Texture Segmentation by biologically-inspired use of Neural Networks and Mathematical Morphology

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Abstract
The segmentation of image objects by humans has recently been modelled as a two-step process by the BCS/FCS model of Grossberg. First, regions of homogeneous greyvalue distribution or with similar texture patterns are recognized. Second, these regions are progressively grown until they fill-in the whole scene or image. Object boundaries are defined when growing regions with different characteristics meet. In this paper, we use this approach in texture segmentation. We show, that the marker-controlled segmentation based on the watershed transformation is best suited for implementing this model. In order to generate appropriate marker and edge images for a wide variety of input images, we present the texture segregation/region growing approach which extends the conventional feature classification approach of texture analysis.

1. Introduction

Texture segmentation is a long-termed research field in image processing [hara85, vangool85, rao90]. Texture refers to the subjective impression of the appearance of a surface structure. There is strong evidence, that human recognition is based on the evaluation of textural information. However, sensor devices like CCD cameras do not recognise textures as such, they only sense the magnitudes of physical properties like brightness and color. It is the task of image processing algorithms to detect the uniform distribution of physical properties over connected regions of a surface which appear as "textures." The physiological mechanisms leading to this impression are still unresolved. However, the concept of feature classification gives a handsome tool for the emulation of perceptual perceivement abilities.

Since the early days of computer vision, the feature classification approach has become the essential texture analysis technique for the treatment of images of textured surfaces. The key steps of the feature classification approach are Image Acquisition, Preprocessing, Feature Calculation, Feature Selection and Feature Classification [hara73, hara85].

Main research fields are the search for well-suited texture feature calculation methods and the design of appropriate classification techniques. Since the upcoming of Soft Computing at the end of the 80's, intelligent techniques have been introduced to apply the feature classification approach to a growing class of surface textures.

New inspirations for improving the feature classification approach came from biology [hulle89, hulle92, toll92] especially from the work maintained by Grossberg and his Boundary/Feature Contour Systems or BCS/FCS model [gross85, gross93, gross89].

The BCS model is based primarily on psychophysical data related to perceptual illusions. Its processing stages are linked to stages in the visual pathway: LGN Parvo->Interblob->Interstripe->V4. The BCS model generates emergent boundary segmentations that combine edge, texture, and shading information. The BCS operations occur automatically and without learning or explicit knowledge of the environment. The system performs orientational decomposition of the input data, followed by short-range competitive and long-range cooperative interactions among neurons. The competitive interactions combine information of different positions and different orientations, and the cooperative interactions allow edge completion. The BCS has been shown to be robust and has been successfully used in different real applications like: processing of synthetic aperture radar images, segmentation of magnetic resonance brain images, and segmentation of images of pieces of meat in an industrial environment.

The FCS is complementary to the BCS, and is a model for invariant brightness perception under variable illumination conditions. This is achieved by using monocular preprocessing and featural filling-in.

In the language of the feature classification approach, the BCS/FCS model extends the whole approach by the inclusion of a second kind of image information, the edge information. However, the Grossberg approach has two main drawbacks. The first drawback is that it is completely model-driven. The BCS/FCS model makes use of neuron dynamics modelled by differential equations. The second one, as a consequence of the first one, is the large processing time. For the adaptation of model data to image data, iterative procedures are used.

Improvements of the Grossberg approach concentrated on the simplification of the processing equations to reduce processing time [vidal93, ruiz95]. However, the experiences of the application of the feature classification approach have seldom been used to improve the Grossberg approach.

In the scope of this paper, a framework is presented wherein the Grossberg approach is revised and which is capable of segmenting *arbitrary* two-dimensional textures. The essential modification is to make the Grossberg approach data-driven. This allows for the application of Soft Computing tools. The modifications are, in summary:

- The model-driven attribute assignment to certain loci of the visual field is replaced by the calculation of texture features in texture windows.
- The uniform approach of edge detection used by Grossberg (mainly based on Gabor filtering) is replaced by an arbitrary edge detection operation.
- The feature region growing, which is controlled by edge intensities in the image, is modelled in the Grossberg approach by a diffusion process. This is replaced by a marker-based watershed transformation.

All together the proposed approach follows the Grossberg paradigm but implement it with different, more efficient algorithms.

The following sections give some considerations about the revisions of the Grossberg approach mentioned above and present the application of the new framework for texture segmentation. The paper is organized as follows. Section 2 gives an overview of the presented texture segregation / region growing (TS/RG) approach. The revisions of the Grossberg approach are detailed and discussed in section 3. Section 4 recalls the definition of watershed transformation and proposes a modification of it, which allows for the use of the watershed transformation as a substitute for the diffusion step in the Grossberg approach. Before concluding, we illustrate the TS/RG approach for segmenting textiles and inner-tube socket scenes.

2. The texture segregation/region growing (TS/RG) approach for texture segmentation

The TS/RG approach for texture segmentation is mainly based on the feature classification approach. A diagram summarizing the proposed TS/RG approach is presented in figure 1. The following definitions are used:

Texture segregation: The process of assigning texture class numbers as labels to every pixel of a texture window. It is assumed that all pixels of a texture window belong to only one texture class.

Texture segmentation by region growing: The process of assigning a texture class to every pixel position in a texture image. This is quite different from texture segregation. A texture window is classified by means of features calculated from the pixel's greyvalues in the window. No further knowledge is given whether all pixels belong to the same texture class or not. The task of segmentation is to provide these additional information by other means. It is performed by means of a region growing procedure (see section 4).

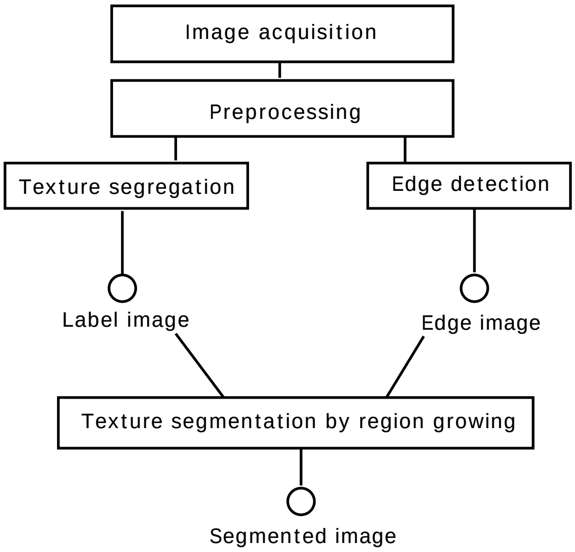

Figure 1: The texture segregation/region growing approach for texture segmentation.

3. Label and edge image generation

For the application of our approach, a label and an edge image need to be found. The label image is the result of the feature classification framework. For feature classification, the image is divided into texture windows. From the greyvalues of the texture window, textural features are computed. Many methods for the computation of textural features have been proposed so far. These methods, which are model-driven, can be divided into some main groups, to name a few: statistical features (including the well-known statistical features of the co-occurrence matrix), frequency-domain based features (e.g. Fourier descriptors), Gaussian Random Field features (e.g. Markov processes, Gibbs fields), fractal features (e.g. Hausdorff dimension, lacunarity), and features derived from Wavelet and Gabor decomposition.

Classifiers for the features are standard ones: minimum distance classifier for simple problems, Bayesian classifier or multilayer backpropagation neural networks for complex textures. A Bayesian classification with multiple self-organizing maps (one for every feature class) was proposed by one of the authors [bieb96].

Also, an approach based on a supervised variant of the ASSOM [koho95a,b] was proposed by two of the authors [ruiz96b, ruiz97].

The generation process of the label image can not solve an important problem in texture segmentation, the positioning of texture boundaries. Texture windows are positioned within the image due to a fixed recipe. Due to varying image contents, they can be "misplaced" in some manner, e.g. they may contain a texture boundary.

One approach would be to define new texture classes for texture windows containing more than one texture. This is an ill-posed approach, due to at least one reason. Consider the classification of a sequence of texture windows. The first window contains texture A only, the last window texture B only. In the sequence, every window contains a decreasing amount of texture A and an increasing amount of texture B. When does the classifier "switch" its recognition from class A to class B? Sure, it is not the "Half-A-Half-B" case. The features of different clusters may not be "neighbours" in the feature space, and the linear change of texture amount may not result in a linear change of the corresponding features. Even misclassifications are possible. Hence, the texture windows containing texture boundaries can not be expected to be a compact class suitable for classification. Also, the more texture classes are given, the harder it is to train a classifier.

The second image is an edge image used for constraining the filling-in of the pre-labelled regions. The intensity value of a pixel of the edge image corresponds to the strength of the edge information at this point (see [mart72, marr80] for edge detection approaches).

4. Watershed transformation

The watershed transformation [beuch82] stems from mathematical morphology [serra82, serra88, soille98]. For a detailed description and implementation issues, refer to [meyer90, beuch93, soille90, vinc91, serra94].

For watershed transformation, the edge image is considered as a topographic surface, the greyvalue of a pixel standing for its elevation. Now, let a drop of water fall onto such a topographic surface. According to the law of gravitation, it will flow down along the steepest slope path until it reaches a given minimum. The whole set of points of the surface whose steepest slope paths reach a given minimum constitutes the catchment basin associated with this minimum. The watersheds are the zones dividing adjacent catchment basins.

In the TS/RG framework, the label image is preprocessed in such a way that image minima correspond to texture segments. Segment opening is the morphological operation of opening applied to one segment only. Repeating this process for all segments and unifying the results, one gets the required preprocessing of the label image. A comprehensive algorithm refered to as emergent opening of all segments assigns value 0 to all pixel positions, where the dilation and erosion of the image with a structuring element differ, and the common value of dilation and erosion to all other pixel positions.

The reason for this preprocessing is as follows: the watershed transformation is applied only onto regions of the image, where the emergent opening of all segments results in greyvalue 0. All other positions have got a texture class assigned from the foregoing segregation. The "cleared" regions are that of uncertain class membership. The decision about class membership is made by the watershed transformation by looking for segments that grow into these regions, but their growing is under control of the intensities of edges.

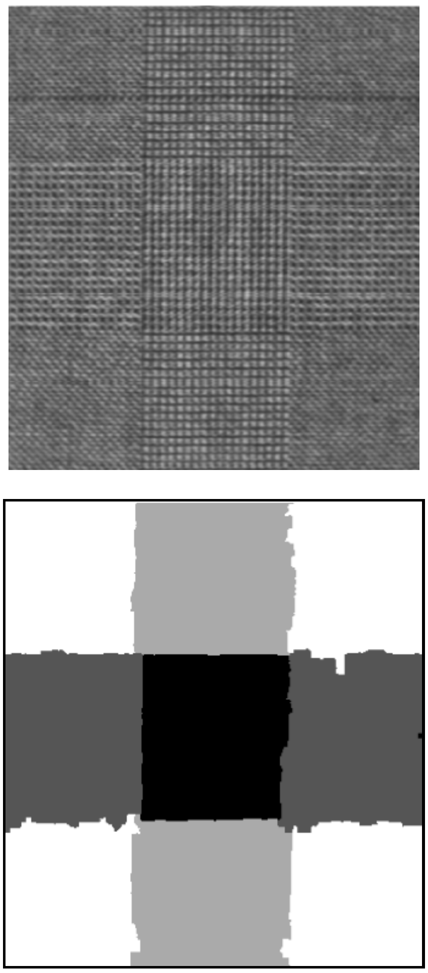

Figure 2: Segmentation of a textile image with four texture regions.

This is the main advantage of the watershed transformation. Naturally, texture boundaries may be represented by image edges or not. If there are only virtual texture boundaries, the region growing is not controlled by edge intensities, the regions grow until they meet the catchment bassin of another minima. However, these is a boundary too! Due to its virtual nature, there is no further evidence for the texture boundary. On the other side, if there are many edge-like structures in the image, they may influence the growing of regions. But an edge which is not a texture boundary has segments of the same label on both sides. When both catchment basins meet on top of this edge, they will not constitute a watershed, because both catchment bassins belong to the same minima (as marked in the label image). Hence, only relevant edges, laying on texture boundaries, constitute real watersheds.

5. Examples

To prove the texture segmentation abilities of the presented framework, some examples are given in the following. In figure 2, the segmentation of a textile image is shown using the proposed approach. For segregation, four texture classes have been defined. From 40 texture windows of size 20x20 pixels per class, 14 co-occurrence feature were computed and a multilayer backpropagation neural network (14 input neurons, 16 hidden neurons and 4 output neurons) was trained for 20,000 generations.

The trained neural network was used to segregate the image, thereby generating the label image. The edge image was generated by the application of standard image processing operations (Gabor filtering with a mask with 45 degree orientation and size of 7 pixels to suppress the small line-like structures, and morpholgical gradient with a structuring element of size 7x7 pixels to improve the edge contrast). After that, the label image was preprocessed by emergent opening of all segments with a structuring element of size 7x7 pixels, and the watershed transformation was applied resulting in the segmented image of figure 2.
The extensibility of the presented approach can be seen from the example of figure 3. The image is taken from a sewage pipe scene. It shows a socket from a perpendicular view. The task is to segmentate the socket scene into its three relevant segments (socket region, wall region and intermediate region). Here, segregation is performed by a simple histogram-based clustering of greyvalues. The image histogram of its greyvalue distribution is separated into its three peaks. This is done automatically by a simplified variation of the watershed transformation [soille96]. For the edge image, a morphological gradient of size 7x7 pixels was used. The preprocessing of the label image is equal to the one used in figure 2. This segmentation approach is part of a

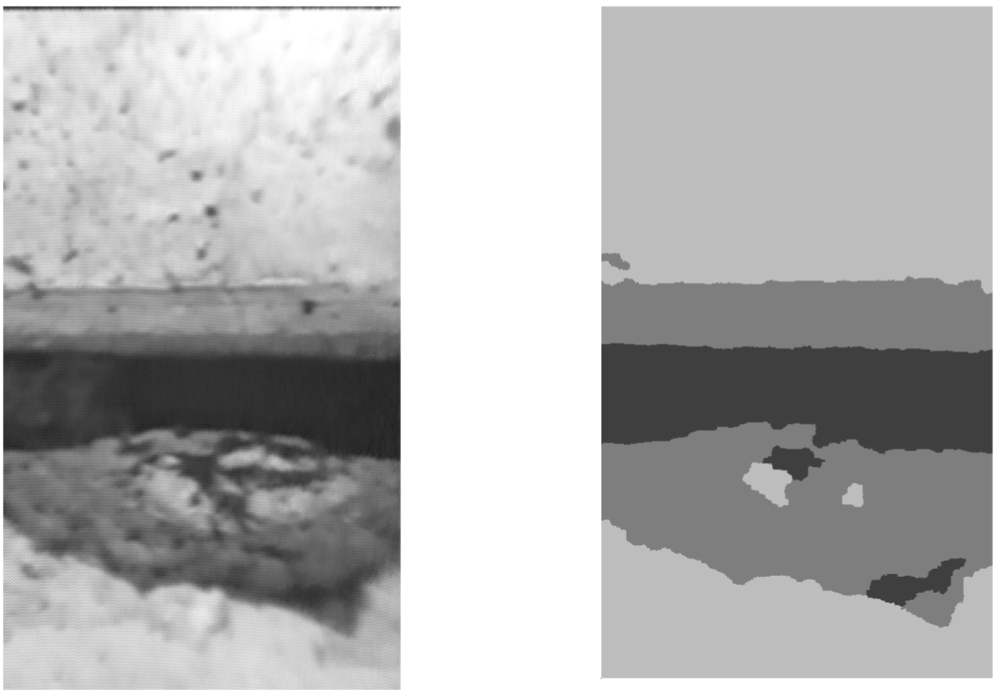

Figure 3: Segmentation of an inner-tube socket scene with three segments (wall, border & socket).

superposed approach to automatization of sewage pipe inspection, as presented in [ruiz95, ruiz96a, loh94].

Concluding Remarks

A new approach for texture segmentation, the texture segregation/region growing approach, was proposed. It is based on a combination of the standard feature classification approach and the watershed transformation. In order to apply the marker-based watershed transformation, an edge image and a label image have to be generated. Therefrom, the approach is quite similar to the BCS/FCS model of Grossberg. However, it modifies the BCS/FCS approach by making some replacements. The FCS part is replaced by the feature classification approach which results in image segregation. Texture classes are used as labels for the pixels contained in the texture window. The BCS part is replaced by either edge operator. This is possible due to the robustness of the watershed transformation against missing or irrelevant edges within the image. Alltogether, the watershed transformation, which replaces the filling-in, is used as a marker-based one, i.e. the minima are assigned before the transformation starts. The markers are taken from the label image after this is processed by the emergent opening of all segments operation. Two examples among a lot of succesfull applications of the framework are given.

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