

# Texture Segmentation Based on Pattern Maps Obtained by Independent Component Analysis

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**Abstract** In this paper, we propose a new feature for texture segmentation that is based on the pixel patterns and thus is independent of the variance of illumination. A gray scale image is transformed into a pattern map in which edges and lines (bars) used to characterize the texture information are classified by pattern matching. The Gabor filters can enhance edge features, however, are not effective in edge pattern classification. We extract the pattern templates from image patches by Independent Component Analysis. Based on the pattern maps, the feature vector is comprised of the numbers of the pixels belonging to each pattern. The calculation of the features is simple and not related to the number of the components, so the proposed method is quite time saving compared with other multichannel segmentation algorithms.

**Keywords** texture segmentation, Edge detection, pattern matching, Independent Component Analysis (ICA), ICA pattern map, texture segmentation,

**Topics:** 7.4 Signal and image processing based on PCA and ICA

**Total pages:** 6 pages

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**Abstract** In this paper, we propose a new feature for texture segmentation that is based on the pixel patterns and thus is independent of the variance of illumination. A gray scale image is transformed into a pattern map in which edges and lines (bars) used to characterize the texture information are classified by pattern matching. The Gabor filters can enhance edge features, however, are not effective in edge pattern classification. We extract the pattern templates from image patches by Independent Component Analysis. Based on the pattern maps, the feature vector is comprised of the numbers of the pixels belonging to each pattern. The calculation of the features is simple and not related to the number of the components, so the proposed method is quite time saving compared with other multichannel segmentation algorithms.

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## 1. Introduction

Texture is a very important feature that can be used to texture segmentation as well as feature representation. To design an effective segmentation algorithm, it is essential to find a texture feature set with good discriminating power. In recent years, the multiresolution and multichannel filtering techniques have been widely used to texture analysis, such as wavelet transforms, and Gabor filters. The substantial of multichannel filtering methods are to enhance edges and lines of different orientations in each feature component. Gabor filters can be considered as being orientation and scale tunable edge and line detectors, and the statistics of these microfeatures are

often used to characterize the underlying texture information [1,2,3]. Features are extracted by filtering the texture image with a selected subset of Gabor filter bank and then calculating predefined statistics within small regions of the filtered images. The widely used statistic terms include energy, entropy and variances. The segmentation accuracy is satisfactory if appropriate Gabor filter banks are chosen. However, the statistics are computed from gray scale values and dependent on the illumination. Furthermore, the computation cost is rather high since each component of the feature vector is calculated separately in each filtered image.

In this paper, we propose a new feature for texture segmentation that is very simple to calculate and free of the influence of illumination. A gray scale image is first transformed into a pattern map in which edge, line and background pixels are classified by pattern matching. The pixels of the map represent the pattern class, which leads to two advantages:

- (1) the pixel values have a much more controllable range than gray scale images;
- (2) the pattern classes reflect the edge and line orientations, which is impossible for gray scale values.

Then, the feature vector is created from the pattern map that the components are the numbers of the pixels belonging to each pattern within a small window. The statistics of this one map is much simpler than that of the multi filtered images, and the calculation time has nothing to do with the number of the components.

To get a pattern map, we need to design a set of pattern templates and assign a pixel to a pattern that matches the neighbor region best. Gabor filter bank can extract texture features, however, it is demonstrated by our experiments that Gabor filters are not effective as the pattern templates in the case

that the textures are irregular and non-periodic.

We obtain the pattern templates by Independent Component Analysis (ICA). Although related researches have been done to demonstrate that ICA process of nature scene images can result in edge detection [4,5,6], there are very few applications of these theories to image processing. Differing from these previous works that try to get edge filters, we apply ICA to nature scene patches and use the results as templates for pattern matching. In output maps, the pixels represent the class number of the patterns that match the neighbor blocks best. In our method, the components of a feature vector can be calculated at once from one pattern map, so the efficiency is much higher than that of the other multichannel filtering methods. Still our approach has a rather satisfied accuracy.

This paper is organized as follows. Section 2 briefly describes the background of texture segmentation by multichannel filtering. In section 3, a novel feature based on pattern maps is proposed for texture segmentation. In section 4, ICA filters are used as the pattern templates to obtain pattern maps, and Section 5 gives a conclusion.

## 2 Texture segmentation by multichannel filtering

In the following multichannel filtering method, Gabor filters defined by Equation. (1) are used to extract the features.

$$g_{-f}(x, y, \sigma_x, \sigma_y, \theta) = \exp\left(-\frac{x_1^2}{2\sigma_x^2} - \frac{y_1^2}{2\sigma_y^2}\right) \cos(2\pi x_1) \quad (1)$$

where  $x_1 = x \cos \theta + y \sin \theta$ ,  $y_1 = -x \sin \theta + y \cos \theta$ ;  $\theta$  is a preferred orientation parameter;  $\omega$  is a radial center frequency;  $\sigma_x$  and  $\sigma_y$  are the standard deviation along  $x, y$ .

Usually a texture image is convolved with a bank of Gabor filters in which only the frequency and the orientation are tuned.

$$W_{mn}(x, y) = I(x, y) \otimes g(x, y, \theta_m, \omega_n) \quad (2)$$

In the filtered images, statistic terms are calculated in a small window  $A=S1*S1$ . The well used statistics are mean  $\mu_{mn}$  and deviation  $\sigma_{mn}$ , and the feature vector is

$$f = [\mu_{00} \quad \sigma_{00} \quad \mu_{10} \quad \sigma_{10} \quad \dots \quad \mu_{mn} \quad \sigma_{mn}] \quad (3)$$

Each Gabor filter with specific orientation and

frequency enhances an edge feature of the texture images, and the features are represented by a set of filtered images. The gray scale features will be affected by the illumination condition. The feature components are calculated separately in the filtered images and so result in costly computation. Furthermore, since the segmentation accuracy is dependent on the filters, genetic algorithms have been proposed [7] to select appropriate filters. These algorithms improve the performance of segmentation, and at the same time bring a computation burden.

## 3 A new feature for texture segmentation

In this section, we propose a new feature that is independent of illumination and relatively time saving.

### 3.1 The feature based on pattern maps

Instead of representing the features in multi-filtered images, we represent the features in one pattern map. A gray scale image is transformed into a pattern map in which edge, and background pixels are classified by pattern matching as Figure 1.

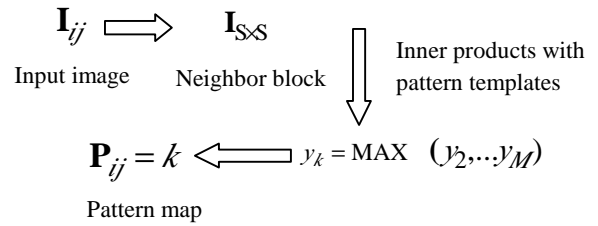


Figure 1 Pattern matching with templates

The pixels in a pattern map are represented by the classes of the patterns that match the neighbor blocks best. So a pattern map has a rather small and controllable value range. Suppose the number of patterns is  $M$ , thus a pattern map is in a range of  $[1, M]$ . For each pixel  $P(x, y)$ , the features in a window  $S1 \times S1$  can be generated as:

$$f_i(x, y) = \sum_{m=-(S1-1)/2}^{(S1-1)/2} \sum_{n=-(S1-1)/2}^{(S1-1)/2} g_i(m+x, n+y) \quad \dots \quad (4)$$

where the function  $g$  is defined as a binary function:

$$g_i(m, n) = \begin{cases} 1 & P(m, n) = i \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

So, the feature  $f_i$  is the number of the pixels belonging to the  $i$ -th pattern. The feature vector is

constructed using  $f_i$  as components:

$$F = (f_1, f_2, \dots, f_N) \quad (6)$$

The feature vectors are calculated by using the following algorithm:

```

Initialize the features for all pixels
 $f_i(x, y) = 0$ ;
For each pixel  $A(x, y)$ ,
  For ( $m = -(S1-1)/2$ ;  $m < (S1-1)/2$ ;  $m++$ )
  For ( $n = -(S1-1)/2$ ;  $n < (S1-1)/2$ ;  $n++$ )
    {  $i = I(x + m, y + n)$ ;
       $f_i(x + m, y + n) ++$ ;
    }

```

We can see that to calculate the feature vector in Eq. (6), for each pixel there are only  $S1 * S1$  times of additions that is independent of the number of feature components  $M$ . In case of Gabor filter banks, however, for  $M$  feature components, the computation includes  $M * S1 * S1$  times of addition. The new feature representation is obviously much simpler and more time saving. However, the segmentation accuracy of the new feature is quite dependent on the pattern template set.

### 3.2 Gabor filters as pattern templates

In the following sections, we use three texture images shown in Figure 2 as the simulation representatives. The 3 images are comprised of textures from Brodatz album [8]. The original image 1 has smaller and regular textures, while image 2 has 5 textures and image 3 has four textures of relatively large and irregular scale.

We use 32 Gabor filters as pattern templates with  $s_x = 1.5$ ,  $s_y = 2.0$ ;  $\sigma_1 = 0.2$ ,  $\sigma_2 = 0.6$ ,  $\sigma_n = n / 16$ ,  $n = 1, \dots, 16$ . The feature window size is  $31 \times 31$ .

Same as multichannel filtering methods, selecting appropriate filters instead of using all can improve the accuracy. For the new feature vector, the larger the component value, the better the responding template fit the textures and thus the more significant the template is. By this criterion, we select the templates  $i$  whose responding feature values over the whole image meet the requirement of  $MAX(f_i) > 100$ .

The feature components are first normalized to a same range, and then the feature vectors of all the pixels are used in K\_means algorithm [9] to segment the texture images into predefined number of uniform regions. The result is demonstrated in Figure 3, where each grayscale value represents a kind of texture. For texture image 3, even though different filters are tried, we failed to get a satisfactory result. The reason may be that the textures are not irregular and the Gabor filters from mathematics formulae are not effective for pattern matching. An alternative to Gabor filters is to get pattern templates from statistics analysis of image patches.

## 4 ICA filters as pattern templates

### 4.1 Independent Component Analysis of image patches

The spatial feature in an image reflect that how the value of one pixel depend on that of its neighbors. In real images, nearby pixels will often have common causes and thus be statistically related. There have been some researches on analyzing the inter-relations between neighbor pixels to learn the receptive fields of primary cortex cells [10,11]. We first give the general model of image analysis.

Suppose that each image patch, represented by the vector  $\mathbf{x}$ , is the linear combination of  $N$  basis functions as:

$$\begin{bmatrix} x_1, x_2, \dots, x_N \end{bmatrix}^T = s_1 \times [a_{11}, a_{21}, \dots, a_{M1}]^T + \dots + s_N \times [a_{1N}, a_{2N}, \dots, a_{MN}]^T \quad (7)$$

The basis functions are consistent and the coefficients vary with images. Imagine that a perceptual system is exposed to a series of images. We can represent the coding process in matrix form as:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \quad (8)$$

where a column of  $\mathbf{x}$  is an image patch, each column of  $\mathbf{A}$  is a basis function  $a_j$ , and a column of  $\mathbf{s}$  is the coefficients responding to the image. Thus, the linear image analysis process is to find a matrix  $\mathbf{W}$ , so that the resulting vector

$$\mathbf{y} = \mathbf{W}\mathbf{x} \quad (9)$$

recovers the underlying causes  $\mathbf{s}$ , possibly permuted and rescaled. Each row of  $\mathbf{W}$  is taken as a filter.

Designing an algorithm to learn  $\mathbf{W}$  depends on what kinds of causes are concerned. If we take the causes as being mutual independent, the Independent Component Analysis (ICA) model can be applied to

resolve this problem.

## 4.2 Texture segmentation based on ICA filters

Bell & Sejnowski have proposed a neural learning algorithm for ICA[12]. The approach is to maximize by stochastic gradient ascent the joint entropy,  $H(g(\mathbf{y}))$ , of the linear transform Eq. (9) squashed by a sigmoidal function  $g$ . The updating formula for  $\mathbf{W}$  is:

$$\Delta \mathbf{W} = (\mathbf{I} + g(\mathbf{y})\mathbf{y}^T)\mathbf{W} \quad (10)$$

where  $\mathbf{y}=\mathbf{W}\mathbf{x}$ , and  $g(y) = 1 - 2/(1 + e^{-y})$  is calculated for each component of  $\mathbf{y}$ . Before the learning procedure,  $\mathbf{x}$  is sphered by subtracting the mean  $\mathbf{m}_x$  and multiplying by a whitening filter:

$$\mathbf{x} = [(\mathbf{x} - \mathbf{m}_x)(\mathbf{x} - \mathbf{m}_x)^T]^{-1/2}(\mathbf{x} - \mathbf{m}_x) \quad (11)$$

Bell applied the ICA model to an ensemble of natural scenes and obtained a set of filters. Until now there are few applications of these filters to image processing. One reason is that in many cases not all the filters are necessary and it is difficult to choose an appropriate subset according to specific circumstances. In the following, we will use the ICA filters for pattern matching.

In our experiment, the training set was generated of 12,000  $8 \times 8$  samples from four nature scenes involving trees, leaves and so on. Each row of  $\mathbf{W}$  is taken as a filter, and the resulted 64 filters are displayed in Figure 4.

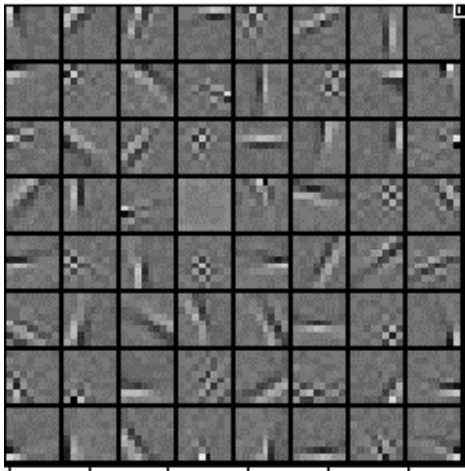


Figure 4  $\mathbf{W}$  of 64 filters obtained by training on whitened data, consisting of Gabor-like oriented filters and checkerboard filters

Olshausen & Field got the similar results by sparseness-maximization network and argued that

this is a family of localized, oriented, bandpass receptive fields [10]. To use ICA filters as pattern templates is based on this argument and that the outputs are mutual independent.

Same as for Gabor filter banks, we select the ICA filter  $i$  whose responding feature values over the whole image meet the requirement of  $MAX(f_i) > 100$ . The Feature components are normalized and K\_means algorithm based on the feature vector is used to segment the texture images. The segmentation results are shown in Figure 5. The texture image 3 that the Gabor filter banks failed to segment is almost partitioned by ICA filters.

As a final comparison, the performance of the Multichannel filtering method, and that of the proposed method (using Gabor filter banks and ICA filters) are list in Table 1. The error rate is measured by the rate of the misclassified pixels. The computation time of the proposed feature is about 9 second that is independent of the number of the filters. The calculation of each Gabor feature component costs 17 seconds. In case of 8 filters, the computation time for average and variance statistics is about 270 seconds. The time listed in Table 1 includes feature extraction, normalization and classification.

Table 1 Segmentation performance comparison

Features Error rate (%)	Gabor Filter features	Gabor Pattern features	ICA pattern features
Image 1	2.3	2.5	2.0
Image 2	7.2	4.5	5.5
Image 3	7.7	33	6.8
Calculation time (sec)	305	42	42

## 5 Conclusions

In this paper, we propose a new feature for texture segmentation that is independent of illumination and time saving. Differing from the multichannel filtering methods in which the features are calculated from several filtered images, the new feature is obtained from one pattern map. This is based on the following considerations: (1) methods based on gray scale values are easily influenced by illumination, (2) calculating the feature components in separate images

results in a expensive computation cost.

We first transform a gray scale image into a pattern map, in which a pixel is represented by the pattern class of its neighbor block. The components of the feature vector are defined as being the number of the pixels belonging to each pattern in the feature window.

The performance of the new feature is dependent on the pattern templates. Gabor filters possess feature extraction ability and can be used as pattern templates. However, it is demonstrated by our experiment that it is difficult to find an appropriate Gabor filter bank for irregular textures.

We then use as pattern templates the filters obtained by applying independent component analysis to nature scene image patches. Although some of the filters are Gabor-like, they are from real images and found by the experiments to be superior to the ones from Gabor functions in extracting the features of irregular textures.

The time saving characteristic makes the new method may also be applied to the texture image retrieval applications where online results with a reasonable accuracy are required.

This work was partly supported by the Outstanding Overseas Chinese Scholars Fund of Chinese Academy of Science.

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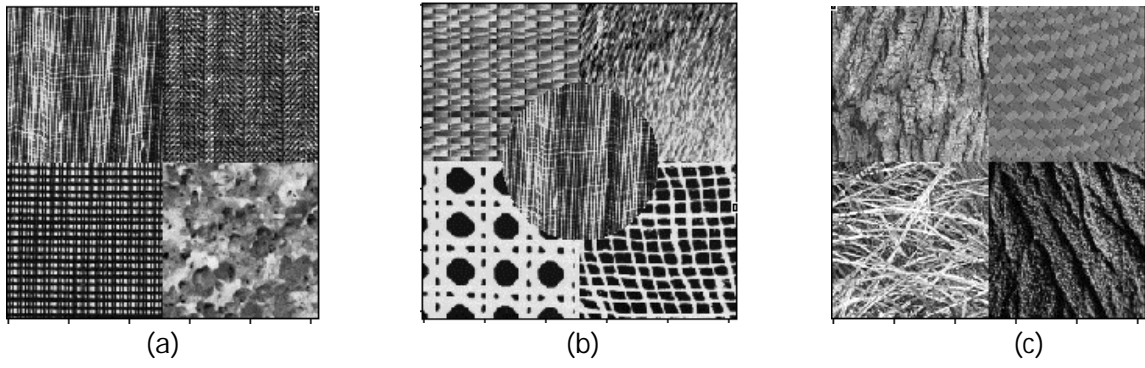


Figure 2 Texture images of  $256 \times 256$  pixels. (a) image 1, (b) image 2, (c) image 3.

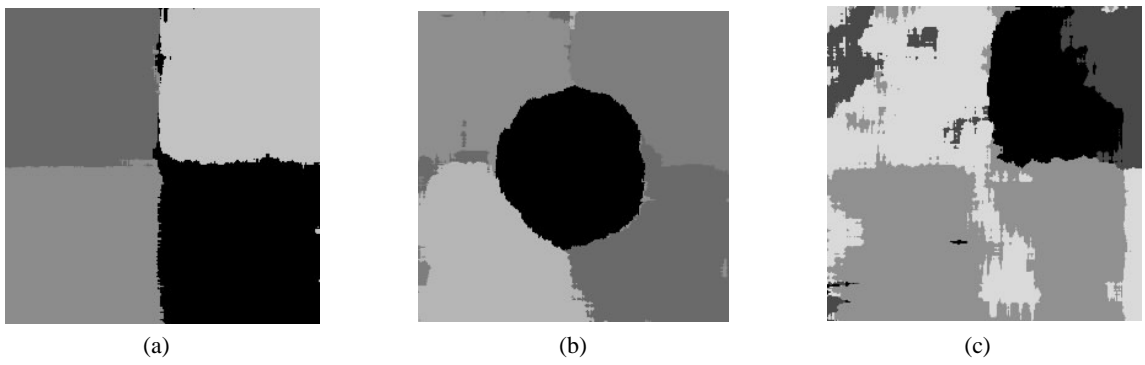


Figure 3 Texture segmentation by the proposed feature using Gabor filters as pattern templates  
Result of (a) image 1, (b) image 2, (c) image 3.

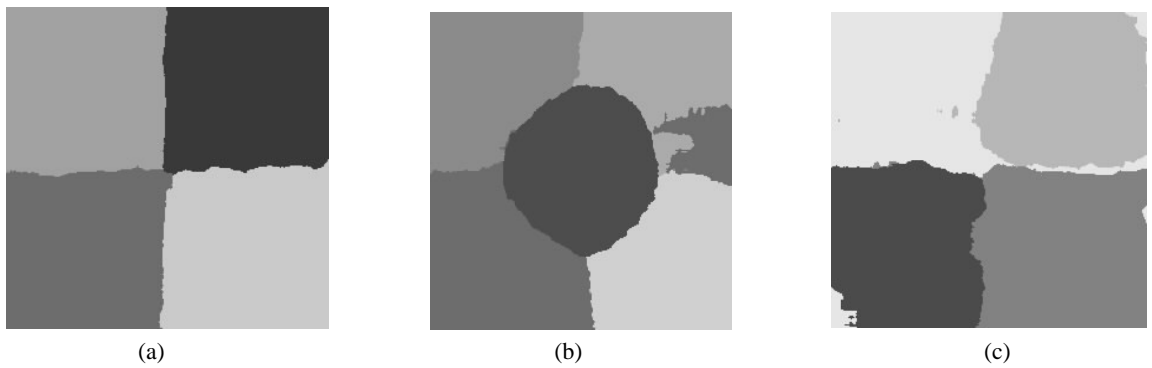


Figure 5 Texture segmentation by the proposed feature using ICA filters as pattern templates  
Result of (a) image 1, (b) image 2, (c) image 3.