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Color Adaptive Neighborhood Mathematical Morphology and its application to pixel-level classification ☆

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ABSTRACT

In this paper spatially adaptive Mathematical Morphology (MM) is studied for color images. More precisely, the General Adaptive Neighborhood Image Processing (GANIP) approach is generalized to color images. The basic principle is to define a set of locally Color Adaptive Neighborhoods (CAN), one for each point of the image, and to use them as adaptive structuring elements (ASE) for morphological operations. These operators have been applied to images in different color spaces and compared with other kinds of ASEs extended to color images. Results show that the proposed method is more respectful with the borders of the objects, as well as with the color transitions within the image. Finally, the proposed adaptive morphological operators are applied to the classification of color texture images.

1. Introduction

Mathematical Morphology (MM) is a theory for image analysis based on set theory. It has been developed from the ideas of Matheron [28] and Serra [32] in the *École des Mines de Paris*. Initially, they established its basis focusing on binary images, but it was later extended to gray level images [35]. Afterwards, Haralick et al. reviewed morphological operators, as well as their relations and properties [23].

Mathematical Morphology has been successfully used in several applications: remote sensing [5], biomedicine [10], quality control in industry [31], geoscience [36] or texture description [19] are just some examples.

For some applications, a drawback in Mathematical Morphology is the fact that the structuring element (SE) used in morphological operations classically have a fixed shape and size, which has serious disadvantages such as creating artificial patterns or removing significant details. In addition, it is not straightforward to set the shape of the SE that best suits certain image structures, as some authors have discussed [37]. Huet and Mattioli presented a method to generate a minimal set of SEs that left the texture invariant and used them to carry out some morphological transformations for texture defect detection [24]. Asano and his co-workers [4] claimed that the best SE to compute the pattern spectrum of a texture would be the one whose shape is the most similar to the granules within it, so they selected the one which reduced the variance of the size distribution.

This kind of selection of SEs makes necessary to have a priori information about the images to be processed (e.g. size and orientation of structures within the images). This is a serious shortcoming, since such knowledge is not always available in real computer vision tasks.

Some works deal with the computation of structuring elements that adapt themselves to the local features of the image at each pixel. Shih and Cheng presented an adaptive edge-linking method based on MM which used an elliptical SE whose orientation and size were adjusted to some local features of the image [34]. Landström and Thurley [26] proposed a framework for adaptive morphology where elliptical structuring elements ranged from lines to disks, and varied their orientation within the data by capturing the eigenvalues and eigenvectors of the Local Tensor Structure. Bouaynaya and her co-workers presented an approach for image restoration and skeletonization which used spatial-variant Mathematical Morphology [7]. The reader interested in more details is referred to [8,9].

Lerallut et al. introduced the concept of morphological amoebas, which are adaptive structuring elements whose shape is locally adapted to the image contour variations, by means of a weighted geodesic distance [27]. Grazzini and Soille also proposed a filtering approach which used Mathematical Morphology aiming at edge-preserving smoothing which also used structuring elements obtained by means of a geodesic distance criterion [21]. Likewise, González-Castro *et al.* used combined geodesic and

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Euclidean distance criteria to compute the SE at each point of the image, in this case for classification purposes, characterizing the textures by means of adaptive pattern spectra [19]. Recently, Ćurić et al. presented salience adaptive structuring elements, that vary both their shape and size according to the salience of edges in the image. They are less flexible than morphological amoebas but their shape is less affected by noise [15].

Debayle and Pinoli presented the so-called General Adaptive Neighborhood Image Processing (GANIP) approach from a theoretical and practical point of view in [16,17], respectively. Within this paradigm a General Adaptive Neighborhood (GAN) is constituted by connected components whose point intensity values – measured in relation to a selected criterion such as luminance, contrast, thickness, etc. – fit within a specified range of homogeneity tolerance. These GANs are used as adaptive structuring elements in morphological operations.

As it has been pointed out, morphological operators were initially defined – and, therefore, used – for binary and gray-scale images. These operators need a total order relationship. The extension of Mathematical Morphology theory to color images is not straightforward as, due to the vectorial nature of color data, there is not such notion. Jesus Angulo studied such morphological color operators and proposed some total orderings for color images [1]. A comprehensive survey on different approaches to multivariate MM can be found in [2].

Adaptive MM for color images has been few investigated. Morphological amoebas [27] and the approach introduced by Grazzini and Soille [21] were extended to multichannel images with filtering purposes. However, they were not used as structuring elements in Color Adaptive Mathematical Morphology.

Debayle and Pinoli extended their GANIP framework to color images by defining Color Adaptive Neighborhoods (CAN) and morphological operations using the lexicographical ordering as total order relationship [18].

In this paper CAN-based morphological operators are defined and studied with a different total order relationship. Finally, these color adaptive morphological operators are used for defining descriptors at pixel-level for classification purposes.

2. General Adaptive Neighborhood Image Processing (GANIP)

In this section a review of the so-called General Adaptive Neighborhood Image Processing (GANIP) framework, introduced by Debayle and Pinoli [16], will be made.

2.1. An overview on the framework

In the GANIP approach a General Adaptive Neighborhood (GAN) is defined for each point of the image to be analyzed. A GAN is a subset of the spatial support D constituted by connected points whose values in relation to a selected criterion (luminance, contrast,...) fit within a homogeneity tolerance.

Let I be the set of gray-level images defined on the spatial support $D \subseteq \mathbb{R}^2$ and valued in an interval $\widetilde{E} \subseteq \mathbb{R}$. Thus, $I = \{f \mid f : D \to \widetilde{E}\}$. Let $f \in I$ be an image, and $f_0 \in I$ be the so-called *pilot* or *reference* image. For each point $x \in D$ belonging to f, the GANs (denoted $V_m^{f_0}(x)$) are subsets in D built upon f_0 (a criterion mapping based on local measurements such as luminance, contrast, etc.) in relation to a homogeneity tolerance $m \in \mathbb{R}^+$. More precisely, $V_m^{f_0}(x)$ has to fulfill two conditions:

- The criterion measurement of its points is close to the one of x
  $\forall y \in V_m^{f_0}(x) : \quad |f_0(y) - f_0(x)| \leqslant m$
- The GAN is a path-connected set (according to the usual Euclidean topology on $D \subseteq \mathbb{R}^2$)

Thus, the GANs are formally defined as:

$$\forall (m, f_0, x) \in \mathbb{R}^+ \times I \times D \quad V_m^{f_0}(x) = C_{\{y \in D;\ |f_0(y) - f_0(x)| \leqslant m\}}(x) \tag{1}$$

where $C_X(x)$ denotes the path connected component of $X \subseteq D$ containing $x \in D$. Therefore, it is ensured that $\forall x \in D\ x \in V_m^{f_0}(x)$.

However, these GANs do not satisfy the *symmetry property*, defined as:

$$\forall (x, y) \in D^2 \quad y \in A(x) \iff x \in A(y) \tag{2}$$

where $\{A(x)\}_{x \in D}$ is a collection of subsets $A(x) \subseteq D$. For this reason, GANs defined in Eq. (1) are called *Weak General Adaptive Neighborhoods* (W-GANs). From a visual point of view, the symmetry property is closely linked to the human visual perception. Moreover, the notion of symmetry is topologically relevant [16].

In order to get this property satisfied, a new set of GANs, called *Strong General Adaptive Neighborhoods* (S-GANs) is defined as:

$$\forall (m, f_0, x) \in \mathbb{R}^+ \times I \times D \quad N_m^{f_0}(x) = \bigcup_{z \in D} \{V_m^{f_0}(z) \mid x \in V_m^{f_0}(z)\} \tag{3}$$

The reader interested in further theoretical aspects on GANs is referred to [16].

2.2. Application to Mathematical Morphology

The two fundamental operators in Mathematical Morphology are *erosion* and *dilation* which are defined respectively as:

$$E_B(f(x)) = inf\{f(w) : w \in B(x)\} \tag{4}$$

$$D_B(f(x)) = \sup\{f(w) : w \in \check{B}(x)\} \tag{5}$$

where $B(x)$ denotes the structuring element B whose origin is located at point x, and $\check{B}$ stands for its reflected subset, defined as

$\check{B}(x) = \{z \mid x \in B(z)\}$.

The idea behind the Adaptive Neighborhood Mathematical Morphology is to substitute the usual structuring elements by the adaptive ones at each pixel of the image.

In the particular case of the GANIP approach, the symmetric S-GANs are used. Therefore GAN-based adaptive erosion and dilation can be expressed as:

$$E_m^{f_0}(f)(x) = \inf_{w \in N_m^{f_0}(x)} (f(w)) \tag{6}$$

$$D_m^{f_0}(f)(x) = \sup_{w \in N_m^{f_0}(x)} (f(w)) \tag{7}$$

Thereafter, more advanced GAN morphological operators can be defined [30].

3. Color morphology

In this section color spaces, color orderings and finally color Mathematical Morphology will be addressed.

As it has been pointed out in Section 2.2, morphological operators need the definition of a total order relationship between the points to be processed. As points in gray-level images are valued in $\mathbb{R}$, there is a natural notion of total order. However, there is not such straightforward notion in vector spaces. Therefore, it is difficult to order data in color images, as each point is a vector of n components (with, generally, $n = 3$).

In addition, the colors in digital images can be represented in different color spaces [25] and the choice of one or other may have influence in the final results [12,38].

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