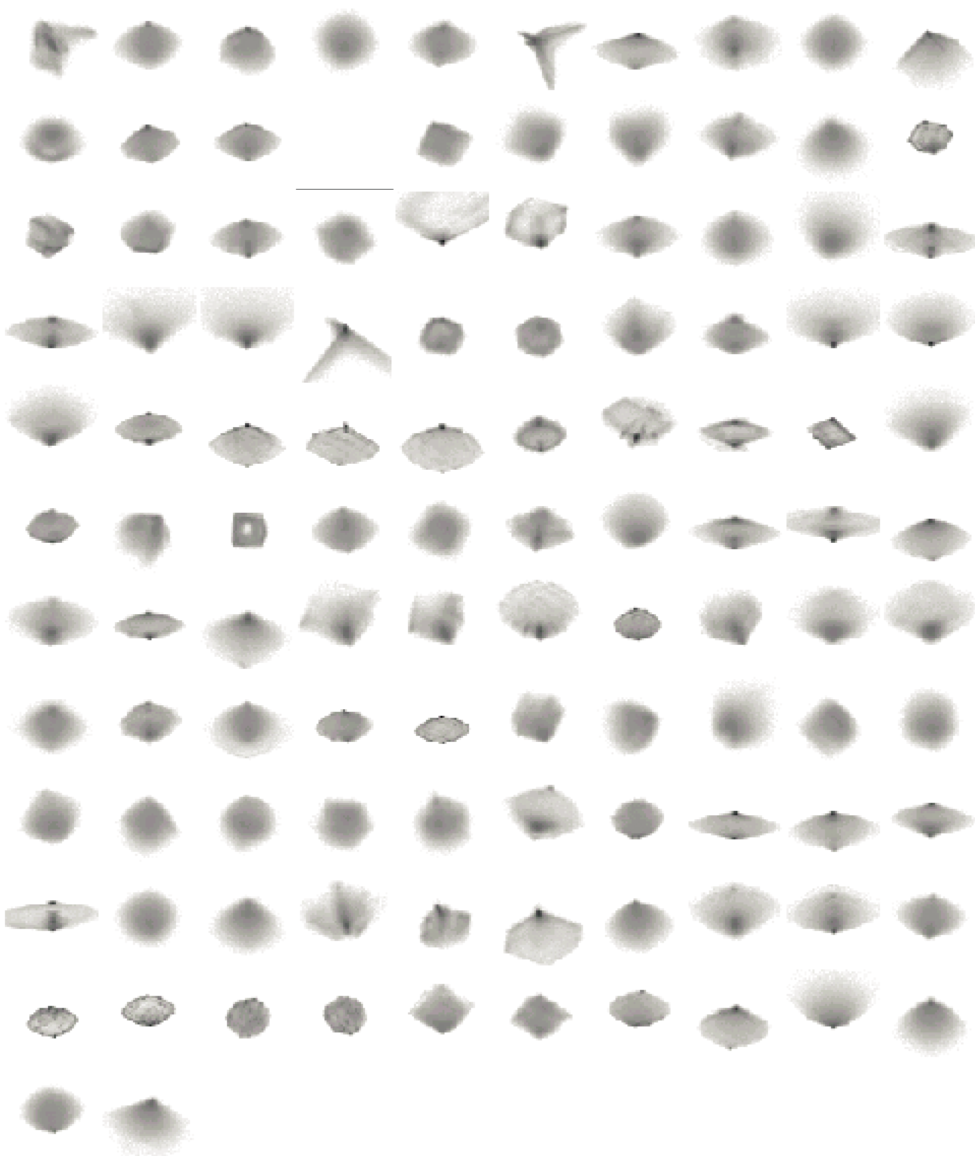

Figure 5.13: Reduction from 11-dimensional pdf to a bidimensional pdf by means of a PCA. Each density represents a Brodatz image (111 images, from D1 to D112 without D14). Accumulation images have been inverted for the sake of visualization.

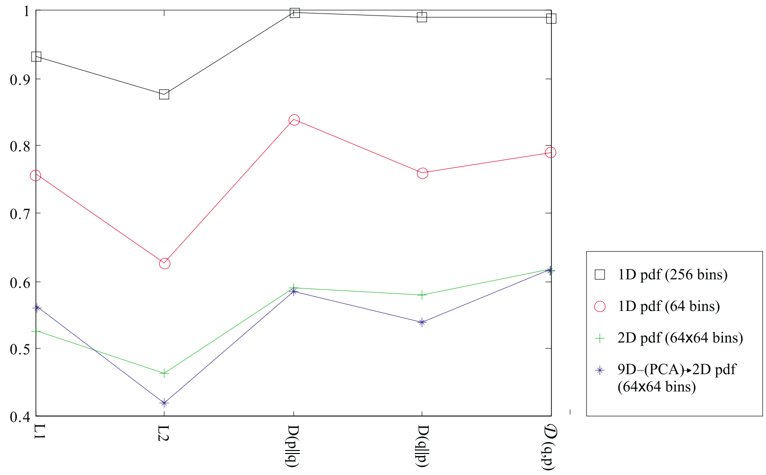

Figure 5.14: Comparison of the classification results.

Figure 5.14 is a summary of all the results related to Brodatz tests. Oddly, better results are achieved with low dimension and high number of bins arriving to a 99.7% of correct classification. As expected, if we reduce the number of bins we also reduce the classification ratio. And if we increase dimensionality of the probability space to 2D pdf, directly or reducing a high dimension space by a PCA, we also obtain a reduction in the classification ratios. Therefore, for classification purposes we prefer a model of low dimension. Concerning to the measure used in the classification process it is clear that measures based on relative entropy are better than classical distances.

We also use this probabilistic scheme to classify the effect pigments collection presented in Sec. 4.5. We use in this experiment a 2D pdf with 32×32 bins. The total amount of classes to classify is 14 with 5 images per class and 24 samples per images (scenario C of Sec. 4.5.2). Therefore, a total of 1680 samples of 128×128 pixels were classified. In this case, we do not break the set of images into learning and tests set. Instead, we classify all the samples against themselves looking for second coincidences (first hit is the original sample). We obtain that 74.3% of samples were classified correctly as belonging to its own image (not the same subimage). But, if we consider a successful classification if a sample is assigned to its class instead of its image, then we reach a 92.8% of correct classification. This result becomes 100% if we take the two closest classes. These results cannot be directly compared to those of Sec. 4.5.4 because they use different sizes on samples and also they use different strategies of classification. As a further study we can compare fairly both effect pigment classification results over the same images and with similar strategies.

5.4.2 Synthesis

First attempts with synthesis quickly showed that a sufficient large number of neighbors are necessary to achieve nonrandom synthesis. Therefore, we choose N_{10} neighborhood for most of the trials. Synthesis tests are done with some textures from the Brodatz album. We have selected a few images with high structural appearance because they are more difficult to reproduce than disordered textures. First tests were based on the work presented in [72], the sequential case can be seen in Fig. 5.15, and hierarchical case in Fig. 5.16. Besides, we have addressed other experiments that consist on reducing our model to a set of independent processes, and guess this model through an ICA process. Results from ICA are shown in Fig. 5.17. If we analyze all those figures we see that better results are in general for the random synthesis case. MAP and LSE generation break the structure of the synthetic images at some point giving worst results.

The extension of the synthesis to the *à trous* multiresolution decomposition is only in a preliminary stage. Figure 5.18 shows three synthesis of a little patch of 32×32 pixels of three Brodatz textures. The three images used in the analysis increase their visual structure from left to right: D57 Handmade paper (left), D93 Fur (middle), D21 French canvas (right). Each group of images represents a case: first column is the decomposition, starting from bottom to top we can see the different approximation levels; the next three columns are the respective synthesis (MAP, LSE, random), we have use the last approximation level (top left) as seed to the synthesis process and it has evolve with the information extracted from the models we have learnt from each level arriving to the final result (bottom images). In this case of multiresolution synthesis is the LSE procedure that gives the best visual results.

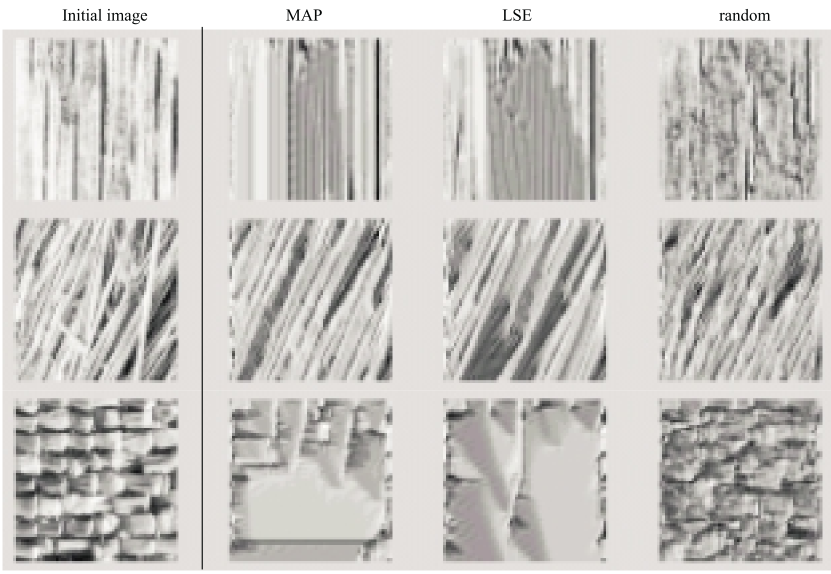

Figure 5.15: Synthesis of three textures. pdf generated with N_{10} neighborhood and estimated with k-means+EM (128 centers). We use a frame of the initial image as seed.

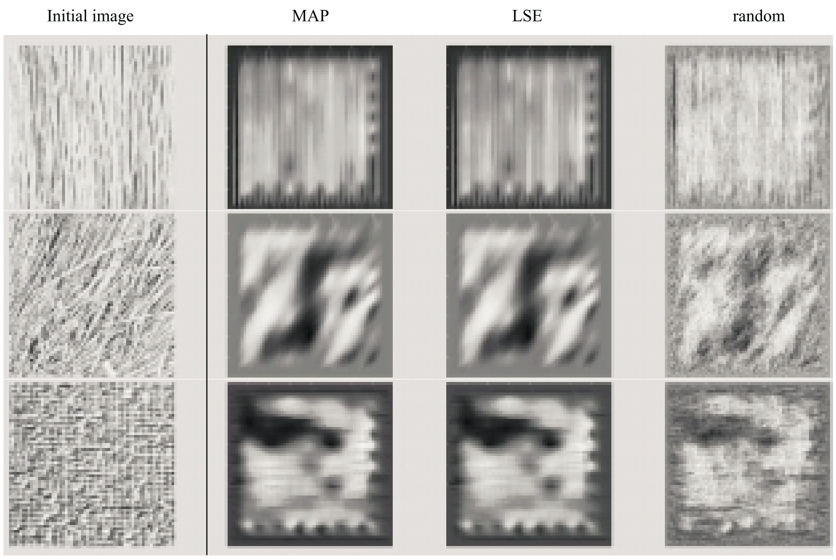

Figure 5.16: Synthesis of three textures using hierarchical scheme.

5.5 Conclusions

This chapter summarizes a set of experiments we have done in the context of simultaneous synthesis and classification of textures by means of a simple probabilistic model, the multidimensional pdf of a neighborhood.

The works of Popat and Picard [73, 72] have been taken as a base to explore this topic and then, we have proposed some new extensions on both areas: classification and synthesis.

Classification is done in a completely new way, using similarity measures and performing a direct comparison of the pdfs. Best results are achieved with the simplest models. Besides, specific measures for pdfs based on relative entropy are more accurate than classical distances.

Synthesis has been approached with several tests addressed to reduce computation as the proposed ICA alternative and some other test devoted to better compile the structure of a texture at different resolutions. The ICA solution gives good visual results for the random case although our problem is not a typical problem of blind sources separation. Multiresolution synthesis is only a preliminary attempt that can be improved building the model from details adapting the support of the pdfs to this case.

In general, algorithms should be optimized in order to allow more complex models, increasing the number of centers or the number of iterations of the refinement step. Also, we have to tests more alternatives in order to arrive to a general model useful for several applications.

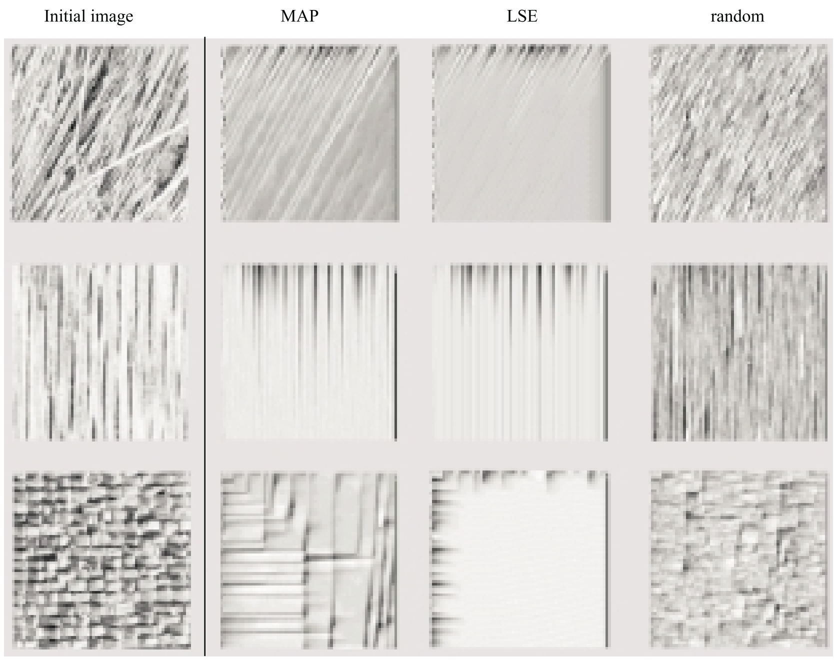

Figure 5.17: Synthesis of three textures using the ICA model. We use a frame of the initial image as seed.

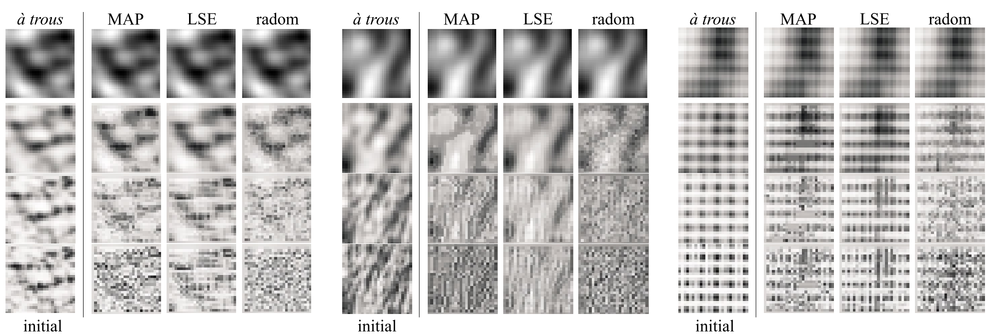

Figure 5.18: Synthesis of three textures using a multiresolution model.