AUTOMATIC GENERATION OF MORPHOLOGICAL OPENING–CLOSING SEQUENCES FOR TEXTURE SEGMENTATION

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1. INTRODUCTION

Texture segmentation is an important task in image processing. The objective is to assign the same value to those pixels in an image which belong to the same texture. This is usually called *pixel-classification*. There exist two fundamental approaches to solve this task.

The first and most general approach we call *classification oriented* by which we mean that the actual labeling is done by some general classifier, i.e. maximum-likelihood. As these classifiers require some feature vector as input, there has to be such a vector for each pixel. By this we not only get some segmentation but we can also identify every texture with respect to the database used to train the classifier. The problem with this approach is that usually the computational costs will be high for *each* image to be classified, as they are determined primarily by the costs of calculating the feature vector for each pixel. These costs may be reduced by using pruning algorithms, but if a single feature relies on the calculation of several image transformations like in [2] or in [4], the performance gain may be small.

In this paper we consider the case that we know which texture combination will appear in an image. A different approach may be used for this problem which we call *transformation oriented*. By this we mean to find a transformation adapted to a particular texture combination allowing a segmentation of the image by applying some threshold algorithm (i.e. as in [3]) on the transformed image.

Our approach therefore consists of three parts: (1) Building a database of texture descriptions, (2) automatic configuration of an appropriate segmentation algorithm for a given texture combination (this is not a particular image, nor any image at all), and (3) segmentation of a particular image.

The intention is that the expensive part is Step 1 and has to be done only once for each texture. Step 2 can be performed quickly and has to be done only once for each texture combination in question. Step 3 finally is very cheap and considered to be used with several images containing the same texture combination.

This paper is organized as follows: In the next section we give an outline of our approach. This consists of an idealized texture model with an appropriate segmentation strategy. To realize step 1 described above we need a texture description, which is exact for the idealized model and approximative for real textures. It is presented in section 2.1. For step 2 we give two alternative configuration algorithms shown in section 4. step 3 is finally described in section 5. Finally we discuss the results in section 6.

2. SEGMENTATION APPROACH

Each texture segmentation approach implies a model of the texture. In this section we first present our *texture model*, for which we then describe the *segmentation strategy*.

2.1. Texture Model

Though we deal with gray-scale textures we use a simplified binary texture model which motivated the segmentation strategy. This is possible because the gray-scale transformations (opening and closing with flat structuring elements[1]) from which the discrimination sequence is build can be viewed as an approximation of the respective binary morphological operation. The results show that this approximation is sufficient for the configuration algorithm.

A texture in our model consists of a squared homogenous lattice, as shown in fig. 1. Parameters are the *distance* and the *width* of the lines. In the example the two textures have very different the line distances but their line widths don't differ much in the .

For the four-step configuration algorithm described in section 4.2 this model is extended to a rectangular lattice.

[1] In the remaining paper we abbreviate *structuring element* by *SE*.

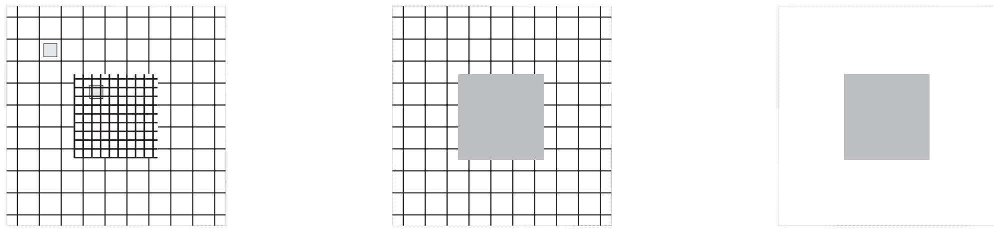

Figure 1: Example of the texture model showing a fine texture surrounded by a coarse texture (*left*). Result of application of opening (*middle*) followed by a closing (*right*).

2.2. Segmentation Strategy

The general task is to discriminate regions whose textures belong to one of two classes within one image. The final decision shall be made by thresholding. The task of the (morphological) operator sequence is then (a) to emphasize one texture, (b) to suppress the other texture and (c) to smooth all areas. Condition (c) ensures that the threshold operation generates complete (homogenous) masks for the textured regions and that the histogram is bi-modal, which allows for automatic threshold selection from histogram.
First we illustrate this strategy for a **two-step sequence with one tructuring element type** using figure 1 as an example: The *first* operation (a closing with a square SE which fits within the big squares but not within the small squares) homogenizes one texture as much as possible while leaving the other one unchanged. The *second* operation (an opening with a square SE wider than the lines of the outer texture) then removes the texture left unchanged by the first operation. To assign the desired pixel values (surrounding texture coded by pixel value '1') the whole image has to be inverted after the second step. This inversion operation has to be generated by the configuration algorithm, too.
From the gray-scale case the final binary image is calculated by thresholding using the threshold obtained from the images histogram by Otsu's algorithm [3].
In the case of a **four-step sequence with orthogonal linear SEs** the strategy becomes more complicated, as the homogenization of the textures will normally be done by *two* operations : The *first* operation homogenizes one texture as much as possible *in one direction*, while leaving the other one unchanged. The *second* and *third* operation then remove the texture left unchanged by the first operation. Finally the *fourth* operation completes the homogenization started with the first operation using the same type of operation (opening or closing), but with the orthogonal SE.

3. STEP 1: TEXTURE DESCRIPTION

The configuration algorithms need a quantitative description of each texture, which allows for an interpretation with respect to the operations to be used in the configured sequence.
This description is computed only once for each texture and stored in a database to be used by the configuration algorithms when a discrimination transformation for a particular texture combination is requested.
As we use morphological openings and closings, granulometries and anti-granulometries offer themselves as a description.
To ease and unify the handling of granulometries and anti-granulometries we introduce the *complete granulometry* (*c.g.*) by

$$\chi_s = \begin{cases} \varepsilon^{|s|}\delta^{|s|} & , \quad s \in \mathbb{Z}, s < 0 \\ \delta^s \varepsilon^s & , \quad s \in \mathbb{Z}, s \geq 0 \end{cases} \tag{1}$$

with erosion ε^s of size s and dilation δ^s, respectively. By this the sign(s) encodes opening and closing.
To get a compact representation for the c.g. for each s we reduce $\chi_s(X)$ (which is an image) to a vector of 2 scalars. Traditionally the *mean* $\mu_s = \mu(\chi_s(X))$ is used as a measure, giving the *pattern spectrum*, which characterizes the size distribution. As we need also some information on the threshold separability we use as a second parameter the *standard deviation* $\sigma_s = \sigma(\chi_s(X))$. By this we characterize each image by the *complete range spectrum* $\sigma_s \pm \mu_s$ (see fig. 2 for an example).
In [5] the use of the real histograms was examined, too, but it did not lead to better results while introducing other problems, especially with textures having spike-like histograms.

4. STEP 2: CONFIGURATION

In this section we present two configuration algorithms: One for *two-step sequences with fixed SE type* and one for *four-step sequences with orthogonal linear SEs.*

In general the approach is the the same: The first operation is found using the range-spectrum defined in section 3 and a comparison criteria presented below. Then the resulting spectrum has to be (very) coarsely estimated so that again a discrimination criteria can be applied and so on. The estimation can only be coarse as it is based on the idealized texture model from sect. 2.1.

4.1. Two-Step Sequences with fixed Structuring Element Types

In this approach we use a two-step sequence with the same SE type at every step. To compensate the latter restriction we calculate three sequences, one for each of the 3 SEs *square, horizontal line, vertical line*. The results of the application of these sequences are weighted by some estimated quality factor and linearly combined before thresholding. It consists of the following steps:

For each SE type

1. Calculate measures c_{tex_1} and c_{tex_2} for the change of the texture after application of an operator of size s (see also fig. 2):

$$
\begin{aligned}
a_{\max}(s) &= \mu_a(s) + \sigma_a(s) \\
a_{\min}(s) &= \mu_a(s) - \sigma_a(s) \\
u(s) &= \min\left(a_{\max}(s), a_{\max}(0)\right) - \\
&\quad \max\left(a_{\min}(s), a_{\min}(0)\right) \\
c(s) &= \begin{cases} \frac{u(s)-u(s_o)}{u(0)-u(s_o)} & , s_o \leq s < 0 \\ 1 & , s = 0 \\ \frac{u(s)-u(s_c)}{u(0)-u(s_c)} & , 0 < s \leq s_c \end{cases}
\end{aligned} \tag{2}
$$

2. From the the index i of

$$
i \;:\; \max_i |c_{\text{tex}_1}(i) - c_{\text{tex}_2}(i)| \tag{3}
$$

obtain the first operator (sign(i) encodes opening or closing and $|i|$ is the size of the SE).

3. Do a (very) coarse estimation of the spectra of the textures after the 1st operator has been applied by treating the spectrum of the texture which has changed less (i.e. χ_{tex_1} at size 30) as unchanged and 'holding' that of the other texture (i.e. χ_{tex_2}):

$$
\begin{aligned}
\mu_b(s) &= \mu_{\text{tex}_1}(s) \quad , \quad \sigma_b(s) = \sigma_{\text{tex}_1}(s) \\
\mu_c(s) &= \begin{cases} \mu_{\text{tex}_1}(s) & \text{for } \begin{cases} s_o \leq s < i & \text{if } i < 0 \\ i < s \leq s_c & \text{if } i > 0 \end{cases} \\ \mu_{\text{tex}_1}(i) & \text{for } \begin{cases} s_o \leq s < i & \text{if } i < 0 \\ i < s \leq s_c & \text{if } i > 0 \end{cases} \end{cases} \\
\sigma_b(s) &= \ldots
\end{aligned} \tag{4}
$$

4. Find the second operator at index j of

$$
\begin{aligned}
D(s) &= \min\left(\mu_b(s) + \sigma_c(s), \mu_d(s) + \sigma_d(s)\right) - \\
&\quad \max\left(\mu_b(s) - \sigma_c(s), \mu_d(s) - \sigma_d(s)\right) \\
d(s) &= |\mu_b(s) - \mu_c(s)| \cdot D / \\
&\quad (\max\left(\mu_b(s) + \sigma_c(s), \mu_d(s) + \sigma_d(s)\right) - \\
&\quad \min\left(\mu_b(s) - \sigma_c(s), \mu_d(s) - \sigma_d(s)\right)) \\
j &: \max_j |c_{\text{tex}_1}(i) - c_{\text{tex}_2}(i)|
\end{aligned} \tag{5}
$$

$d(j)$ is the overall quality measure used for weighting on step 3 of the segmentation algorithm (sect. 5).

5. Look if the resulting image has to be inverted. This depends on which texture is mainly influenced by the first operation. It can be determined from sign$((\mu_b(s) + \sigma_c(s)) - (\mu_d(s) + \sigma_d(s)))$.

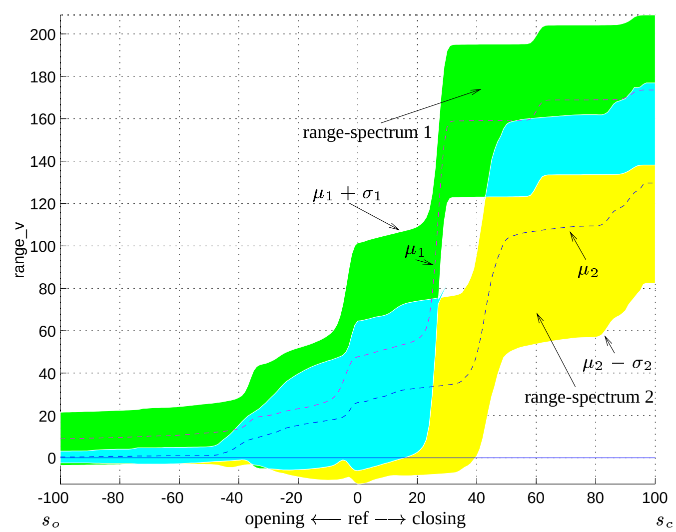

Figure 2: Parameters of the *range-spectrum* ($\mu \pm \sigma$). The overlapping of the range-spectra of two textures is the central discrimination measure.

4.2. Four-Step Sequences with Orthogonal Linear Structuring Elements

We now extend the configuration approach presented in the previous section to a four-step sequences with orthogonal linear SEs (i.e. horizontal and vertical lines). The main difference is that now the *type* of the SEs has to be determined, too.

1. *For each SE*: Calculate the optimal operation by using eq. 2 and the resulting quality by using eq. 5.
2. Use the operation with greater quality as *first* operation of the sequence.
3. Estimate the resulting spectra:
   (a) For the same SE type as at the first step: Estimate like at step 3 of the previous algorithm.
   (b) For the orthogonal SE type: Instead of holding the spectrum which has changed more (like in the previous case) 'mix' it (independently for μ and σ) with the (original) spectrum of the orthogonal SE type. Mixing of a function $x(s)$ ($x \in \{\mu, \sigma\}$) with a function $g(s)$ ('$g$uide' – attracts x) into a function $y(s)$ is done by

$$
\begin{aligned}
g_{\mathrm{n}}(s) &= \max(0, g(s) - g(0) + x(0)) \\
w_{11}(s) &= \left| \frac{g_{\mathrm{n}}(s) - g(0)}{\max\limits_{s_o \le s < 0} g(s) - \min\limits_{s_o \le s < 0} g(s)} \right| \\
w_{12}(s) &= \left| \frac{g_{\mathrm{n}}(s) - x(s)}{g(0)} \right| \\
w_{11}(s) &= \left| \frac{g_{\mathrm{n}}(s) - g(0)}{\max\limits_{0 < s \le s_c} g(s) - \min\limits_{0 < s \le s_c} g(s)} \right| \\
w_{22}(s) &= \left| \frac{g_{\mathrm{n}}(s) - x(s)}{g(0)} \right|
\end{aligned}
$$

$$
w(s) = \begin{cases} .7w_{11}(s) + .3w_{12}(s) & , s_o \le s < 0 \\ .7w_{21}(s) + .3w_{22}(s) & , 0 < s \le s_c \end{cases}
$$

$$
y = \begin{cases} \max(x + w \cdot (g_{\mathrm{n}} - x), \min(x, g)) & , s_o \le s < 0 \\ \min(x + w \cdot (g_{\mathrm{n}} - x), \max(x, g)) & , 0 < s \le s_c \end{cases}
$$

4. Find the *third* operation of the sequence from these spectra using the criteria from step 4 of the previous algorithm.
5. Estimate the spectrum after the second operation: The SE of the *third* operation will always be orthogonal to the SE of the second operation. The spectrum which has changed more after application of the second operation is 'held' (like before), the other one is kept unchanged.
6. Find the *second* operation of the sequence from these spectra like on step 4.
7. The SE of the *fourth* operation is always orthogonal to the SE of the first operation. Thus it is found from the original spectrum using the same criteria as on step 2.
8. Finally inversion has to be done if at any of the steps 1 to 3 inversion appeared to be necessary.

5. STEP 3: SEGMENTATION

To segment a particular image using a sequence generated by one of the algorithms from section 4 we have first to distinguish, which configuration algorithm was used:

1. Two-step sequence according to sect. 4.1:
   Actually for each of three SE types a sequence has been calculated, together with a quality measure. Each of them has to be applied and the results have to linearly combined using their quality measures.
2. Four-step sequence according to sect. 4.2:
   One sequence has been calculated which has to be applied.

The following operations are the same in both cases: Histogram equalization, determination of the threshold by Otsu's algorithm [3] and its application to the transformed image. The 'first' texture will always be coded by a '1' and the 'second' texture by a '0'.

6. RESULTS

The algorithms have been tested using 7 textures from the Brodatz album [1] and 6 synthetical textures in all possible combinations. Image sizes were 512x512 pixel, each texture had its histogram expanded to the full 8bit range. Granulometries and anti-granulometries were calculated up to 100x100 pixel SE size.

As an example fig. 3 (*left*) shows two Brodatz textures and fig. 3 (*right*), fig. 6 show the result of the application of the generated sequences.

There are certainly cases in which the algorithms do not find a proper segmentation sequence though it exists. The reason is mostly that the chosen texture description does not reflect changes to structures which occupy only a small part of the image's volume (i.e. the removal of the surrounding texture by an opening). Normalization like in eq. 2 can compensate this only partially. The development of better features, i.e. based on concurrence-matrices like in [4] is promising.

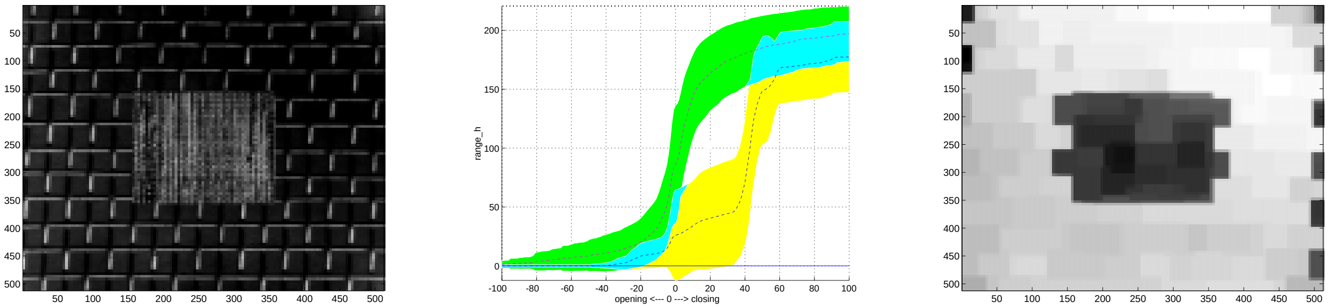

Figure 3: Example: Original image X (*left*). Plot of the spectra ($\mu \pm \sigma$) for square SE. Result Y of the sequence $Y = \text{invert}((X \bullet \text{square}(33)) \circ \text{square}(26))$ (*right*)

6.1. Two-Step Sequence

The spectra (for a square SE) are shown together in fig. 3 (*middle*). Figure 3 (*right*) shows the result after the application of $Y = \text{invert}(X \bullet \text{square}(29) \circ \text{square}(26))$ which was generated for the square-SE by the algorithm described in section 4.1. Classification by threshold will be very good.

6.2. Four-Step Sequence

The spectra (for the vertical SE) are shown together in fig. 4 and fig. 5 shows the estimated spectra for the horizontal SE. The result of the application of the sequence $Y = \text{invert}(X \bullet \text{hor\_line}(51) \circ \text{vert\_line}(39) \circ \text{hor\_line}(90) \bullet \text{hor\_line}(86))$ (fig. 6) is even better than that of the two step sequence.

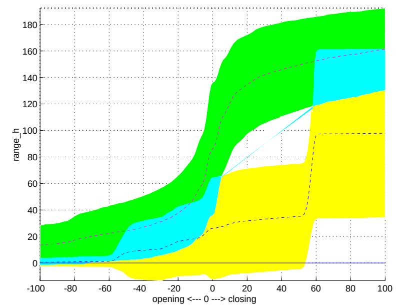

Figure 4: Plot of the spectra ($\mu \pm \sigma$) for the vertical SE.

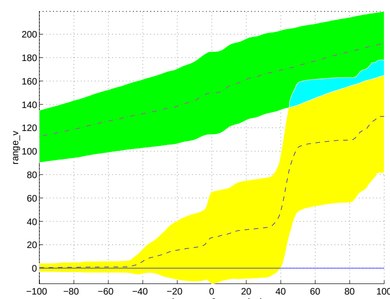

Figure 5: Plot of the estimated spectra for the horizontal SE.

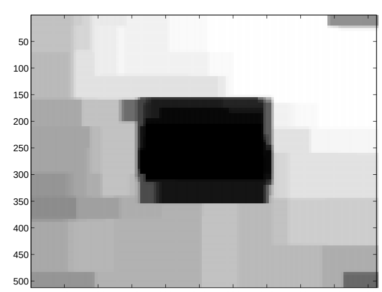

Figure 6: Result Y of the sequence $Y = \text{invert}(X \bullet \text{hor\_line}(51) \circ \text{vert\_line}(39) \circ \text{hor\_line}(90) \bullet \text{hor\_line}(86))$

7. REFERENCES

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