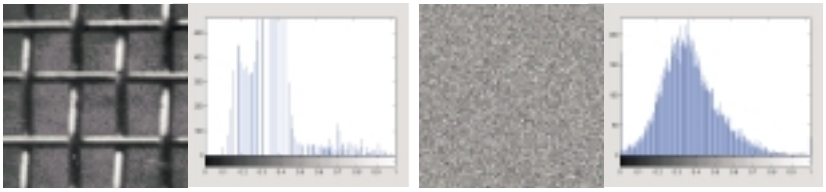

Figure 5.6: Initial image and its histogram, and image generated from a pdf (N_{10} neighborhood) and its histogram.

Figure 5.7: Error on synthesis due to the initialization. First image is the initial, next group of three images are MAP, LSE, and random synthesis with an initialization to 128 gray level, next group are similar but with a frame of the initial image as initialization.

random values start the synthesis. Therefore, as starting seed we are going to use from now on a thin frame of the same reference image (see right part of Fig. 5.7).

We have followed other approaches to obtain the synthesis. One is based on the representation of the probability model as a product of independent single probabilities in order to reduce computations. A second one explores the possibilities to include a multiresolution scheme in this synthesis to avoid large neighborhoods and the curse of dimensionality.

Independent component model

An attempt to reduce time in calculation and to reduce complexity of the pdf model is to see it composed by several independent processes. If we do this assumption we can model our n-dimensional probability model as a product of n 1D probabilities. The procedure to estimate the independent sources of a complex signal is well known and we use an ICA algorithm (Independent Component Analysis) to find them [15]. ICA stands as an elegant and powerful solution to the problem of independent source separation, with a broad range of applications. The use of this strategy does not mean that our data can be expressed completely as a product of independent processes; this is used only as an approximation and simplification of a far more complex reality. The hypothesis is that our data D (samples are column vectors) is the result of a linear mixing of some independent sources S ($S = BD$).

The implementation consists of a previous analysis stage where the mixing matrix B that passes from data to sources is calculated with an ICA algorithm. Data comes from a N_{10} neighborhood as in previous cases. Then, in the synthesis stage, for each neighborhood with the help of the previous matrix we go to all the possible sources that give those values. The probability is constructed as the product of all the partial probabilities. Later, as in other cases we try MAP, LSE or random strategies in the

synthesis. Results are shown in Fig. 5.17.

Multiresolution synthesis

The sequential case needs large neighborhoods in order to model in a correct way textures where repetitive patterns are long distance apart. To reduce this drawback [72] proposes a hierarchical scheme and introduces a solution slightly based in filter banks. We explore a new solution based on the *à trous* decomposition explained in Sec. 2.2.5 and sometimes used along this work.

We start with an *à trous* decomposition. Instead of basing the algorithm on the synthesis of detail coefficients, we keep the approximation at each level. Remember that approximations at a certain level can be deduced by adding the details image of this level to the previous approximation level. We use approximation instead of details because the spread of possible values is limited by the rank of gray levels on the reference image. Then, we build a model for each level in the decomposition and try to synthesize from coarse to fine levels.

We try three possibilities at this point:

- synthesis of each level separately with the same neighborhood, using previous results only as seed;
- synthesis of each level separately but adapting the neighborhood to the scale, using previous results only as seed;
- synthesis of each level using information from this level and the previous level.

Results for three cases are very similar with little improvements as complexity grows, but they should be still considered as a preliminary study. See results for the third case in Fig. 5.18.

5.4 Results

5.4.1 Classification

Classification as we pinpoint before is based on a direct comparison of the models. Tests have been done basically over the most important part of Brodatz collection (111 images). In this experiment, for each image we have defined four areas: the big one used to build the model for each class, and three small areas to be classified. These test areas are disjoint to the learning area to do not overestimate results. This solution has been adopted because only one image per class is given. Other texture collections are available on the web, but this is the most referenced in texture classification works. Figure 5.8 explains how results are shown. Results are presented in form of distance map images: the first three rows represent distances of all the images over the entire set of models (one row for each of the test areas). In its subimages, the gray level represents distance or dissimilarity. Therefore low values mean that images have a similarity to that class. Next row shows the accumulation of the minimal points in the previous three cases, as a measure of how good the classification is. Columns represent the five metrics tested to classify: L_1, L_2, $D(p||q)$, $D(q||p)$, and $\mathcal{D}(p,q)$.

Finally, in the bottom row we average the result for the three testing regions and write the classification ratio for each 'distance' measure.

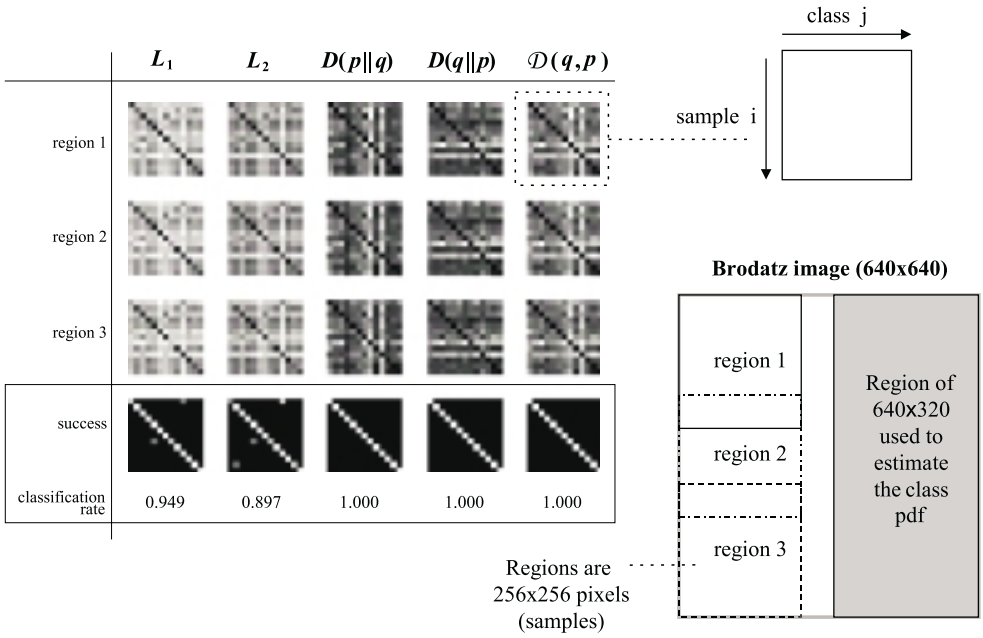

Figure 5.8: Evaluation of the classification results comparing several similarity measures and distances (example with the first 13 classes of the Brodatz set).

We have done different tests changing the model: exploring the relevance of dimensionality, the size of the model (number of bins), and checking whether it is useful to reduce the number of dimensions of our model. Figures 5.9 to 5.12 show results of experiments where parameters of the texture description model proposed have been changed, they are evaluated over the same data, i.e. 111 images of the Brodatz album.

First two figures deal with 1D pdf (histograms) with different number of bins. We have the same amount of data in the second case but represented with a more compact way. Next two figures are results for 2D pdfs; first one is obtained with the N_1 neighborhood and the second comes from a reduction of an 11D pdf, obtained with N_{10}, to a 2D pdf by a Principal Component Analysis. Principal component analysis (PCA) involves the transformation of a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables called principal components. The objective of principal component analysis is: to discover or to reduce the dimensionality of the data set, and to identify new meaningful underlying variables. Transformed data is arranged according to its relevance. Therefore, we take the two first components that have the most valuable information. Figure 5.13 shows how are those models projected to 2D. We made strong assumption of gaussianity that is not always valid, and therefore it should be taken into account as an attempt.

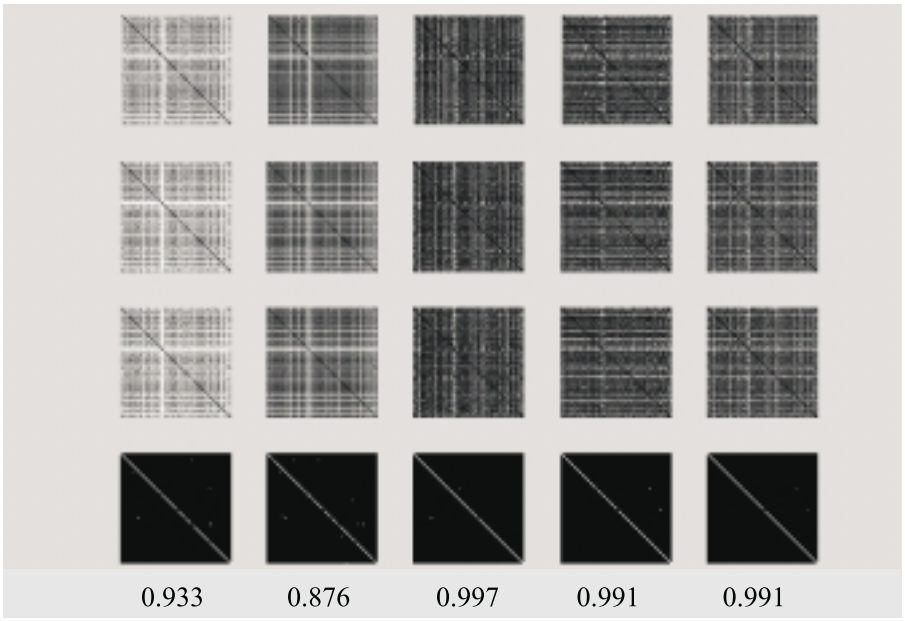

Figure 5.9: Classification rates for 1D pdf (histogram) with 256 bins.

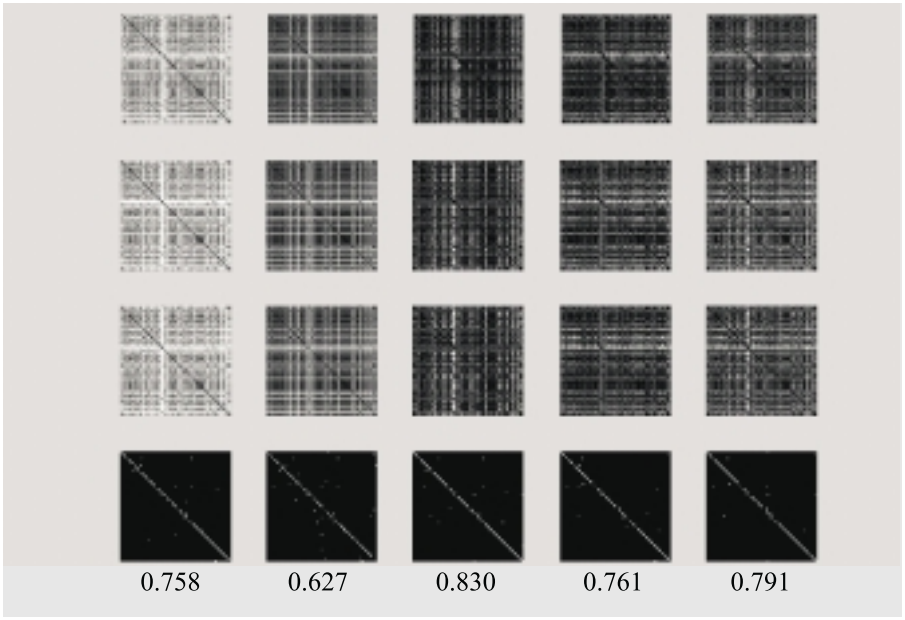

Figure 5.10: Classification rates for 1D pdf (histogram) with 64 bins.

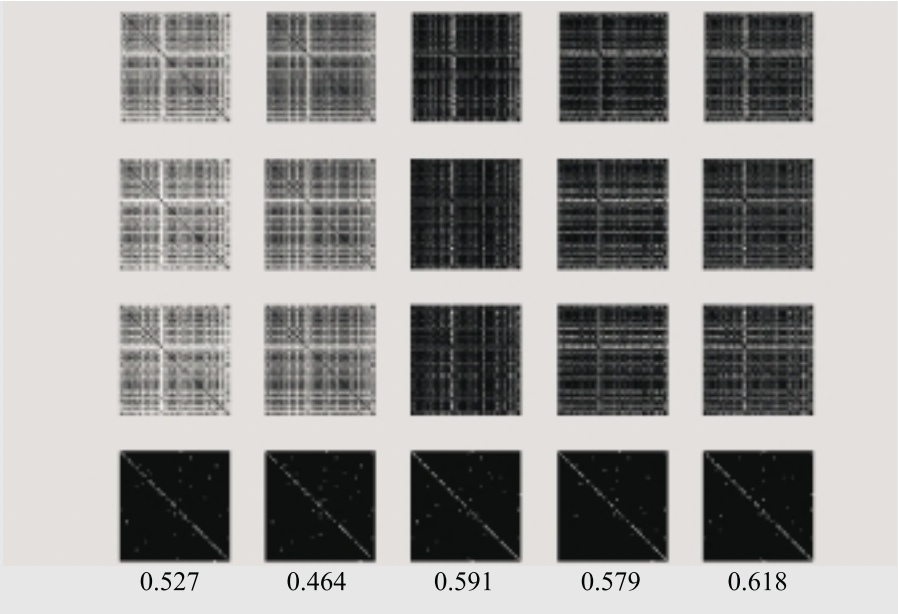

Figure 5.11: Classification rates for 2D pdf with 64×64 bins.

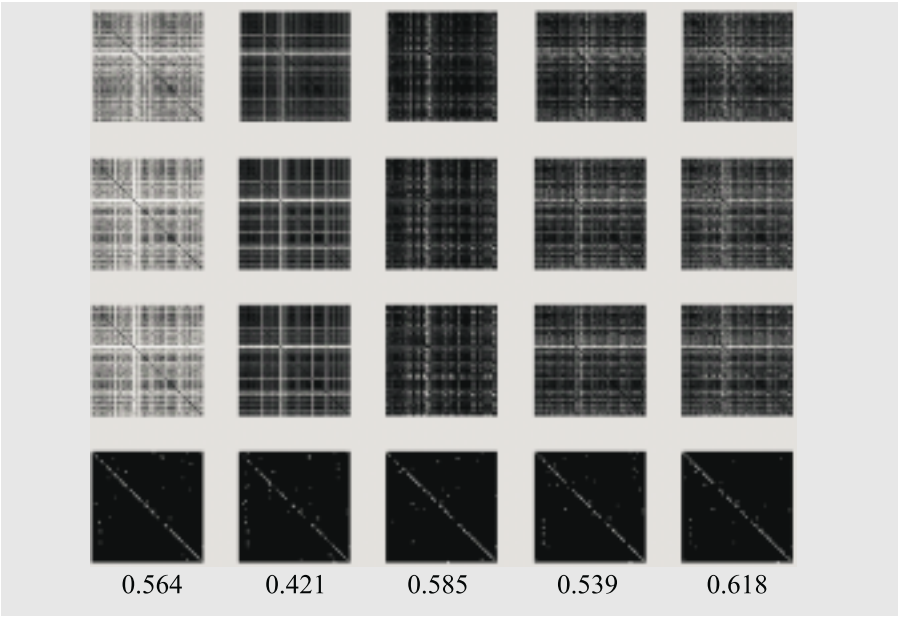

Figure 5.12: Classification rates for 11D pdf projected to a 2D space by a PCA (64×64 bins).