9-10-2000

Two-stage texture segmentation using complementary features

Jiebo Luo
Andreas Savakis

Follow this and additional works at: http://scholarworks.rit.edu/article

Recommended Citation
Image Processing 3 (2000) 564-567

This Article is brought to you for free and open access by RIT Scholar Works. It has been accepted for inclusion in Articles by an authorized administrator of RIT Scholar Works. For more information, please contact ritsscholarworks@rit.edu.
Two-Stage Texture Segmentation Using Complementary Features

Jiebo Luo
Imaging Science Division
Eastman Kodak Company
Rochester, NY 14650

Andreas E. Savakis
Department of Computer Engineering
Rochester Institute of Technology
Rochester, NY 14623

Abstract
In this paper, a two-stage texture segmentation approach is proposed where an initial segmentation map is obtained through unsupervised clustering of MRSAR features and is followed by self-supervised or bootstrapped classification of wavelet features. The self-supervised stage is based on a segmentation confidence map, where the regions of "high confidence" and "low confidence" are identified on the MRSAR segmentation result using multilevel morphological erosion. The second-stage wavelet classifier is trained from the "high-confidence" samples and is used to reclassify only the "low-confidence" pixels. The final reclassification is based on rules that combine minimum distance and spatial constraints. Additionally, an improved coefficient feature normalization procedure is used during the classification process of both stages. The proposed two-stage approach leverages on the advantages of both MRSAR and wavelet features, and incorporates an adaptive neighborhood-based spatial constraint. Experimental results show that the misclassification error can be significantly reduced compared to morphological cleaning operations alone.

1. Motivation
Texture is a fundamental characteristic of natural images that, in addition to color, plays an important role in human visual perception and provides information for image understanding and scene interpretation. A large volume of research over the past three decades has addressed the problem of texture segmentation and has produced a number of review articles and comparative studies [1, 2, 3, 4]. Unsupervised image segmentation may be defined as the problem of separating image regions of uniform texture without prior knowledge of the texture types. Texture segmentation is not the same problem as texture differentiation or classification, where a supervised system is trained to differentiate between known textures.

Much of the texture segmentation work has concentrated on extracting features that are suitable for texture modeling, followed by feature clustering or classification so that image regions of uniform texture may be identified [5]. Classic texture features include those derived from Laws filters, co-occurrence matrices (CO), and cortex transform modulation functions (CTMF). More recently, a number of new texture features have been considered for texture analysis and segmentation, including multiresolution simultaneous autoregressive (MRSAR) models, Markov random field (MRF) models, Gabor filters, wavelet coefficients, and fractal dimension. The results of comparing the relative merits of the different types of features have been inconclusive and a clear winner has not emerged in all cases [4]. In general, each set of texture features offers unique advantages but also has limitations compared to other feature types.

Meanwhile, one common problem in using feature clustering for image segmentation is that noise in the extracted features may result in misclassification, which takes the form of holes and other fragments. When trying to minimize the problem due to noisy features, another interesting yet challenging problem in texture segmentation is encountered, which may be described as the boundary effect. It usually appears as inaccurate segmentation of boundaries or superfluous narrow regions at the boundary between two textures [6]. It has been conjectured that the boundary effect is caused by misclassification when the trajectory of the feature vectors makes a transition through feature space [7]. To make matters worse, the misclassification may be interpreted as a third texture, depending on the nature of the features for a particular image.

We believe that complementary types of features, when carefully chosen, may be used jointly to improve the segmentation results obtained by using any single one of the feature types. In particular, multiresolution simultaneous autoregressive (MRSAR) and wavelet features may be viewed as complementary: MRSAR features have large support and provide good texture dis-
features offer good localization at the expense of lower signal-to-noise ratio. Typically occurs near the texture boundaries, while wavelet features suffer from misclassification that usually occurs near the texture boundaries. Therefore, the following operations were defined in [7]:

1. M-erosion: pixels whose neighbors are in the same class are left unchanged, otherwise the pixel is labeled "uncertain," i.e., there is low confidence in the classification result. Labeling is done by assigning zero value to the "uncertain" pixels while all other segmentation regions retain their original nonzero values.

2. M-dilation: "uncertain" pixels are assigned to the most popular class within an 8-neighborhood. In essence, application of M-erosion followed by M-dilation propagates "high confidence" regions into the "uncertain" areas based solely on spatial proximity [7].

2.3. Reclassification of Low-Confidence Regions

Wavelet features are considered here as alternative features for reclassification for several reasons: (1) they are fundamentally different from neighborhood-based MRSAR and MRF types of texture features and capture the texture characteristics in a different way; (2) they are more sensitive to higher resolution variations because of relatively smaller spatial support; and (3) the computational cost is low compared to MRSAR.

In this study, we perform a 3-level wavelet decomposition of the image using Daubechies 9/7 biorthogonal wavelets and construct a 9-dimensional feature vector by properly interpolating the nine high-frequency subbands. An alternative is to use an over-complete wavelet expansion without the need for interpolation. It may also be viable to use other filterbanks that are more suitable for texture segmentation. Before interpolation, the subband coefficients are replaced by their absolute values and are smoothed using a $3 \times 3$ local window. In our experiments, we found that the signal-to-noise ratio of wavelet features is not as high as for MRSAR. As a result, the segmentation maps obtained using wavelet features often appear more noisy than those obtained using MRSAR features. Moreover, wavelet features cannot differentiate certain textures that are similar in terms of short correlation (see Fig. 4(d)). On the other hand, MRSAR features are capable of capturing correlation over long distances but often fall short at texture boundaries.

The advantages and disadvantages of MRSAR and wavelet features complement each other and inspired us to devise the two-stage segmentation approach presented here. Note that the initial segmentation map was obtained through unsupervised clustering of the MRSAR features. Therefore, training of the wavelet classifier can be considered as self-supervised or boot-
strapped according to the “confidence” map. The re-
classification is finally based on a minimum distance
criterion. In this study, we choose the simple nearest-
neighbor classifier for refinement, although a maximum
likelihood classifier can be readily trained. In particu-
lar, for each class present in the multilevel confidence
map, all the “high-confidence” pixels serve as training
samples and are used to determine the corresponding
class centroids in the wavelet feature space. The stages
for the joint segmentation are illustrated in Fig. 1,
where solid arrows indicate process flow and broken
arrows indicate information flow. Note that mor-
phological M-erosion and M-dilation with a small kernel
is used in the end to perform minor cleaning of the
segmentation map.

Spatial constraints are imposed in the reclassifica-
tion of uncertain pixels such that an “uncertain” pixel
can only be reclassified to locally available classes. In
short, this limits the classification errors that would be
committed by the second set of texture features.

3. EXPERIMENTAL RESULTS

The results are based on texture mosaic images com-
posed of patterns from the Brodatz set [8], where the
size of each uniform texture patch is 128 × 128. The
uncertainty maps are created by “m-ary” morphologi-
cal erosion operations. The segmentation results by
either MRSAR or wavelet features are obtained using
a k-means clustering algorithm. Results in Figures 2
are annotated using the following convention: (a) orig-
inal image, (b) uncertainty map, (c) segmentation by
MRSAR, (d) segmentation by wavelet, (e) refined MR-
SAR segmentation, (f) refined joint segmentation, (g)
error in morphological refinement, and (h) error in joint
refinement.

In general, the segmentation maps by wavelet fea-
tures are more noisy and contain more fragments. The
final segmentation is obtained from morphologically
clenched MRSAR segmentation and from the two-stage
segmentation/refinement using MRSAR and wavelet
features, respectively. Segmentation error maps are
also shown for a visual comparison of the results ob-
tained from the two methods. The best segmentation
is obtained using the joint method in (f), where the seg-
mentation error is reduced by more than half compared
to the refined MRSAR method.

4. DISCUSSION AND CONCLUSION

A two-stage approach to texture segmentation is pre-
sented in this paper, for taking advantage of the relative
strengths of different feature types. The proposed two-
stage scheme can be generalized beyond MRSAR and
wavelet features. In general, the criterion for selecting
two sets of features can be based on the following rule:
the first set of features that is used for the initial seg-
mentation should have high signal-to-noise ratio in the
interior of homogeneous textured regions while the sec-
ond set of features should have high spatial resolution.
A single set of features is unlikely to have both prop-
erties due to the fact that texture is an area-oriented
characteristic and texture features are computed within
a local neighborhood. Features based on larger local
neighborhood windows capture longer correlation and
are more robust, however, they suffer from poor spatial
resolution near boundaries between textures. On the
other hand, features based on smaller local neighbor-
hood windows tend to have better spatial resolution,
but may be noisy and sensitive to subtle textural dif-
fences. The proposed two-stage segmentation scheme
is designed to play to the strength of two sufficiently
different sets of texture features while overcoming their
drawbacks. Combined with an efficient way of identi-
fying “uncertain” regions where misclassification is likely
to occur, and a self-supervised or bootstrapped training
mechanism, it offers an alternative superior to postpro-
cessing by morphological operations alone.

5. REFERENCES

ture segmentation and feature extraction techniques,”
CVGIP: Image Understanding, vol. 57, pp. 359–372,
1993.
mentation techniques,” Pattern Recognition, vol. 26,
“Evaluation of texture segmentation algorithms,” in
Proc. IEEE Int. Conf. Computer Vision Pattern Recog-
mentation using multiresolution simultaneous autoreg-
gressive models,” Pattern Recognition, vol. 25, no. 2,
to texture segmentation using multiple Gabor filters,”
Fig. 1. The stages of joint segmentation.

Fig. 2. A four-patch texture mosaic: (a) original image, (b) uncertainty map, (c) segmentation by MRSAR, (d) segmentation by wavelet, (e) refined MRSAR segmentation, (f) refined joint segmentation, (g) error (4.4%) by morphological refinement, and (h) error (2.1%) by joint refinement.

Fig. 3. Determination of spatially adaptive neighborhood for reclassification. In the example cases, the current uncertain pixel is indicated by the small open circle and the neighboring regions are indicated by $R_i$.

Fig. 4. A five-patch texture mosaic: (a) original image, (b) uncertainty map, (c) segmentation by MRSAR, (d) segmentation by wavelet, (e) refined MRSAR segmentation, (f) refined joint segmentation, (g) error (6.2%) by morphological refinement, and (h) error (3.2%) by joint refinement.