# Texture Segmentation by Fuzzy Clustering of Spatial Patterns

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**Abstract.** An approach to perceptual segmentation of textured images by fuzzy clustering of spatial patterns is proposed in this paper. The dissimilarity between a texture feature, which is modeled as a spatial pattern, and each cluster is calculated as a combination of the Euclidean distance in the feature space and the spatial dissimilarity, which reflects how much of the pattern's neighborhood is occupied by other clusters. The proposed algorithm has been applied to the segmentation of texture mosaics. The results of comparative ex-periments demonstrate that the proposed approach can segment textured im-ages more effectively and provide more robust segmentations.*

## 1 Introduction

Texture segmentation, which has long been an important and challenging topic in image processing, can be achieved by adopting two independent sub-processes: texture feature extraction and feature clustering [1]. However, texture segmentation is different from traditional clustering problem in that each texture feature implies the spatial information of the texture patch it represented. Features of the same texture region are not only numerically similar, but spatially compact. Therefore, some spatial constraints must be incorporated into the clustering algorithm.

There are many methods to utilize the spatial information. A straightforward one is to include the coordinates as features [2]. Many other approaches adopt the Markov random field (MRF) model and interpret the spatial constraint in terms of the potential of each pixel clique [3]. A recent approach uses a linear filter to explore the spatial constraint [4]. If all pixels in a patch belong to the same class, the center pixel will be smoothed by its neighbors so that eventually all pixels in the window have high and similar membership values in one of the clusters. Although outperforming conventional algorithms, those methods often suffer from various inaccuracies.

In this paper, we solve the texture segmentation problem from the point of view of fuzzy clustering of spatial patterns. To incorporate the spatial information into the

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object function of fuzzy clustering, we define a novel metric of dissimilarity between a feature and a cluster to reflect not only the distance in feature space, but the location of the feature. We present the results of our approach when used to segment the mosaics of Brodatz textures [5]. We also compare them with the results obtained by using an MRF-based algorithm [3] and the spatial fuzzy clustering algorithm [4].

## 2 Segmentation Algorithm

An image is a 2D array of pixels defined on a $W \times H$ rectangular lattice. Each pixel can be represented by a feature vector, which is named as a pattern in the terminology of clustering. The pattern corresponding to the pixel lying on a site $s \in S$ is denoted as $x_s$. The value of pattern $x_s$ indicates its position in feature space, and the subscript $s$ specifies its position on the lattice. Pattern $x_s$ implies both the feature information and the spatial information, and hence is called a spatial pattern in this paper. Accordingly, a textured image can be modeled as a spatial pattern set $X = \{x_s : s \in S\}$. Texture segmentation is equivalent to clustering of the spatial pattern set $X$, which can be achieved by minimizing the following sum of dissimilarity

$$J_m(U,V) = \sum_{s \in S} \sum_{r=1}^{C} u_{rs}^m d_{rs}^2 \tag{1}$$

where $C$ is the desired number of texture patterns, $m$ is a fuzzy factor $(m > 1)$, $u_{rs}$ is the membership of the pattern $x_s$ to the $r$-th cluster, and $d_{rs}$ is the dissimilarity between $x_s$ and the prototype $v_r$. Similar to traditional clustering algorithms, a local minimum can be reached by performing the Picard iteration [6].

Generally, the dissimilarity $d_{rs}$ is computed by using a distance measure defined in the feature space, which, however, is not fully competent for clustering of spatial patterns because of the lack of the spatial constraints. Here, we define the dissimilarity $d_{rs}$ as a combination of the feature distance and the spatial dissimilarity with respect to the position of pattern $x_s$ on the lattice

$$d_{rs} = d_{rs}^F + \alpha \cdot d_{rs}^S \ , \tag{2}$$

Where $d_{rs}^F$ is the Euclidean distance, $d_{rs}^S$ is the normalized spatial dissimilarity, and the coefficient $\alpha$ presents a trade-off between them.

Our philosophy of defining the spatial dissimilarity is that if a pixel $s$ lies in the $r$-th textured region, the pattern $x_s$ and the prototype $v_r$ must have a small dissimilarity. The normalized spatial dissimilarity $d_{rs}^S$ is defined as follows, reflecting how much of the pattern $x_s$' neighbourhood is occupied by the $r$-th cluster

$$d_{rs}^S = 1 - \sum_{t \in \eta_s} u_{rt} \beta_t \Big/ \sum_{c=1}^{C} \sum_{t \in \eta_s} u_{ct} \beta_t \ , \tag{3}$$

where $\eta_s$ is the set of sites that are contained in site $s$ ' neighbourhood and the factor

$$\beta_t = h\left(\sqrt{(t_i - s_i)^2 + (t_j - s_j)^2}\right) \tag{4}$$

characterizes the contribution of each neighbor to the overall dissimilarity. In our experiments, we choose $h(.)$ as a sigmoid function.

Apparently, the importance of the feature distance $d_{rs}^F$ and the spatial dissimilarity $d_{rs}^S$ is not invariant during the clustering process. In the early stage, the spatial information implied in the fuzzy partition is not reliable, and the clustering should be dominated by $d_{rs}^F$. As the partition gradually approaching a convergence, the spatial dissimilarity should play an increasingly important role so that the misclassification can be corrected. Therefore, a variable weight factor $\alpha(n)$, which satisfies a sigmoid function, is used in our experiments to substitute for the constant $\alpha$.

## 3 Experimental Results

To assess its ability to segment textured images, the proposed algorithm has been compared with two commonly used segmentation approach, one is based on the MRF model [3] and the other is based on spatial fuzzy clustering (SFC) [4]. The comparative experiments have been carried out on a set of four-class texture mosaics, which are generated by using twelve natural textures chosen from the Brodatz album. With the purpose of comprehensive investigation, the test image set MⅣ is made of ${}_{12}C_4 = 495$ samples. The 6-dimensional feature [7] derived from Conditional Markov (CM) model is uniformly used by all three approaches to make a fair comparison.

Two test cases, together with their corresponding segmentations, are presented in Fig. 1. Both the percentage of incorrectly classified pixels and the time cost

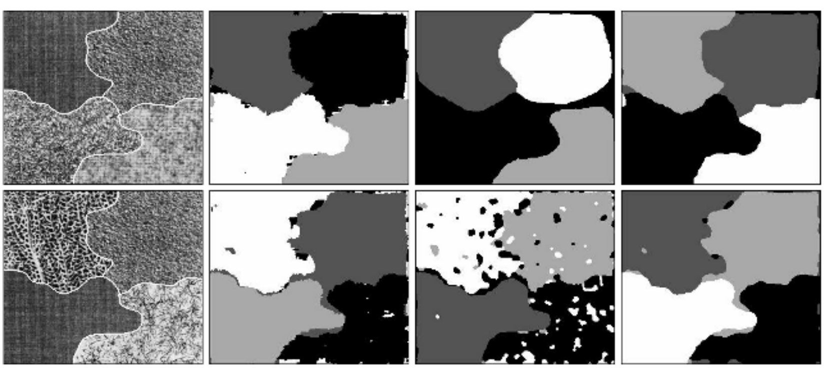

**Fig. 1.** 2 test cases (MⅣ1 and MⅣ2) and their segmentations by applying (the 2nd column) the SFC algorithm, (the 3rd column) the MRF algorithm and (right column) the proposed algorithm

**Table 1.** Performance of three segmentation algorithms

| Image Index | Error Percentage | | | Time Cost | | |
|---|---|---|---|---|---|---|
| | SFC | MRF | Proposed | SFC | MRF | Proposed |
| MⅣ1 | 4.95 % | 9.94 % | 4.23 % | 3.50 s | 5.58 s | 4.92 s |
| MⅣ2 | 6.98 % | 12.18 % | 5.30 % | 4.09 s | 5.70 s | 5.24 s |
| Average | 12.10 % | 17.38 % | 10.26 % | 5.11 s | 5.78 s | 6.44 s |

(Intel Pentium Ⅳ 4.0 GHz Processor, 2G Memory) of those two cases are given in Table 1. The average performance of those three approaches over the entire image set is also listed in Table 1. It is obvious that the proposed approach can achieve more accurate segmentation, especially in suppressing small mis-segmented regions, but at a cost of the slightly increased computational complexity.

## 4 Conclusions

In this paper, a textured image is modeled by a set of spatial patterns and texture segmentation can be achieved by from the point of view of fuzzy clustering of spatial patterns. The dissimilarity between a spatial pattern and each cluster is defined by using both the feature value and the spatial information. Comparative experiments on texture mosaics have demonstrated that the novel algorithm is more effective.

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