Technique for Detecting Specific Textural Regions in Images

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Abstract. In this paper, we considered a problem of detecting specific textural regions in digital images. A task for detecting specific textural regions is addressed as a problem for segmenting textural images. We proposed a technique based on modified super-pixel segmentation algorithm with post-processing procedure. A vector image pixel description is augmented with texture features computed from structure tensor components. Augmented pixel description enables to take into account texture coherence and orientation as well as spatial and color properties of image regions. To obtain an acceptable segmentation quality, a minimum information criterion is used. A computational experiment involves artificial and real images. The developed technique is applied to images of paintings for localizing groups of brushstrokes. Results of the experiment show efficiency of the proposed technique.

1. Introduction

This work is related to a problem of detecting textural regions with a specific textural pattern. The pattern includes groups of elongated objects or stripes with uniform spatial orientation and different color, brightness, and spatial frequency. For example, this type of pattern can be generated by groups of brushstrokes, and it is typical for images of paintings.

The tasks of detecting textural regions are urgent for computer-assisted analyzing images of facture of paintings [1]. One of the components of the facture is produced by groups of brushstrokes forming details in paintings. In an image, a brushstroke usually looks like a group of curves with uniform geometric characteristics (length, width, curvature, and orientation) and different color. In images of paintings, brushstrokes produce a texture depending on a particular painting style. Textural features can be used for the quantitative representation of a painter’s artistic manner [2-5]. To localize informative regions with a specific texture pattern, segmentation techniques should be applied.

For segmenting textural images, a number of techniques have been developed. The most efficient ones are based on co-occurrence matrix and Haralick features [6], Laws’ energy features [7,8], Gabor filters [9,10], autocorrelation, Markov random fields, and some others. These techniques are efficient in many cases. But in case of texture with a wide range of wave numbers, it will be necessary to form several co-occurrence matrices to capture different spatial relations between pixels. When texture is composed of non-uniformly oriented patterns, a bank of differently oriented Gabor filters should be
applied. Laws’ energy features are computationally expensive and in some cases cannot provide the acceptable precision of segmentation. In this work, a technique for detecting specific textural regions is proposed. We modify the superpixel algorithm SLIC [11] in two ways. First, we include textural features computed from structural tensor components into pixel description. And then we apply a postprocessing procedure merging superpixels. The proposed technique enables to take into account spatial, color, and textural properties of image regions.

2. Technique for detecting textural regions
To detect image regions with particular texture patterns, we propose to modify the SLIC segmentation technique [11]. In addition to spatial and color components, we include a textural one into pixel feature description. This component enables to segment image areas with coherent and uniformly oriented textural patterns. Textural feature values will be computed as the functions of structure tensor elements and eigenvalues. In the next section, we give a brief description of SLIC algorithm and introduce the augmented pixel description.

2.1. SLIC segmentation algorithm
The main idea of the SLIC segmentation algorithm [11] is to cluster pixels in restricted areas, into which the analyzed image is partitioned in a regular manner. A five-dimensional vector $p = (c_1, c_2, c_3, x, y)^T$ characterizes each point of the image, where $c_1, c_2, c_3$ are the point coordinates in the selected color space, $x, y$ are the spatial coordinates of an image pixel. The authors of the algorithm used CIE Lab color space.

The algorithm includes the following steps.
1. The image is divided into $K$ fragments of size $a \times a$, which are taken as an initial approximation of superpixel clusters. Geometric centers $C_k$ of the fragments are selected as the initial centers of superpixels.
2. Fragment centers are moved to the lowest color gradient position in a $3 \times 3$ neighborhood.
3. The local clusters are formed in a $2a \times 2a$ neighborhood of the centers $C_k$ similarly to the k-means algorithm. The distance $d_p$ between the center and the fragment point is computed as a combination of Euclidean distances $d_c$ and $d_s$ of the color and spatial components describing point:

$$d_c = \sqrt{(c_{j1} - c_{i1})^2 + (c_{j2} - c_{i2})^2 + (c_{j3} - c_{i3})^2}$$
$$d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$$
$$d_p = \sqrt{d_c^2 + \left(\frac{d_s}{a}\right)^2} m^2$$

where $m$ is a parameter specifying the ratio of the contributions of the two components of the image description in the distance value $d_p$; $i$ and $j$ are the point numbers.
4. New cluster centers are determined, and the displacements of cluster centers are computed.
5. Steps 3 and 4 are repeated as long as the displacements of centers between iterations will not exceed a predetermined value.

To allocate homogeneous regions corresponding to objects fixed in the image, it is necessary to merge superpixels. For this purpose, a post-processing procedure should be applied (see below).

2.2. Augmented feature space
Structure tensor is defined as a second-moment matrix at a point $x = (x, y)^T$ weighted by a window function [12]:
\[ \mu_j(x) = \int_{z \in y^2} (Df(z)(Df(z))^T w_g(x - z) dz \]  

where \( w_g(x - p) \) is a Gaussian window [13], \( Df = (f_x, f_y)^T, f \in C^2 \) is a function describing grayscale image relief. The angle of simple neighborhood orientation \( \varphi \) is computed as:

\[ \varphi = \frac{1}{2} \arctan \frac{2\mu_{f,1,1}}{\mu_{f,2,0} - \mu_{f,0,2}} \]  

where \( \mu_{f,i,j} \) are the components of the structure tensor (2).

Local coherence measure of image gradients is computed as follows [8]:

\[ c_c = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2} \]  

where \( \lambda_1, \lambda_2 \) are the eigenvalues of the matrix \( \mu_j(x) \).

Taking into account textural features given above, we obtain the augmented vector of pixel description:

\[ p = (c_1, c_2, c_3, x, y, c_c, \varphi)^T \]  

For computing distance between image points in the extended space (5), we introduce textural components (3) and (4) into formula (1):

\[ d_c = \sqrt{w_1^2 d_1^2 + w_2^2 d_2^2 + w_3^2 d_3^2 + w_4^2 d_4^2} \]

\[ d_{cc} = (c_{ij} - c_{ji}) d_\varphi = (\varphi_i - \varphi_j) \sum_i w_i^2 = 1 \]

The degree of importance of a component is defined by a correspondent weighting coefficient \( w_i \).

As in [14], to merge superpixels into homogeneous regions corresponding to objects in the original image, a post-processing procedure is applied. To make a decision on merging, a threshold decision rule is formulated. This rule allows merging if the following condition is taking place:

\[ d(C_i, C_j) \leq T(t) \]

where \( d(C_i, C_j) \) is the distance between centers of adjacent superpixels with numbers \( i \) and \( j \) in the selected space; \( T \) is a threshold value, \( t \) is a parameter; \( T = g_c t, g_c \) is a constant. We use \( g_c = 1 \). In the next section, we obtain a condition for choosing \( t \).

3. Segmentation quality

For choosing parameter of the postprocessing procedure obtaining acceptable segmentation quality we use information-theoretical criterion proposed in [14]. We consider our segmentation technique as a discrete stochastic information system. Let the initial and segmented images be the input and the output of this information system. Suppose levels of lightness in images are the random variables \( U \) and \( V \). The criterion is derived from the information redundancy measure and takes the form

\[ R = \frac{H(V | U)}{H(V)} \]  

where \( H(V) \) is an entropy of the system output, \( H(V | U) \) is a conditional entropy of the output \( V \) under the condition that the input is equal to \( U \). It is necessary to find conditions for a minimum of \( R \) in terms of information characteristics of images.
Suppose the segmentation algorithm generates a set \( V = \{V_1, V_2, ..., V_J\} \) of \( J \) images partitioned into \( k \) segments, \( k = 1, 2, ..., K \), \( V_i = \bigcup_{j=1}^{K} S_j \), where \( S_j \) is a segment of the image \( V_j \). Images \( V_j \) are obtained at different values of \( t \).

**Statement.** The criterion value \( R \), computed for an image \( V^* \) partitioned into \( k = k^* \) segments, achieves its minimum iff the following condition

\[
\frac{H(U, V^*) - H(U, V)}{H(V^*) - H(V)} < R(V^*) < \frac{H(U, V^*) - H(U, V)}{H(V^*) - H(V)}
\]

is taking place. Here \( H(U, V) \) is a joint entropy of the system, indices “+” and “–” denote the image \( V_j \) partitioned into \( k > k^* \) or \( k < k^* \) segments, respectively.

**Proof.** Suppose the minimum of \( R \) computed for an image \( V_j = V^* \) partitioned into \( k = k^* \) segments achieves minimum. Then the following inequalities are taking place:

\[
R(V^+) - R(V^*) > 0 \quad \text{for all } k > k^*
\]

\[
R(V^-) - R(V^*) > 0 \quad \text{for all } k < k^*
\]

Substituting equation (8) into inequalities (10) and (11) and taking into account that

\[
H(U | V) = H(U, V) - H(U)
\]

where \( H(U) \) is the entropy of an input image, we obtain:

\[
\frac{H(U, V^*) - H(U)}{H(V^*)} - \frac{H(U, V^*) - H(U)}{H(V^*)} > 0
\]

\[
\frac{H(U, V^-) - H(U, V^*)}{H(V^-)} - \frac{H(U, V^-) - H(U, V^*)}{H(V^-)} < 0
\]

After simple transformations we get

\[
\frac{H(U, V^*) - H(U, V^*)}{H(V^*)} > \frac{H(U, V^*) - H(U)}{H(V^*)}
\]

\[
\frac{H(U, V^-) - H(U, V^*)}{H(V^-)} < \frac{H(U, V^-) - H(U)}{H(V^-)}
\]

Combining (13) and (14) and taking into account (8) and (12), we obtain condition (9).

**Inverse.** Suppose for some segmented image \( V^* = V_j \), \( k = k^* \) and condition (9) is taking place. Using expressions (8) and (12) and transforming, we get inequalities (10) and (11). From (10) and (11) it follows that the \( R \) criterion has a minimum when the image \( V_j \) is partitioned into \( k^* \) segments.

Expressions \( \Delta H(U, V) = H(U, V_{min}) - H(U, V^*) \) and \( \Delta H(V) = H(V_{min}) - H(V^*) \) in condition (9) define losses of information when segments are merging by the postprocessing procedure (7). Here we denote the image \( V_j \) corresponding to the minimum of \( R \) by \( V_{min} \). Condition (9) gives the relationship between the entropies of the segmented images \( V \in V \), which provides criterion \( R \) with the minimum.

Condition (9) is illustrated in figures 1 and 2 obtained for an image from BSDS 500 dataset [18]. In figure 1, the behavior of entropies of the segmentation system, depending on the number of segments in the output image \( V \), is shown. In figure 2 the dependences of the \( R \) criterion and ratio
\[ \Delta H(U,V)/\Delta H(V) \] values on the number of segments \( k \) are given. Minimum of \( R \) is reached at \( k = 61 \). It can be seen that \( \Delta H(U,V^-)/\Delta H(V^-) > R(V_{\text{min}}) \) when \( k > 61 \) and \( \Delta H(U,V^-)/\Delta H(V^-) < R(V_{\text{min}}) \) when \( k < 61 \).

In the next section, a computer experiment showing the applicability of the proposed technique to some image types is described.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Behavior of entropy values of the segmentation system when the number of segments \( k \) in output image changes.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{The \( R \) criterion and the ratio \( \Delta H(U,V)/\Delta H(V) \) values computed for output images with various number of segments \( k \).}
\end{figure}

4. Experiments

To show the efficiency of the proposed technique, a computing experiment is carried out. The experiment includes three steps. At the first step, modified superpixel algorithm SLIC (further we refer to it as SLICm) will be applied to artificial (synthesized) textural image. At the second step, textural mosaic from USC [7] will be used. At the last step, we will detect regions of interest with a specific type of facture in images of paintings.

4.1. Segmentation of artificial textural image

The first part of the experiment deals with applying modified algorithm SLICm to synthesized test image shown in figure 3(a). This image includes two types of wave-like texture with changing wave number and oriented at angles of 45 and 135 degrees. The image was segmented using SLICm algorithm with augmented pixel description and classical SLIC algorithm with pixel description including only spatial and color components. The results are shown in figures 3(b) and 3(c). The image given in figure 3(b) shows that classical SLIC algorithm failed to segment correctly image with various texture types. In this experiment, the following parameters were taken: window function size \( a_w = 5 \) pixels, threshold parameter \( t = 0.45 \), weighting coefficients \( w_2 = 0.01 \), \( w_3 = 0.01 \), \( w_4 = 0.8 \). Here parameter \( a_w \) is set rather small to provide good segmentation precision. Weighting coefficients \( w_i \) are chosen taking into account properties of the patterns of texture. The main characteristics of texture shown in figure 3(a) are orientation and coherence. Therefore \( w_3 \) and \( w_4 \) in formula (6) are set relatively large. In our case, color is not dominating property of a region of interest, so we chose \( w_2 \) relatively small. To obtain connectivity of segmented regions, coefficient \( w_1 \) has a non-zero value. Final tuning is made empirically. Introducing textural features into pixel description enabled to obtain segmentation precision in the range of two pixels (see figure 3(c)).
4.2. Segmentation of textural mosaic

In the second part of the experiment, we use textural mosaic [15] composed of Brodatz textural patterns [15] at University of Southern California. Textural mosaic of size 512 by 512 pixels is shown in figure 4(a). The corresponding texture map is shown in figure 4(b). In this section, we compare results obtained using the proposed method based on SLICm algorithm and method based on Laws’ energy features [8]. The main idea of Laws’ method is as follows. An input image is processed by a combination of filters with five element masks. Then filtered images are used for computing energy maps. Afterward, applying \( k \)-means clustering to energy maps, image regions with uniform texture are detected. In the experiment, for computing energy maps we use the window of size 15\( \times \)15. The number of clusters is set to \( k = 9 \). Parameter values are chosen for obtaining the best clustering of regions of interest (see figure 4(b)). The result of segmenting mosaic using Laws’ method is shown in figure 5(a).

In figure 5(b), a segmented image obtained using the proposed modification of superpixel algorithm is shown. In this experiment, the following parameter values are set: size of the window function \( w_a = 7 \) pixels, threshold parameter \( t = 0.33 \), weighting coefficients \( w_1^2 = 0.1 \), \( w_2^2 = 0 \), \( w_3^2 = 0.1 \), and \( w_4^2 = 0.8 \). Window function size \( w_a \) is chosen according to the size of the texture elements. Weighting coefficients \( w_i \) are set taking into account features of the textural regions. The main feature of the six patterns of interest is texture orientation. For this reason, \( w_4 \) value is the largest. In our case, we do not use color as a feature of regions of interest, so we set \( w_2^2 = 0 \). To provide connectivity of segments and take into account texture coherency, we set \( w_1^2 = 0.1 \) and \( w_3^2 = 0.1 \). The final parameter tuning can be made empirically.

Figure 3. Segmentation of artificial image: (a) input image; (b) segmentation result obtained using SLIC algorithm; (c) segmentation result obtained using the SLICm technique.

Figure 4. Test image: (a) USC mosaic image; texture map with marked regions of interest.
The parameter $t$ is chosen from the condition of a minimum of the criterion (8) [14]. In Figure 5 one can see segmented regions with high values of coherence measure and uniform texture orientation. Segmented regions are colored in red and white, oversegmented regions are colored in rose. Undersegmentation of some regions is conditioned by zero gradient value in corresponding regions of input image. The results of the experiment in figure 5 (a) and (b) are shown after applying morphological “fill hole” operation [17]. A wide range of segmentation quality evaluation measures is known, for example, see [18, 19]. For quantitative comparing results presented in figure 5 (a) and (b), a measure of overlap of regions $\Omega$ and $\Omega'$ of segmented images is applied [18]:

$$O(\Omega, \Omega') = \frac{\Omega \cap \Omega'}{\Omega \cup \Omega'}$$

![Figure 5. Results of segmenting mosaic image: (a) using Laws’ energy features; (b) using SLICm technique.](image)

Segments obtained using Laws’ method and the proposed method are compared with corresponding segment $\Omega_{\text{map}}$ in texture map (see figure 4(b)). Overlap factor values computed for six regions of the textural mosaic are presented in table 1. From data given in table 1, it follows that the proposed modified SLICm algorithm overperforms algorithm based on Laws’ energy features for all of six chosen regions of the mosaic. In the experiment, non-optimized implementation of SLICm algorithm spent 2.49 seconds, implementation of Laws’ energy technique spent 32.6 seconds.

| Number of segment | $O(\Omega_{\text{Laws}}, \Omega_{\text{map}})$ | $O(\Omega_{\text{SLICm}}, \Omega_{\text{map}})$ |
|-------------------|---------------------------------------------|---------------------------------------------|
| 1                 | 0.662                                       | 0.873                                       |
| 2                 | 0.719                                       | 0.81                                        |
| 3                 | 0.613                                       | 0.68                                        |
| 4                 | 0.618                                       | 0.776                                       |
| 5                 | 0.773                                       | 0.83                                        |
| 6                 | 0.474                                       | 0.675                                       |

### 4.3. Segmentation of painting images

One of the tasks in computer-assisted assessment of paintings is concerned with localizing a group of brushstrokes in the image of facture. Such a group can be characterized by the uniform orientation of brush strokes and color. Proposed above modified superpixel segmentation algorithm SLICm meets this task in full. In this case, the high value of coherence measure (4) indicates the presence of brushstrokes and orientation of simple neighborhoods (3) characterizes direction of brush movement. In addition, uniformly oriented brushstrokes can be grouped by color. In the experiment, we use images of portraits created by different artists in 16-19 centuries. The results will be demonstrated on
Portrait of Cecilia Renata by Peter Danckerts de Rij (see figure 6(a)) and Portrait of Count P.I. Panin by F. Rokotov (see figure 8(a)) from the State Historical Museum collection.

The most significant regions found in the image of the portrait by Peter Danckerts de Rij are shown in figure 6(b). These results were obtained at the following parameter values: \( t = 0.5 \), \( w_1^2 = 0.2 \), \( w_2^2 = w_3^2 = 0.1 \), and \( w_4^2 = 0.6 \). Detected regions include pixels with the uniform orientation of texture. Image segments produced by the SLICm algorithm are processed using morphological closing with a structuring element of the size of 5 pixels, "fill hole", and opening operations [17]. Parameter values, as before, are chosen taking into account properties of particular image class. Threshold parameter of the postprocessing procedure \( t = 0.5 \) corresponding to the number of segments \( k = 491 \) is chosen using methodology proposed in [14]. Parameter choice is illustrated in figure 7. In this figure, a dependence of criterion \( R \) on the number of segments \( k \) is shown. Minimum of \( R \) corresponds to an image partitioned into 461 segments. This image is obtained at parameter value \( t = 0.5 \).

Masks of the textural regions detected in the image of the Portrait of Count P.I. Panin are shown in figure 8(b). The regions were produced by the SLICm algorithm at \( t = 0.32 \), \( w_1^2 = w_2^2 = 0.25 \), \( w_3^2 = 0.2 \), and \( w_4^2 = 0.3 \).

5. Conclusions

In this paper, the problem of detecting specific textural regions in digital images was studied. This problem was addressed to a problem for segmenting textural images. A technique based on modified superpixel segmentation algorithm with a post-processing procedure was proposed. A vector image pixel description was augmented with local orientation angle and coherency measure computed using components of structure tensor. To obtain an acceptable quality of segmentation, condition of minimum information redundancy measure is used. The efficiency of the proposed technique was demonstrated on artificial and images of paintings. Results of applying the presented technique and the technique based on Laws’s energy features to a texture mosaic were compared. According to the results obtained, the modified SLICm technique outperforms Laws’ method in segmentation quality and computational expenses. The proposed technique can be applied to detect informative regions in images of fine art paintings.

Future research will be aimed on testing some alternative textural features to localize specific textural regions of interest.

Figure 6. Detecting groups of brushstrokes in image of paintings: (a) fragment from digital image of Portrait of Cecilia Renata by Peter Danckerts de Rij; (b) masks of detected textural regions of interest.
Figure 7. Criterion $R$ value computed for segmentations with various numbers of segments $k$. Segmentation are generated by image shown in figure 6(a).

Figure 8. Detecting groups of brushstrokes in image of paintings: (a) fragment of Portrait of Count P.I. Panin by F. Rokotov; (b) masks of detected textural regions of interest.

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