L2D6	21	100.0	95.0	96.3	82.5	92.5	86.9	88.1
W2L2D8	21	100.0	95.6	97.5	83.1	96.3	86.3	88.3
W2L2D10	21	100.0	94.4	96.3	83.8	97.5	90.6	89.6
W2L2D12	21	100.0	96.3	95.0	83.1	93.8	92.5	90.6
W2L2D14	21	100.0	95.0	95.0	84.4	96.3	88.8	89.4
W2L2D16	21	100.0	94.4	98.8	84.4	93.8	90.0	89.6
W2L2D18	21	100.0	95.0	95.0	85.6	95.0	88.1	89.6
W2L2D20	21	100.0	95.3	97.5	85.0	97.5	86.3	88.9
W3L2D2	30	100.0	95.6	95.0	78.8	96.3	87.5	87.3
W3L2D4	30	100.0	93.8	96.3	80.0	100.0	90.6	88.1
W3L2D6	30	100.0	96.3	97.5	78.8	100.0	87.5	87.5
W3L2D8	30	100.0	93.8	96.3	80.6	97.5	87.5	87.3
W3L2D10	30	100.0	93.8	96.3	82.5	98.8	88.8	88.4
W3L2D12	30	100.0	95.6	97.5	81.3	96.3	91.3	89.4
W3L2D14	30	100.0	95.0	98.8	84.4	97.5	89.4	89.6
W3L2D16	30	100.0	95.6	97.5	81.9	97.5	89.4	89.0
W3L2D18	30	100.0	93.1	96.3	81.9	96.3	88.8	87.9
W3L2D20	30	100.0	93.1	97.5	83.1	96.3	88.8	88.3
W4L2D2	39	100.0	95.0	97.5	82.5	100.0	88.1	88.5
W4L2D4	39	100.0	95.0	96.3	80.6	100.0	89.4	88.3
W4L2D6	39	100.0	95.6	97.5	76.9	100.0	87.5	86.7
W4L2D8	39	100.0	95.0	97.5	78.8	100.0	90.0	87.9
W4L2D10	39	100.0	95.6	97.5	81.3	100.0	90.0	89.0
W4L2D12	39	100.0	92.5	93.8	83.1	100.0	93.1	89.6
W4L2D14	39	100.0	93.1	97.5	83.1	100.0	88.8	88.3
W4L2D16	39	100.0	93.8	97.5	79.4	100.0	85.6	86.3
W4L2D18	39	100.0	93.8	96.3	79.4	100.0	90.6	87.9
W4L2D20	39	100.0	92.5	97.5	82.5	100.0	88.1	87.7
W5L2D2	48	100.0	94.4	95.0	81.3	98.8	86.9	87.5
W5L2D4	48	100.0	96.3	97.5	81.3	100.0	88.1	88.6
W5L2D6	48	100.0	95.0	96.3	78.8	100.0	86.9	86.9
W5L2D8	48	100.0	95.6	97.5	76.9	100.0	82.5	85.0
W5L2D10	48	100.0	96.3	97.5	80.6	100.0	88.1	88.3
W5L2D12	48	100.0	93.1	96.3	81.3	100.0	90.0	88.1
W5L2D14	48	100.0	94.4	97.5	79.4	98.8	91.3	88.4
W5L2D16	48	100.0	93.1	97.5	80.6	100.0	88.8	87.5
W6L2D2	57	100.0	94.4	97.5	76.3	100.0	86.9	85.9
W6L2D4	57	100.0	96.3	96.3	80.6	100.0	86.9	87.9
W6L2D6	57	100.0	95.6	97.5	76.9	100.0	86.9	86.5
W6L2D8	57	100.0	92.5	97.5	78.1	100.0	80.0	83.5
W7L2D2	66	100.0	92.5	97.5	77.5	100.0	85.6	85.2
W7L2D4	66	100.0	95.6	96.3	80.0	100.0	87.5	87.7

Table A.3: Classification ratios for the three models: Du, Es, Tb. The first two columns are number of features used for classification purposes and the number of decomposition levels. Next columns represent different bases (*e.g* D2 is Daublechies, and so on). The number inside the table are the classification percentage (% is suposed in all the results, it has been omitted for clearity)

#f	#l	D2	D4	D6	D8	D10	D12	D14	D16	D18	D20
						Du					
12	1	93.1	94.4	95.6	95.0	95.6	95.6	96.3	95.0	95.0	95.0
21	2	93.8	95.6	95.0	95.6	94.4	96.3	95.0	94.4	95.0	95.3
30	3	95.6	93.8	96.3	93.8	93.8	95.6	95.0	95.6	93.1	93.1
39	4	95.0	95.0	95.6	95.0	95.6	92.5	93.1	93.8	93.8	92.5
48	5	94.4	96.3	95.0	95.6	96.3	93.1	94.4	93.1		
57	6	94.4	96.3	95.6	92.5						
66	7	92.5	95.6								
						Es					
12	1	84.4	83.8	85.0	82.5	81.9	80.6	81.3	81.9	82.5	83.1
21	2	82.5	82.5	82.5	83.1	83.8	83.1	84.4	84.4	85.6	85.0
30	3	78.8	80.0	78.8	80.6	82.5	81.3	84.4	81.9	81.9	83.1
39	4	82.5	80.6	76.9	78.8	81.3	83.1	83.1	79.4	79.4	82.5
48	5	81.3	81.3	78.8	76.9	80.6	81.3	79.4	80.6		
57	6	76.3	80.6	76.9	78.1						
66	7	77.5	80.0								
						Tb					
12	1	88.8	88.1	84.4	86.3	86.3	86.3	88.1	90.0	88.8	86.3
21	2	89.4	85.6	86.9	86.3	90.6	92.5	88.8	90.0	88.1	86.3
30	3	87.5	90.6	87.5	87.5	88.8	91.3	89.4	89.4	88.8	88.8
39	4	88.1	89.4	87.5	90.0	90.0	93.1	88.8	85.6	90.6	88.1
48	5	86.9	88.1	86.9	82.5	88.1	90.0	91.3	88.8		
57	6	86.9	86.9	86.9	80.0						
66	7	85.6	87.5								
						total					
12	1	88.8	88.8	88.3	87.9	87.9	87.5	88.6	89.0	88.8	88.1
21	2	88.6	87.9	88.1	88.3	89.6	90.6	89.4	89.6	89.6	88.9
30	3	87.3	88.1	87.5	87.3	88.4	89.4	89.6	89.0	87.9	88.3
39	4	88.5	88.3	86.7	87.9	89.0	89.6	88.3	86.3	87.9	87.7
48	5	87.5	88.6	86.9	85.0	88.3	88.1	88.4	87.5		
57	6	85.9	87.9	86.5	83.5						
66	7	85.2	87.7								

Table A.4: Classification ratios for the *à trous* algorithm (energy features). In this experiment we have varied the number of levels and base of decomposition.

			Du			Es			Tb			total	
#f	#l	B0	B1	B2	B0	B1	B2	B0	B1	B2	B0	B1	B2
6	1	93.1	93.8	93.1	81.9	85.0	83.1	88.8	86.3	87.5	87.9	88.4	87.9
9	2	94.4	94.4	93.8	85.0	83.8	83.8	91.3	93.8	93.8	90.2	90.7	90.5
12	3	94.4	95.6	94.4	81.3	84.4	80.6	86.9	95.6	89.4	87.5	91.9	88.1
15	4	94.4	93.8	93.8	82.5	84.4	82.5	86.9	95.6	91.3	87.9	91.3	89.2
18	5	94.4	94.4	93.1	80.0	82.5	81.9	88.8	83.8	92.5	87.7	86.9	89.2
21	6	93.8	93.1	91.9	81.9	81.9	80.6	86.3	86.3	93.8	87.3	87.1	88.8
24	7	91.9	92.5	90.0	82.5	80.6	80.0	86.9	85.6	90.0	87.1	86.2	86.7

Table A.5: Classification ratios for wavelet and wavelet packet decomposition schemes with and without illumination information.

	W1	W2	W3	WP2	WP1,2
#f	12	21	30	48	60
with mean and variance					
D2	88.8	88.6	87.3	83.1	88.6
D4	88.8	87.9	88.1	85.0	87.5
D6	88.3	88.1	87.5	85.9	86.2
without mean and variance					
D2	84.6	84.8	83.2	80.8	76.9
D4	85.9	85.4	82.3	77.7	82.9
D6	85.8	85.4	83.8	80.9	83.4

Table A.6: Classification ratios for the three models and for learning and test sets. Features comes from the *à trous* algorithm for different strategies exploring color.

		Du		Es		Tb		total
Scheme	#f	l	t	l	t	l	t	test
CNT2L2B1	12	100,0	94,4	96,3	86,9	100,0	86,9	89,4
CNT3L2B1	21	98,8	91,3	92,5	87,5	97,5	83,1	87,3
CNT4L2B1	33	100,0	91,9	95,0	86,3	98,8	83,1	87,1
CCT2L2B1	18	100,0	95,0	91,3	82,5	100,0	91,9	89,8
CCT3L2B1	24	100,0	95,6	97,5	87,5	100,0	95,0	92,7
CCT4L2B1	30	100,0	93,8	96,3	85,6	98,8	81,3	86,9
T3L2B1RGBgris	6	100,0	97,5	92,5	77,5	85,0	80,0	85,0
T3L2B1sMV	12	100,0	91,9	87,5	82,5	91,3	74,4	82,9
CCT3L2B1	24	100,0	95,6	97,5	87,5	100,0	95,0	92,7
CCKLP+MT3L2B1	24	100,0	95,6	93,8	86,9	100,0	95,0	92,5
KLE+MT3L2B1	12	100,0	96,3	92,5	81,9	100,0	85,0	87,7
KLP+MT3L2B1	12	100,0	95,6	92,5	78,1	100,0	86,3	86,7
T2L2B1(R)	5	100,0	95,6	90,0	80,6	87,5	86,3	87,5
T2L2B1(G)	5	100,0	96,9	90,0	82,5	83,8	81,9	87,1
T2L2B1(B)	5	100,0	96,9	92,5	82,5	86,3	80,6	86,7
T3L2B1(R)	6	100,0	96,3	91,3	78,1	90,0	83,8	86,1
T3L2B1(G)	6	100,0	98,1	92,5	78,1	85,0	80,6	85,6
T3L2B1(B)	6	100,0	96,3	92,5	80,0	87,5	75,0	83,8
T4L2B1(R)	7	100,0	93,8	91,3	76,9	91,3	77,5	82,7
T4L2B1(G)	7	100,0	97,5	92,5	78,1	90,0	74,4	83,3
T4L2B1(B)	7	100,0	96,9	92,5	80,0	87,5	70,0	82,3
CNT2L2B1(R)	6	100,0	96,9	91,3	85,0	90,0	86,3	89,4
CNT2L2B1(G)	6	100,0	95,6	93,8	85,6	85,0	78,8	86,7
CNT2L2B1(B)	6	100,0	95,6	92,5	85,6	80,0	74,4	85,2
CNT3L2B1(R)	9	100,0	98,1	92,5	84,4	87,5	83,1	88,5
CNT3L2B1(G)	9	100,0	97,5	95,0	86,3	85,0	78,1	87,3
CNT3L2B1(B)	9	100,0	96,9	93,8	84,4	87,5	72,5	84,6
CNT4L2B1(R)	13	100,0	96,3	92,5	84,4	92,5	76,3	85,7
CNT4L2B1(G)	13	98,8	88,8	95,0	84,4	91,3	71,9	81,7
CNT4L2B1(B)	13	98,8	88,1	95,0	85,0	88,8	70,0	81,0
KLE+MT3L2B1(C1)	6	100,0	97,5	92,5	77,5	88,0	80,0	85,0
KLE+MT3L2B1(C2)	6	98,8	96,3	93,8	78,8	90,0	81,3	85,5
KLE+MT3L2B1(C3)	6	100,0	97,5	91,3	79,4	95,0	86,9	87,9

A.2 Paints

Table A.7: Classification ratios for paints at $\times 500$ magnification and for learning and test sets. Features comes from the *à trous* algorithm for different strategies exploring basically relation among levels and channels.

Features	#f	l	t
T2L2B1, grey, without mean and variance	3	54.7	29.2
T3L2B1, grey, without mean and variance	4	65.6	32.3
T4L2B1, grey, without mean and variance	5	64.1	21.9
CNT2L2B1, grey, without mean and variance	4	54.7	29.2
CNT3L2B1, grey, without mean and variance	7	65.6	32.3
CNT4L2B1, grey, without mean and variance	11	64.1	21.9
CNT2L2B1	12	89.1	57.3
CNT3L2B1	21	96.9	64.6
CNT4L2B1	33	96.9	57.3
CCT2L2B1	18	100.0	72.9
CCT3L2B1	24	100.0	63.5
CCT4L2B1	30	100.0	68.8

A.3 Marble

Table A.8: Classification ratios for marble images and for learning and test sets. Features comes from the *à trous* algorithm for different strategies exploring basically relation among levels and channels.

Features	#f	l	t
mean and variance	2	29.20	15.25
T2L2B1, without mean and variance	3	48.60	26.40
T3L2B1, without mean and variance	4	57.10	34.70
T4L2B1, without mean and variance	5	66.65	36.10
T2L2B1	4	43.05	26.40
T3L2B1	7	59.70	33.35
T4L2B1	11	63.90	37.50
CNT2L2B1, without mean and variance	12	52.75	27.75
CNT3L2B1, without mean and variance	21	61.10	34.70
CNT4L2B1, without mean and variance	33	66.65	36.10
CNT2L2B1	18	52.80	25.00
CNT3L2B1	24	63.90	36.10
CNT4L2B1	30	83.30	45.80
CNT4L2B0	30	65.25	47.20
CNT4L2B2	30	79.15	37.50
CNT4L2B3	30	80.55	38.85

A.4 Brodatz

Table A.9: Classification ratios for Brodatz images and for learning and test sets. Features comes from the *à trous* algorithm for different strategies exploring basically relation among levels and channels. Two set of images have been used: 111 images and 55 images.

		111 images		55 images	
Features	#f	l	t	l	t
mean and variance	2	32.45	23.50	54,90	43,90
T3L2B1, without mean and variance	4	48.10	38.30	92,85	87,75
CNT3L2B1, without mean and variance	7	59.50	47.65	96,70	93,55
T3L2B1	4	74.70	61.30	92,95	83,40
CNT3L2B1	7	78.45	66.05	93,65	86,25

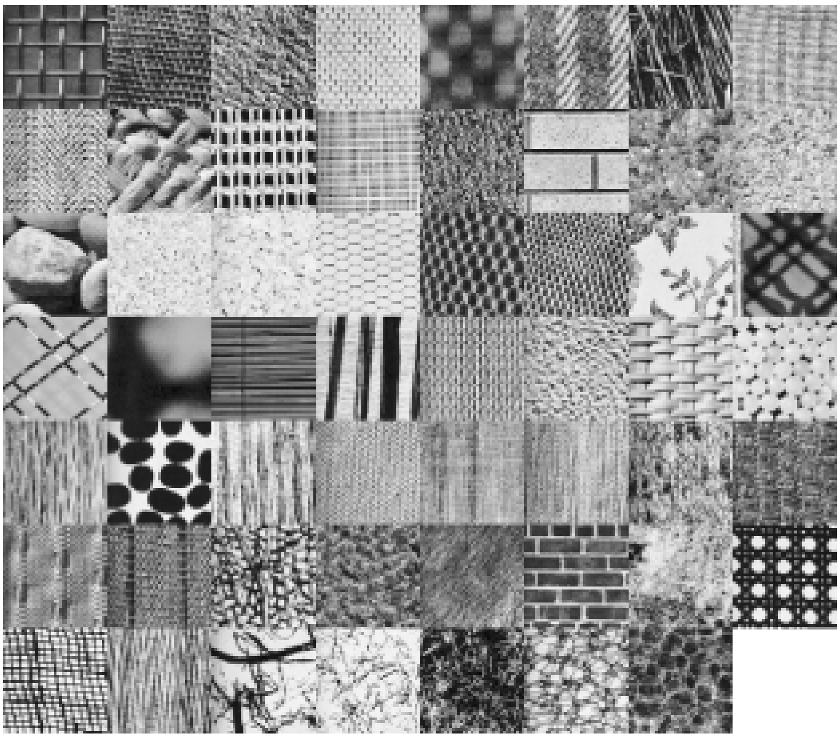

Figure A.1: 55 subimages from the Brodatz album [13] (images are regions of 160×160 of a big one of 640×640).

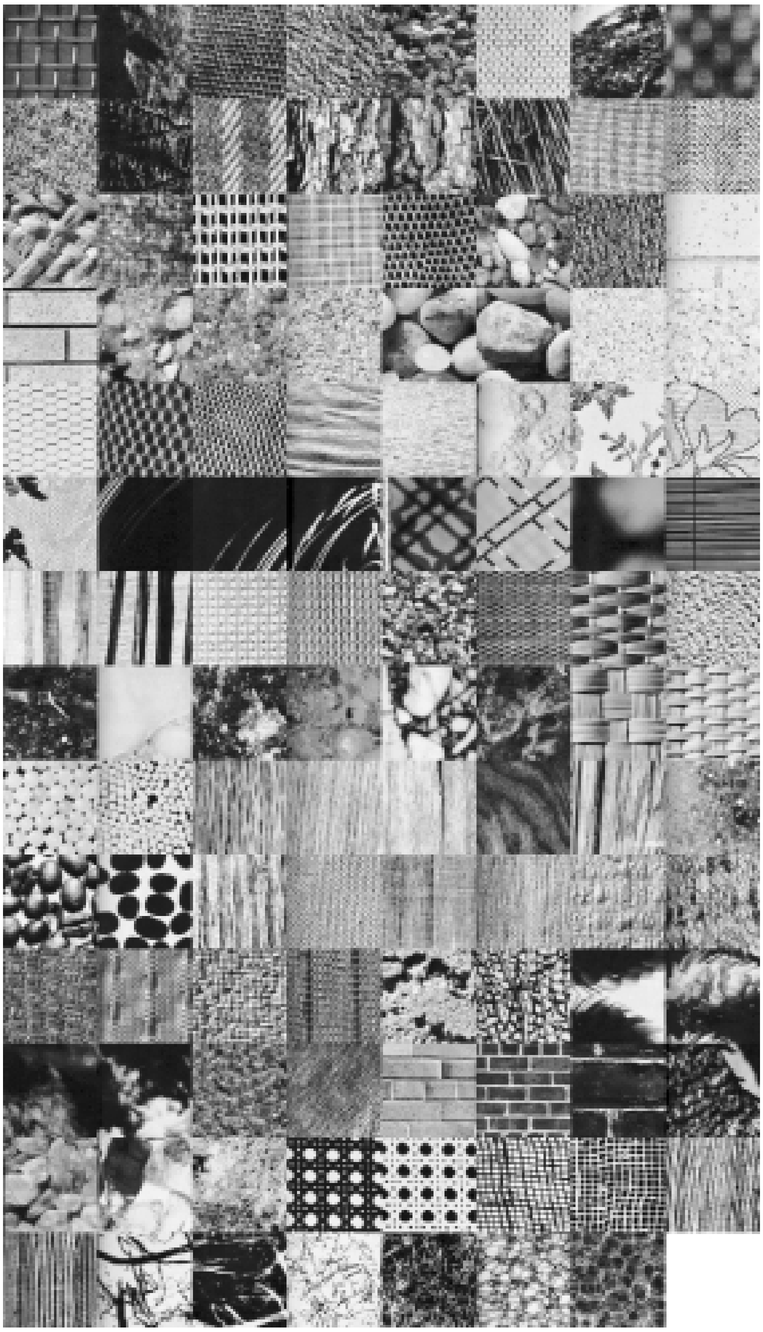

Figure A.2: 111 subimages from the Brodatz album [13] (images are regions of 160×160 of a big one of 640×640).

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