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A morphological approach for distinguishing texture and individual features in images ☆

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ABSTRACT

We present a morphological texture contrast (MTC) operator that allows detection of textural and non-texture regions in images. We show that in contrast to other approaches, the MTC discriminates between texture details and isolated features and does not extend borders of texture regions. A comparison with other methods used for texture detection is provided. Using the ideas underlying the MTC operator, we develop a complementary operator called morphological feature contrast (MFC) that allows extraction of isolated features while not being confused by texture details. We illustrate an application of the MFC operator to extraction of isolated objects such as individual trees or buildings that should be distinguished from forests or urban centers. We also propose an MFC based detector of isolated linear features and compare it with an alternative approach used for detection of edges and lines in cluttered scenes. We furthermore derive an extended version of the MFC that can be directly applied to vector-valued images.

1. Introduction

This paper focuses on the problem of distinguishing isolated features from features that are part of a texture. We will refer to the latter features as texture details. Isolated features, also called individual features, are, for example, isolated ridges (bars) or small blobs in images (peaks in the 1D case). This problem may occur when one wants to detect texture regions, and at the same time distinguish them from isolated features that should not be assigned to a texture class. A dual problem occurs when it is necessary to detect isolated features avoiding detection of parts of neighboring or background texture even if texture details are similar to features of interest. For example, one may want to detect individual trees distinguishing them from trees of a forest. Here we consider both problems, namely detection of texture and of individual features.

Although a large variety of texture classification methods has been developed, much less attention has been given to the apparently simpler problem of texture detection that discriminates between texture (of any type) and non-texture regions. This is not a simple task if accurate localization is required and if texture must be distinguished from individual features.

In [3] it was proposed to use the difference between maximal and minimal intensities (MaxMin diff.) in a pixel neighborhood for a fast segmentation of an image into textured and non-texture regions. A standard deviation (StD) is frequently used as a measure of texture that describes its smoothness [9]. In [16], where the Local Binary Patterns (LBP) approach was developed, the authors also suggested to incorporate a variance based descriptor for texture classification purposes. While the LBP descriptor is related to inherent texture properties, a complementary variance based descriptor measures texture contrast. The amplitude modulation function (AMF), derived from the amplitude-modulation frequency-modulation model [14], can locally capture texture contrast. Although each of the texture contrast descriptors mentioned above can be used to discriminate between texture regions and non-texture areas, also called smooth areas in this paper, they cannot distinguish individual features from texture details.

Several descriptors were suggested to approach this problem. In [26] the difference between closing and opening, called texture range (TER), was suggested to distinguish individual step and ramp edges from texture edges. The TER operator, however, cannot distinguish isolated features, such as ridges and blobs, from texture details of comparable size. Recently, in [18] the PanTex index was developed to detect settlements in panchromatic satellite

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imagery. The operator is able to distinguish texture areas from individual linear features such as roads or borders between homogenous cultivated fields in satellite images. The PanTex index is defined as a minimal contrast among contrast measures derived from the gray-level co-occurrence matrixes (GLCM) [12], computed for different orientations of displacement vectors. The PanTex method, however, does not distinguish other individual features, such as isolated peaks or small isotropic blobs, from texture. The component count (CC) method [1] is based on the product of two measures computed in small image blocks. The first one is the sum of the number of connected components (component count) in the background and the foreground obtained by simple binarization of image blocks. The second measure is the difference between average intensities in the background and the foreground. This descriptor is supposed to discriminate blocks covering texture and individual step edges at the borders between homogenous regions. A similar idea of counting the number of local extrema (texture primitives) for detection of texture regions was proposed earlier in [13]. Since this method does not take into account contrast of texture primitives, it can be very sensitive to noise.

Another disadvantage that all the above texture descriptors, excluding the TER, have in common, is that they extend or blur the borders of texture regions, preventing accurate localization of texture borders. Recently, we introduced a morphological texture contrast (MTC) descriptor that does not suffer from the above disadvantages [27]. This operator, reviewed in Section 2, measures the difference between upper and lower texture envelopes estimated by means of alternating morphological filters [22,23]. Its qualitative performance was illustrated in [27], where only few remotely sensed images were used and no quantitative comparison was provided. In Section 3 we provide a quantitative comparison using artificially created images and a qualitative comparison using a set of standard test images. In this paper, we also define an alternative texture descriptor that is computed as difference between alternating sequential filters (ASF diff.) and compare it to the MTC.

As we stated in the beginning of this section, the dual problem to the problem of texture detection is detecting individual features while distinguishing them from texture details. This problem has mainly been treated in the context of edge detection capable of discarding texture surroundings. For example, recently in [10] a surround inhibition mechanism was introduced to improve edge detection at region boundaries. Dubuc and Zucker [4] proposed a normal complexity measure that is able to separate isolated curves and isolated edges from texture in binary images. The paper provides an original theoretical framework, but it seems to be computationally very expensive.

In Section 4 we show how the ideas underlying the MTC operator lead to a Morphological Feature Contrast (MFC) operator that aims at the detection of small isolated objects, rather than edges, in textured background. We illustrate the potential of the MFC operator on gray-scale images and derive its extension to vector-valued images. Additionally, we show how the MFC operator can be incorporated into a scheme for extracting isolated linear features. We show the advantages of this scheme over the approach for the detection of contours with texture background suppression introduced in [10]. A preliminary short version of our work was recently presented in [29].

2. Detection of texture regions: the morphological texture contrast operator and the ASF difference

Below, we define the morphological texture contrast (MTC) transformation $\psi_{\mathrm{MTC}}(f)$ that we recently introduced in [27] for distinguishing texture regions (such as forests, urban areas and rocky mountains) in satellite images from smooth areas, which may also contain individual structures that should not to be assigned to texture.[1] Qualitatively, MTC's response is summarized in the first row of Table 1.

Table 1
Qualitative behavior of the MTC and ASF diff. versus the MFC operators.

	Texture	Isolated features	Isol. features within texture	Smooth regions
MTC & ASF diff.	High	Low	High	Low
MFC	Low	High	High	Low

The MTC is based on alternating morphological filters, $\gamma_r\varphi_r$ and $\varphi_r\gamma_r$, which are closing φ followed by opening γ and opening followed by closing, respectively. r denotes the size of the structuring element (SE). Alternating filters are usually employed for noise filtering. We use them to estimate texture envelopes. The difference between upper and lower envelopes defines a measure of texture contrast, which can serve as an indicator of the presence of texture

$$\psi_{\mathrm{MTC}}(f) = |\gamma_r\varphi_r(f) - \varphi_r\gamma_r(f)|^+, \tag{1}$$

where the argument f denotes a 1D signal or a 2D gray-scale image, and $|\cdot|^+$ is defined as

$$|v|^+ \triangleq \begin{cases} v, & v > 0, \\ 0, & \text{otherwise}. \end{cases} \tag{2}$$

A remarkable property of these envelopes is that they coincide at individual features, thereby yielding low response at individual features even if they are of high contrast (see an example in Fig. 1). Since in the 2D case, $\varphi_r\gamma_r$ and $\gamma_r\varphi_r$ are not ordered [22,23], a lower envelope might be above an upper envelope. However, Proposition 3 below shows that regions where this happens are small in the sense that an erosion with a structuring element of size r completely removes these regions. In the following discussion we will show that r defines the minimal size of texture regions to be detected (see Eq. (4)). Therefore, the regions where $\gamma_r\varphi_r < \varphi_r\gamma_r$ are small enough to be considered as non-texture regions. They are correspondingly removed by the $|\cdot|^+$ operator in the definition of ψ_{MTC} above.

Let us denote morphological erosion of a set or a function by ε. Large letters will denote sets. Structuring elements are identical for all morphological operators in the following propositions.

Proposition 1. *The following inequality holds:* $\varepsilon\gamma\varphi \geqslant \varepsilon\varphi\gamma$.

Proof. We have $\varepsilon\varphi \geqslant \varepsilon\varphi\gamma$ due to the increasing property of closing and erosion, and antiextensivity of opening. Proposition 1 follows directly from the last inequality and due to $\varepsilon\gamma = \varepsilon$. □

Proposition 2. *Given the ordering condition* $g_1(x) < g_2(x),\ x \in D$ *the following inequality holds:* $[\varepsilon(g_1)](y) < [\varepsilon(g_2)](y),\ y \in \varepsilon(D)$.

Proof. Let us denote by B_y a structuring element shifted to position y. For $y \in \varepsilon(D)$ we have $[\varepsilon(g_1)](y) = \min_{x\in B_y \subseteq D} g_1(x) < \min_{x\in B_y \subseteq D} g_2(x) = [\varepsilon(g_2)](y)$, where the inequality follows from the given ordering condition.

Proposition 3. *Given the set* $X = \{x : \gamma\varphi < \varphi\gamma\}$, *the set* $Y = \{y : y \in \varepsilon(X)\}$ *is an empty set.*

[1] This work was motivated by an archaeological project [15] that targets detection of individual architectural remains located in open grassland areas.

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