46 Texture Classification with Reduced Multidimensional Histograms

Erkki Oja and Kimmo Valkealahti

Texture refers to visual or tactile surface characteristics which are described by such terms as smoothness, roughness, regularity, uniformity, and granularity. Texture plays an important role in the visual perception of objects. Figure 102 shows six surface images, which are more or less immediately perceived as distinct textures. The luminance distributions of the textures are equalized so that their one-dimensional gray-level distributions are equal, i.e., the number of times each gray level occurs is the same in all textures. As in vision, computerized discrimination of texture images with identical gray-level distributions is based on spatial relationships among pixels.

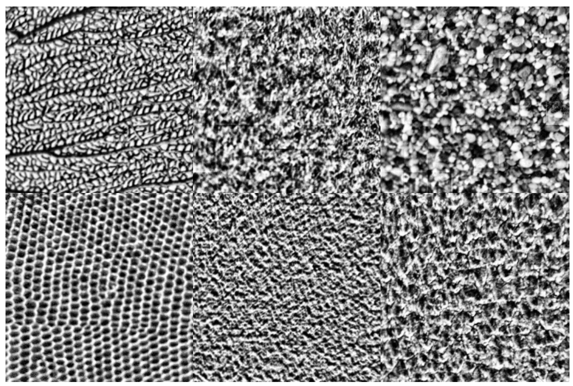


Figure 102: Textures with identical luminance distributions.

In 1962, vision researcher Bela Julesz proposed his famous conjecture that texture pairs with identical two-dimensional gray-level distributions, i.e., joint distributions of values of two pixels with any spatial separation, are not visually discernible [1]. Julesz's subsequent studies provided counterexamples to this conjecture [2], such as the three textures in Fig. 103 whose three-dimensional black-and-white distributions are the same for all combinations of three pixels. A recent study of Purpura et al. [6] showed that the primary visual cortex, the first stage of cortical processing, extracts multidimensional contextual dependencies in texture images.

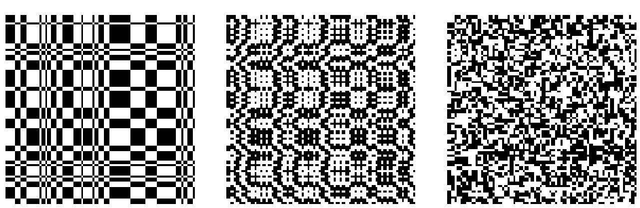
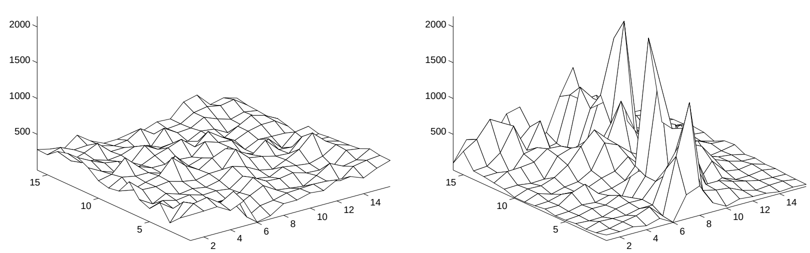


Figure 103: Black-and-white textures with identical three-dimensional distributions.

Julesz's early conjecture is still frequently cited to support the use of only two-dimensional co-occurrence statistics for machine-based discrimination of natural textures. Observations on vision made us suggest that the analysis of multidimensional dependencies benefits computerized texture discrimination. The analysis of multidimensional dependencies requires the use of multidimensional histograms, which is complicated by rapid expansion of histograms with increasing number of pixels and quantization levels. Histogram expansion, without increase in sample size, leads to decrease in bin frequency and consequently, to decrease in the reliability of probability distribution approximations. At small sample sizes typical of texture analysis, large multidimensional histograms must therefore be reduced by combining adjacent bins. At present, there are no standard reduction methods for this purpose. Our study has three main goals: comparison of multidimensional statistics with conventional methods in texture classification, development of methods for reduction of multidimensional histograms, and selection of multidimensional co-occurrence features and parameters of the classifier with respect to their performance in texture classification.

Our first experiments with both unreduced and reduced multidimensional histograms showed that their performance may exceed that of two-dimensional histograms [4,5]. Effective reduction of multidimensional histograms, leading to decrease in the classification error rate, was obtained using vector quantization with the self-organizing map [3]. In this reduction method, the co-occurrence vectors of pixel values in a predefined spatial arrangement are quantized using the reference vectors of a trained two-dimensional self-organizing map. The reference vectors of a trained map are adapted to the high-density regions in the co-occurrence distribution of the samples used for the training of the map. A reduced texture histogram is obtained when the reference vectors of a trained map are used as histogram bins to collect a two-dimensional map histogram of quantized vectors from a texture sample. Texture classification is then carried out by matching sample histograms with precomputed texture model histograms. With this approach we showed, both for monochrome and color textures, that codebooks trained with the self-organizing map algorithm provided significantly higher classification accuracy than two- and multidimensional unreduced histograms.



sea fan pebbles

Figure 104: Seven-dimensional histograms reduced by the self-organizing map.

The self-organizing map preserves similarity relationships within the data so that reference vectors near each other resemble each other. Thus, a histogram reduced with the map is easy to visualize. This is demonstrated by Fig. 104 showing the map histograms of upper left and right textures in Fig. 102, sea fan and pebbles. The reduced histograms represent seven-dimensional distributions of high-pass-filtered co-occurrence vectors whose components were sampled within 3-by-3-pixel windows. The local uniformity of the pebble texture is reflected in the high peaks in the histogram. In the sea fan texture, the edges in different directions are represented by separate histogram bins which results in a flat histogram.

A method for the selection of co-occurrence features and histogram size was also developed. To minimize the expected quantization error, vector quantizer algorithms tend to concentrate reference vectors along the directions with largest variance. This arrangement of a limited number of reference vectors may not be the best for classification. Our studies showed that whitening of co-occurrence distribution may improve classification accuracy. The complexity of a texture classifier is determined by the number and dimension of the reference vectors. The classification accuracy decreases if the number of parameters becomes too high or too low. In our study, the trade-off was found using a genetic algorithm to minimize the classification error rate. The most recent results of this research appeared in [7], as well as in the D.Sc. Thesis of Mr. Valkealahti (1998).

In conclusion, our studies suggest that texture classification is improved by increasing dimensionality of co-occurrence features, that the self-organizing map is suitable for the reduction of multidimensional co-occurrence histograms, and that the classification accuracies can be substantially improved by optimization of features used in construction of features vectors and by optimization of classifier parameters.

References

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