Restatement of the research problem

4 Discussion

We presented a theoretically and computationally simple yet efficient multiresolution approach to gray-scale and rotation invariant texture classification based on "uniform" local binary patterns and nonparametric discrimination of sample and prototype distributions. "Uniform" patterns were recognized to be a fundamental property of texture as they provide a vast majority of local texture patterns in examined textures, corresponding to texture microstructures such as edges. By estimating the distributions of these microstructures, we combined structural and statistical texture analysis.

We developed a generalized gray-scale and rotation invariant operator $LBP^{riu2}_{P,R}$, which allows for detecting "uniform" patterns in circular neighborhoods of any quantization of the angular space and at any spatial resolution. We also presented a simple method for combining responses of multiple operators for multiresolution analysis by assuming that the operator responses are independent.

Excellent experimental results obtained in two problems of true rotation invariance where the classifier was trained at one particular rotation angle and tested with samples from other rotation angles demonstrate that good discrimination can be achieved with the occurrence statistics of "uniform" rotation invariant local binary patterns.

The proposed approach is very robust in terms of gray-scale variations caused, e.g., by changes in illumination intensity since the $LBP^{riu2}_{P,R}$ operator is by definition invariant against any monotonic transformation of the gray scale. This should make it very attractive in situations where nonuniform illumination conditions are a concern, e.g., in visual inspection. Gray-scale invariance is also necessary if the gray-scale properties of the training and testing data are different. This was clearly demonstrated in our recent study on supervised texture segmentation with the same image set that was used by Randen and Husoy in their recent extensive comparative study [32]. In our experiments, the basic 3×3 LBP operator provided better performance than any of the methods benchmarked by Randen and Husoy for 10 of the 12 texture mosaics and, in most cases, by a clear margin [28]. Results in Experiment #2, involving three illuminants with different spectra and large intraclass color variations in source textures demonstrate that the proposed approach is also robust in terms of color variations.

Significance of results

Comparison with other studies

Computational simplicity is another advantage as the operators can be realized with a few comparisons in a small neighborhood and a lookup table. This facilitates a very straightforward and efficient implementation, which may be mandatory in time critical applications.

If gray-scale invariance is not required, performance can be further improved by combining the $LBP^{riu2}_{P,R}$ operator with the rotation invariant variance measure $VAR_{P,R}$ that characterizes the contrast of local image texture. As we observed in the experiments, the joint distributions of these orthogonal operators are very powerful tools for rotation invariant texture analysis.

Explanation and discussion of results

The spatial size of the operators is of interest. Some may find our experimental results surprisingly good considering how small spatial support our operators have, for example, in comparison to much larger Gabor filters that are often used in texture analysis. However, the built-in spatial support of our operators is inherently larger as only a limited subset of patterns can reside adjacent to a particular pattern. Still, our operators may not be suitable for discriminating textures where the dominant features appear at a very large scale. This can be addressed by increasing the spatial predicate R, which allows generalizing the operators to any neighborhood size.

The performance can be further enhanced by multiresolution analysis. We presented a straightforward method for combining operators of different spatial resolutions for this purpose. Experimental results involving three different spatial resolutions showed that multiresolution analysis is beneficial, except in those cases where a single resolution was already sufficient for a very good discrimination. Ultimately, we would want to incorporate scale invariance, in addition to gray-scale and rotation invariance.

Regarding future work, one thing deserving a closer look is the use of a task specific subset of rotation invariant patterns, which may, in some cases, provide better performance than "uniform" patterns. Patterns or pattern combinations are evaluated with some criterion, e.g., classification accuracy on a training data, and the combination providing the best accuracy is chosen. Since combinatorial explosion may prevent an exhaustive search through all possible subsets, suboptimal solutions such as stepwise or beam search should be considered. We have explored this approach in a classification problem involving 16 textures from the Curet database [10] with an $11.25°$ tilt between training and testing images [24]. Thanks to its invariance against monotonic gray-scale transformations, the methodology is applicable to textures with minor 3D transformations, corresponding to such textures which a human can easily, without attention, classify to the same categories as the original textures. Successful discrimination of Curet textures captured from slightly different viewpoints demonstrates the robustness of the approach with respect to small distortions caused by height variations, local shadowing, etc.

Future research

In a similar fashion to deriving a task-specific subset of patterns, instead of using a general purpose set of operators, the parameters P and R could be "tuned" for the task in hand or even for each texture class separately. We also reported that when classification errors occur, the model of the true class very often ranks second. This suggests that classification could be carried out in stages by selecting operators which best discriminate among remaining alternatives.

Implication of results

Our findings suggest that complementary information of local spatial patterns and contrast plays an important role in texture discrimination. There are studies on human perception that support this conclusion. For example, Tamura et al. [34] designated coarseness, edge orientation, and contrast as perceptually important textural properties. The LBP histograms provide information of texture orientation and coarseness, while the local gray-scale variance characterizes contrast. Similarly, Beck et al. [3] suggested that texture segmentation of human perception might occur as a result of

Reference to other studies

differences in the first-order statistics of textural elements and their parts, i.e., in the LBP histogram.

Appendix

Note

Test suites (include images) used in this paper and a Matlab implementation of the proposed method are available at the Outex site (http://www.outex.oulu.fi). The original setup of Experiment #1 is available as test suite *Contrib_TC_00000* (single problem) and the revised setup is available as test suite *Contrib_TC_00001* (10 problems corresponding to training with each of the 10 rotation angles in turn). Experiment #2 is available as test suites *Outex_TC_00010* (rotation invariant texture classification, single problem) and *Outex_TC_00012* (rotation and illumination invariant texture classification, two problems).

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