Morphological texture gradients: Definition and application to colour and texture watershed segmentation

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Plan

Introduction

Motivation

- Watershed-based algorithms for image segmentation are built on a scalar gradient
- A colour gradient should be calculated to apply the watershed on a colour image, e.g., colour gradient in a luminance/saturation/hue representation

$$\varrho_{col}(\mathbf{f})(x) = (1 - f_S(x)) \times \varrho(f_L)(x) + f_S(x) \times \varrho^{\circ}(f_H)(x) + \varrho(f_S)(x),$$

- The colour image is previously filtered by a connected operator, typically a leveling, which simplifies textures and eliminates small details, but preserving the contours of remaining objects

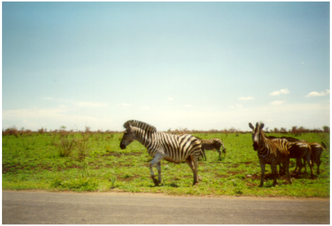
Introduction

Motivation

- For colour images, a marginal leveling can be applied for each component R, G, B or a total colour leveling can be calculated, i.e.,

$$\widehat{\mathbf{f}} = \lambda(ASF_{nB}(\mathbf{f}), \mathbf{f}),$$

where ASF_{nB} is an alternate sequential filter of size n.



$\mathbf{f}$

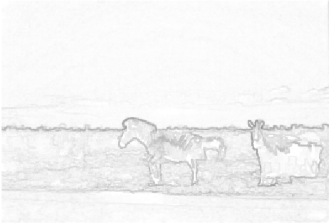
$\widehat{\mathbf{f}}$

Introduction

Motivation

- Colour gradient of leveled image:

$\widehat{\mathbf{f}}$

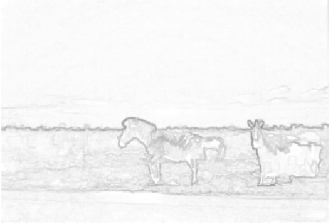


$\varrho_{col}(\widehat{\mathbf{f}})$

Introduction

Motivation

- Marker-based watershed segmentation:



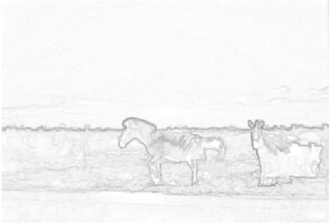
$\varrho_{col}(\widehat{\mathbf{f}})$

$\mathbf{f}$, $mrks$

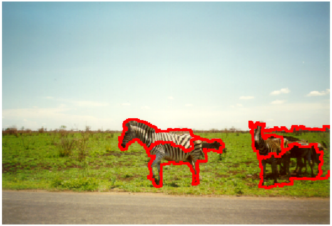
Introduction

Motivation

- Marker-based watershed segmentation:



$\varrho_{col}(\widehat{\mathbf{f}})$



$Wshed(\varrho_{col}, mrks)$

Introduction

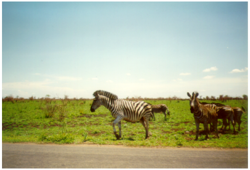
Motivation

- Colour information does not make possible to extract correctly the object contours
- Texture is in certain images a very discriminating information for object separation
- However, to introduce texture into the segmentation is not so simple as for the colour: texture is a regional notion which is difficult to quantify and to use for a watershed-based image segmentation

Introduction

Motivation

- *Sofu, Evangelopoulus and Maragos decomposition* (ICIP'05): Morphological version of model $f = u + v$ (where u is the "cartoon component" with homogeneous zones of the objects and v is the "texture oscillation") using a leveling.



$\mathbf{f}$

$\widehat{\mathbf{f}}$

$f_L - \widehat{f_L}$

Introduction

Aim

- Our starting point is also a colour image decomposition of $\mathbf{f}$ into two components:
$$\mathbf{f} \triangleq \widehat{\mathbf{f}} \uplus f_{tex},$$
where $\widehat{\mathbf{f}}$ is the *object layer* and f_{tex} is the *texture layer*
- The texture layer is obtained as the residue of the components of luminance, i.e., $f_{tex} = f_L - \widehat{f_L}$, because the texture variations are mainly associated to the luminance
- A multi-scale local analysis from the texture layer is built using morphological operators to define the gradients of texture.
- The proposed texture gradient is then combined with the colour gradient to produce mixed segmentations by watershed

Granulometry

- Study of the size distribution of the objects of an image
- Formally, for the discrete case, a granulometry is a family of openings $\Gamma = (\gamma_n)_{n \geq 0}$ that depends on a positive parameter n (which expresses a size factor). Moreover, a granulometry by closings (or anti-granulometry) can be defined as a family of increasing closings $\Phi = (\varphi_n)_{n \geq 0}$.
- In practice, the most useful granulometry and anti-granulometry are those associated to morphological openings/closings: $\gamma_n(f) = \delta_{nB}(\varepsilon_{nB}(f))$ and $\varphi_n(f) = \varepsilon_{nB}(\delta_{nB}(f))$ respectively, where B is a structuring element of unit size (typically a disc or a segment of straight line) and $n = 1, 2, \cdots$.

Granulometry

- The granulometric curve, or pattern spectrum of f with respect to Γ and Φ is the following normalised mapping:

$$PS(f,n) = \frac{1}{\mathcal{M}(f)} \begin{cases} \mathcal{M}(\gamma_n(f)) - \mathcal{M}(\gamma_{n+1}(f)), & \textit{for} \;\; n \geq 0 \\ \mathcal{M}(\varphi_{|n|}(f)) - \mathcal{M}(\varphi_{|n|-1}(f)), & \textit{for} \;\; n \leq -1 \end{cases}$$

  where $\mathcal{M}$ is the integral of scalar function values.
- The value of pattern spectrum $PS(f,n)$ for each size n corresponds to a measurement of bright structures of size n (similarly, the dark structures are obtained by closings).
- Granulometric size distributions can be used as descriptors for texture classification.

Local granulometric analysis

- Texture descriptor $PS(f, n)$ is global to the image f, and if f contains more than one texture, the classification should be carried out at pixel level.
- The local pattern spectrum $PS^{W_x}(f, n)$, is obtained by computing the function $PS(f_{W_x}, n)$ for each pixel x, where f_{W_x} is the restriction of the image f to the window $W_x = size_h \times size_v$ centered at pixel x.
- As result of this computation, a granulometric curve is obtained for each pixel.

Local granulometric analysis

- In our case, this local granulometric analysis must be done on the texture layer f_{tex}
- The series of images which code this analysis is denoted by $\{t_k^{\Gamma\Phi}(x)\}_{k\in K} = \mathbf{t}^{\Gamma\Phi}(x)$, where

$$t_k^{\Gamma\Phi}(x) = PS^{W_x}(f_{tex}, k).$$

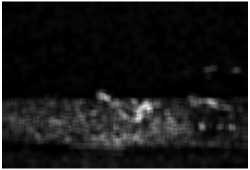
- The function $t_k^{\Gamma\Phi}(x)$ is named the *image of local energy of size k* ($k \geq 0$ for the bright structures and $k \leq -1$ for the dark structures).

Local granulometric analysis

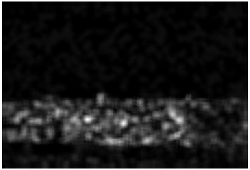
Texture layer and local granulometry (window $W_x = 10 \times 10$) by isotropic openings:

f_{tex}

$t_2^{\Gamma}(x) = PS^{W_x}(f_{tex}, 2)$



$t_4^{\Gamma}(x) = PS^{W_x}(f_{tex}, 4)$



$t_6^{\Gamma}(x) = PS^{W_x}(f_{tex}, 6)$

$t_8^{\Gamma}(x) = PS^{W_x}(f_{tex}, 8)$

Leveling-based multi-scale analysis

- Let $ASF_n(f) = \varphi_n\gamma_n \cdots \ \varphi_2\gamma_2 \ \varphi_1\gamma_1(f)$ be the alternate sequential filter of size n
- The family $\Xi = (ASF_n)_{n\geq 0}$ verifies the semi-group law of absorption and consequently, it allows to define multi-scale simplification (or selection, by considering the residues) of the structures of f_{tex}
- In addition, if each scale is associated to a leveling, the new family of transformations, $\Lambda = (\lambda_n)_{n\geq 0}$ such that $\lambda_n(f) = \lambda(ASF_n(f), f)$, provides a decomposition of the reconstructed objects according to each scale n
- It should be noted that using the levelings, both bright/dark objects of size n appear in the same image

Leveling-based multi-scale analysis

- Leveling-based quantitative analysis of the objects associated to each size n, by defining a pseudo-granulometric curve, named Λ-pattern spectrum:

$$\Lambda PS(f,n) = \mathcal{M}(\lambda_n(f)) - \mathcal{M}(\lambda_{n-1}(f)),$$

  for $n \geq 0$
- A local version of $\Lambda PS(f,n)$ is defined by computing the measure in a window W centered in each pixel
- The associated series of images of local energy, i.e.,

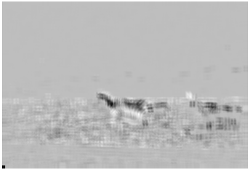
$$t_k^{\Lambda}(x) = \Lambda PS^{W_x}(f_{tex}, k),$$

  gives an alternative multi-scale representation (typically $k \in K = \{2, 4, \cdots, 16\}$)

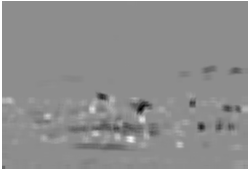
Local granulometric analysis

Texture layer and leveling-based local pseudo-granulometry (window $W_x = 10 \times 10$):

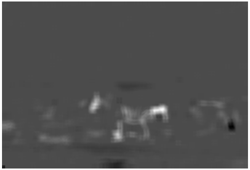
f_{tex}



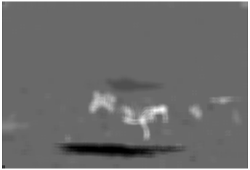
$t_2^{\Lambda}(x) = \Lambda PS^{W_x}(f_{tex}, 2)$



$t_4^{\Lambda}(x) = \Lambda PS^{W_x}(f_{tex}, 4)$



$t_6^{\Lambda}(x) = \Lambda PS^{W_x}(f_{tex}, 6)$



$t_8^{\Lambda}(x) = \Lambda PS^{W_x}(f_{tex}, 8)$

Texture gradients

- In each point x, the morphological gradient $\varrho(x)$ of unit size $B(x)$ of an image g can be written in terms of increments, i.e., $\varrho(g)(x) = \delta_B(g)(x) - \varepsilon_B(g)(x) = \vee[g(x) - g(y), y \in B(x)]$
- It is possible to use an Euclidean distance to define a gradient of morphological type for the series of images of local energy, i.e.,

$$\varrho_{tex}(f_{tex})(x) = \vee_y [d_E(\mathbf{t}(x), \mathbf{t}(y)), y \in B(x)],$$

where $d_E(\mathbf{t}(x), \mathbf{t}(y)) = \sqrt{\sum_{k \in K} (t_k(x) - t_k(y))^2}$ is the Euclidean distance between the two pixels x and y for all the images of local energy.

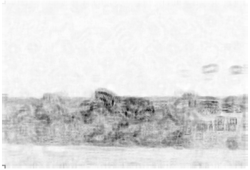
- It is also possible to define another kind of gradient, by combining by sup the gradients of each scalar image of energy, i.e.,

$$\varrho_{tex}(f_{tex})(x) = \bigvee_{k \in K} [\varrho(t_k(x))]$$

Texture gradients

Examples derived from the images of local energy $\{t_k^{\Gamma\Phi}(x)\}$ and $\{t_k^{\Lambda}(x)\}$, respectively $\varrho_{tex}^{\Gamma\Phi}(x)$ and $\varrho_{tex}^{\Lambda}(x)$:

f_{tex}



$\varrho_{tex}^{\Gamma\Phi}(f_{tex})$, Euclidean

$\varrho_{tex}^{\Gamma\Phi}(f_{tex})$, Sup

$\varrho_{tex}^{\Lambda}(f_{tex})$, Euclidean

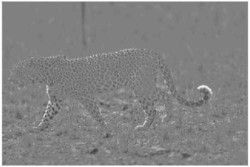
$\varrho_{tex}^{\Lambda}(f_{tex})$, Sup

Texture gradients

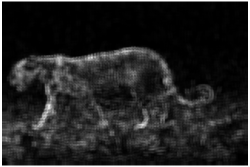
Colour/texture decomposition, two images of local energy, morphological texture gradient:

$\mathbf{f}$

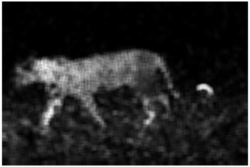
$\widehat{\mathbf{f}}$



f_{tex}



$PS^{W_x}(f_{tex}, 2)$



$PS^{W_x}(f_{tex}, 4)$

$\varrho^{\Gamma}_{tex}(f_{tex})$

Structural gradients

- The approach to produce a structural segmentation consists in constructing a joint gradient of colour and texture
- Once both a colour gradient and a texture gradient are available, it seems obvious that we can combine them to obtain the called structural gradient:

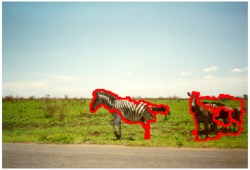
$$\begin{aligned} \varrho_{str}^{I-\alpha}(\mathbf{f})(x) &= \varrho_{col}(\widehat{\mathbf{f}})(x) + \alpha\varrho_{tex}(f_{tex})(x), \\ \varrho_{str}^{II-\alpha}(\mathbf{f})(x) &= (1-\alpha)\varrho_{col}(\widehat{\mathbf{f}})(x) + \alpha\varrho_{tex}(f_{tex})(x), \end{aligned}$$

  where $0 \leq \alpha \leq 1$
- The aim of $\varrho_{str}^{I-\alpha}(\mathbf{f})(x)$ is to incorporate the information of texture gradient as a secondary term with respect to the colour, whereas the barycentric formulation $\varrho_{str}^{II-\alpha}(\mathbf{f})(x)$ defines a trade-off between texture/colour gradients

Structural gradients

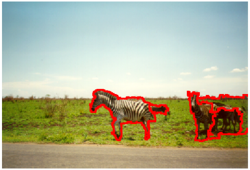
Examples of markers-based watershed segmentation with texture gradients and structural gradients (colour+texture), i.e. $Wshed(\varrho, mrks)$.

$\varrho^{\Gamma\Phi}_{tex}(f_{tex})$



$\varrho^{I-\alpha=1}_{str-\Gamma\Phi}$

$\varrho^{II-\alpha=0.8}_{str-\Gamma\Phi}$



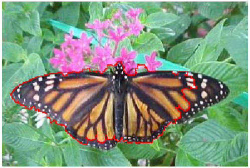
$\varrho^{II-\alpha=0.2}_{str-\Gamma\Phi}$

$\varrho^{\Lambda}_{tex}(f_{tex})$

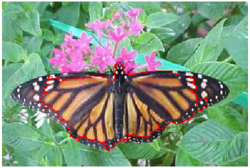
$\varrho^{I-\alpha=1}_{str-\Lambda}$

Structural gradients

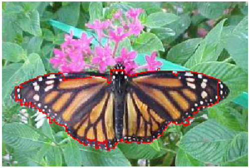
Watershed-based colour segmentation vs. structural segmentation:



$\varrho_{col}(\widehat{\mathbf{f}})$



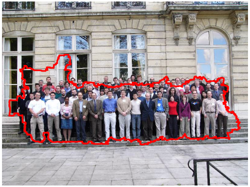
$\varrho^{I-\alpha=1}_{str-\Gamma\Phi}$



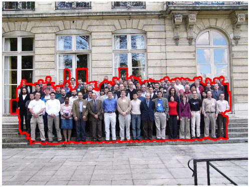
$\varrho^{I-\alpha=1}_{str-\Lambda}$

Structural gradients

Watershed-based colour segmentation vs. structural segmentation:



$\varrho_{col}(\widehat{\mathbf{f}})$

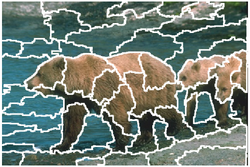


$\varrho^{I-\alpha=1}_{str-\Gamma\Phi}$

$\varrho^{I-\alpha=1}_{str-\Lambda}$

Structural gradients

Watershed-based colour segmentation vs. structural segmentation:



$\varrho_{col}(\widehat{\mathbf{f}})$

$\varrho^{I-\alpha=1}_{str-\Gamma\Phi}$

$\varrho^{I-\alpha=1}_{str-\Lambda}$

Structural gradients

Watershed-based colour segmentation vs. structural segmentation:

$\varrho_{col}(\widehat{\mathbf{f}})$

$\varrho^{I-\alpha=1}_{str-\Gamma\Phi}$

$\varrho^{I-\alpha=1}_{str-\Lambda}$

Structural gradients

Watershed-based colour segmentation vs. structural segmentation:

$\varrho_{col}(\widehat{\mathbf{f}})$

$\varrho^{I-\alpha=1}_{str-\Gamma\Phi}$

$\varrho^{I-\alpha=1}_{str-\Lambda}$

Conclusions

- Morphological approach to calculate texture gradients
- How to use them for image segmentation according to the texture; and more generally, for joint colour/texture segmentation (i.e., structural segmentation)
- These gradients are directly usable for morphological segmentation by watershed and that the partitions obtained with structural gradients are, in most of cases, more relevant than those obtained only with colour gradients
- We showed that the areas of texture are better determined and that the over-segmentation of large and homogeneous zones is reduced

Perspectives

- Definition of colour-texture decompositions, without limiting the texture layer to the luminance information
- To evaluate the interest of residues of colour openings/levelings (for instance, colour operators defined by means of total orderings in the luminance/ saturation/ hue representation)
- To consider that the weighting values are not constant for all the image points; to define for instance $\varrho_{str}^{II-\alpha}(\mathbf{f})(x) = (1 - \alpha(x))\varrho_{col}(\widehat{\mathbf{f}})(x) + \alpha(x)\varrho_{tex}(f_{tex})(x)$, where $\alpha(x)$ is the local weighting function, to allow a coupling of information adapted to the local image characteristics