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A Bi-Scale-Space for the Analysis of Blobs

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Abstract. We present a scale-space with separate scales in the greyscale and spatial dimensions, using ideas from mathematical morphology. Dynamics are used for greyscale (luminance) filtering and openings or closings with scaled disks for spatial scaling. Dynamics cater naturally for the inclusion relationships between regions and give a very good measure of the salience (scale) of a region in greyscale terms - however dynamics lack any notion of spatial extent or scale. In contrast, spatial closings or openings with scaled flat disks provide a natural measure of size or spatial scale without regard to greyscale variation. The two techniques together - both monotonic with respect to scale - provide a full basis for analysis of the image.
We show the strict monotonicity properties of these operations, that is, the strict reduction of number and size of regions with increasing scales, and we give an example of use in the classification of textures.

1 Introduction

Scale-Space analysis occupies an important place in the lexicon of contemporary computer image analysis. Often attributed to Witkin [10] (but independently discovered much earlier in Japan [9]), scale-space filtering consists ofprogressively simplifying an image (by removing "small-scale" objects) untill there is nothing of importance left. An analysis of teh order of disappearance and the paths traced by image objects and features across the varying scales, that is in scale-space, can be used in, for example, object recognition and matching [5] or motion trajectorary matching [6]. The example used in the present paper involves the characterisation of image texture.

Many natural textures can be characterized as dark or light "blobs" over a broad range of scales in both the spatial and luminance dimensions. A scale-space approach of successive simplification with operators of increasing scale can aid in the analysis or characterization of these textures.

Images contain two basically incompatible types of scales — spatial scales which govern the size of objects, and luminance scales which goven the brightness or contrast of objects against their backgrounds. These dimensions are fundamentally inconsistent which leads to constraints when we want to create measurements on the image which have a physical significance — a property called *dimensionality* in [7]. The problem occurs if any of our operators couple the physically different dimensions of luminance and length. In previous work, we used the poweroids as scaled structuring elements to give a certain scale-space which, as a whole, retained dimensionality [3]. However, at any single scale, this approach still couples size and contrast and dimensionality is lost. This seems unavoidable since, with a single scale parameter, we can only control either size, contrast, or some coupled combination of the two. We now present a more direct approach — we keep these dimensions separate to create a scale space with 2 scales: grey-scale and spatial-scale. We'll call this a *bi-scale-space*.

From another perspective this work is a development of the *Granold* theory for the representation of textures which was presented in [4]. In that work we also kept brightness and size separate but used greylevel thresholds for characterising the image in the greyscale dimension. Now however, we will use dynamics [2],as a much more natural measure of grey-scale. Dynamics quite naturally capture the notion of the grey-level distance between an object (as defined by extrema in the image) and it's "background" and, without needing segmentation, caters naturally for inclusions and nestings of objects.

We will introduce the notation by reviewing the main results of granold theory in the next section, followed in section 3 by an outline of the proposed blob detection and bi-scale-space method, a demonstration of the proposed method to the analysis of texture in the cell nucleus is presented in section 4, followed by concluding remarks.

2 Notation and granold theory

Let,

$$\mathcal{F} : \mathbb{Z}^2 \to \mathbb{Z}, \tag{1}$$

where $\mathbb{Z}$ is the integers, denote the family of greyscale images. And,

$$\mathcal{B} : \mathbb{Z}^2 \to \{0, 1\}, \tag{2}$$

the family of binary images.

We define two parameterised mappings or operators; the first takes a greyscale image to a binary image,

$$\Phi_g : \mathcal{F} \to \mathcal{B}, \tag{3}$$

the second is an operator on binary images,

$$\Psi_s : \mathcal{B} \to \mathcal{B}. \tag{4}$$

The parameters are intended to be scale parameters: g is a grey-scale parameter, and s is a spatial scale parameter, therefore we need them to obey some basic properties.

1. They are non-negative: $g > 0, s > 0$.

2. The mappings are monotone decreasing for the scale parameters. For any images $f \in \mathcal{F}$ and $b \in \mathcal{B}$,

$$g2 > g1 \;\Rightarrow\; \Phi_{g2} f \subseteq \Phi_{g1} f, \tag{5}$$
$$s2 > s1 \;\Rightarrow\; \Psi_{s2} b \subseteq \Psi_{s1} b, \tag{6}$$

   where $\subseteq$ has it's usual meaning for binary images.
3. They go to zero at high scales. For any images $f \in \mathcal{F}$ and $b \in \mathcal{B}$, there exists some scales G and S for which,

$$g > G \;\Rightarrow\; \Phi_g f = \emptyset, \tag{7}$$
$$s > S \;\Rightarrow\; \Psi_s b = \emptyset, \tag{8}$$

   where $\emptyset$ is the empty binary image.
4. Zero spatial scale leaves binary images unchanged. For $b \in \mathcal{B}$,

$$s = 0 \;\Rightarrow\; \Psi_s b = b. \tag{9}$$

   There is not a corresponding property for the grey-scale parameter. Note: this is a change from the condition on thresholds presented previously in [4].
5. The spatial scale operator is increasing. For $a, b \in \mathcal{B}$,

$$a \subseteq b \;\Rightarrow\; \Psi_s a \subseteq b \Psi_s b. \tag{10}$$

3 A bi-scale-space for blobs

We shall suppose our image for bi-scale-space analysis consists of dark "blobs" (light blobs can be handled by inverting the image first). We will first find the blobs with a blob finding algorithm to be described, and then filter them in both greyscale and spatial dimensions. Armed with the notation and framework above we now propose to use the contrast dynamics, introduced by Grimaud [2], as the natural measure of the grey-scale associated with a dark blob. At the most fundamental level, a dark blob possesses a single local or regional minima. Contrast dynamics provide a way of associating a measure to each such minima. The measure is simply how high we have to climb from the minima in order to find a path out of the catchment basin to a lower minima. This value is essentially the depth of the minima and caters naturally for the case where minima are nested within catchment basins of other minima. For further discussion and algorithms see [8].

Therefore the first step of our bi-scale-space algorithm consists of computing the dynamics of our image.The grey-scale parameter is introduced by simply thresholding the dynamics, that is, keeping only those minima whos dynamic exceeds the value g. Note for $g = 0$ all the minima are retained whilst for $g > dynamic_range(image)$ no minima are retained. Also note that by this construction, the number of retained minima is a monotonic decreasing function of g, as required.

The next step consists of segmenting out the dark blobs surrounding these retained minima. For this task, a fairly standard marker based blob detection algorithm is employed. Similar algorithms are discussed in [1]. The algorithm starts with the retained minima from the previous step as inner markers:

1. Perform a marker based watershed directly on the image. The watershed lines become the outer markers as they "mark" the outside of the blobs.
2. Perform a marker based watershed on the gradient of the image using both the inner and outer markers combined. This delineates the blobs surrounding the inner markers.

Fig. 1 shows this algorithm at work detecting dark blobs in a sample image.

Following this procedure we have formed an operator meeting all the conditions of the mapping Φ_g as introduced previously: from an input image we can create a grey-scale based decomposition into binary images. A typical sequence is shown in Fig. 2.

The final step is to introduce a spatial scale parameter into the process. The operator chosen here is straightforward: the morphological opening by a scaled disc of diameter s. This seems to us to best capture the idea of spatial scale – if a binary object can contain a disk of diameter s then it seems reasonable to say its spatial scale exceeds s. Therefor the spatial scale-space filter Ψ_s is the morphological binary opening. This important operator is discussed in many books, including [8]. Note on the digital grid we have to use a digital approximation to a scaled disk but this does not interfere with the scaling principle of the operator. Note also: that an opening with $s = 0$ (a point) preserves the binary image, a large opening removes all the objects, opening is anti-extensive and increasing, thus satisfying all the conditions of the operator $sizeOp_s$, introduced earlier. Thus from a given binary image we can obtain a sequence depending on s. A typical such sequence is shown in Fig. 3.

In summary, our bi-scale-space operator becomes the composition:

$$T_{gs}\, f = \Psi_s \Phi_g\, f. \tag{11}$$

4 Methodology and Results

Our demonstration image is part of the "texture" within the nucleus of an epithelial cell from the uterine cervix, prerepared with Papanicolaou stain and imaged under oil at 100x magnification. This image is shown in Fig. 4.

The operators were coded as high-level scripts within the Voir image analysis prototyping environment.[1].

Fig. 5 shows selected points in the the bi-scale-space decomposition of the image. Both of the scale parameters are essentially integer valued (for images on a discrete grid) but a logarithmic progression is shown in the figure for conciseness.

[1] VOIR - Vision, Objects and Images in R. CSIRO Mathematical and Information Sciences, Locked Bag 17, Nth Ryde NSW 1670,Australia. `http://www.cmis.csiro.au/IAP/software_voir.htm`

5 Discussion and Conclusion

We have presented a scale-space type filtering approach for blob images whereby the blobs are first identified and then filtered with respect to grey-scale saliance and then with respect to spatial size. This gives a scale-space with two independent scale parameters (grey-scale and spatial-scale) which we have called a bi-scale-space.

The scale-space possesses good monotonicity properties whereby increasing either scale reduces the number or area of the remaining blobs — new detail can never be introduced into the representation by increasing scale.

The analysis also has a stopping point since the all the blobs dissapear for sufficiently large scale — for both types of scale.

Any point in the scale-space matrix can be computed independently of other points simply by applying the composite operator $T_{gs} = \Psi_s \Phi_g$.

By making some suitable measurement (such as "Total Area") on the bi-scale-space images, it should be possible to plot the rate of decrease of this measure with change in scale thus forming peaks in places of rapid change. These bi-scale-spectrums may be a good characterisation of the properties of the original image texture. Note: a similar idea is used in the granold spectrum technique [4].

References

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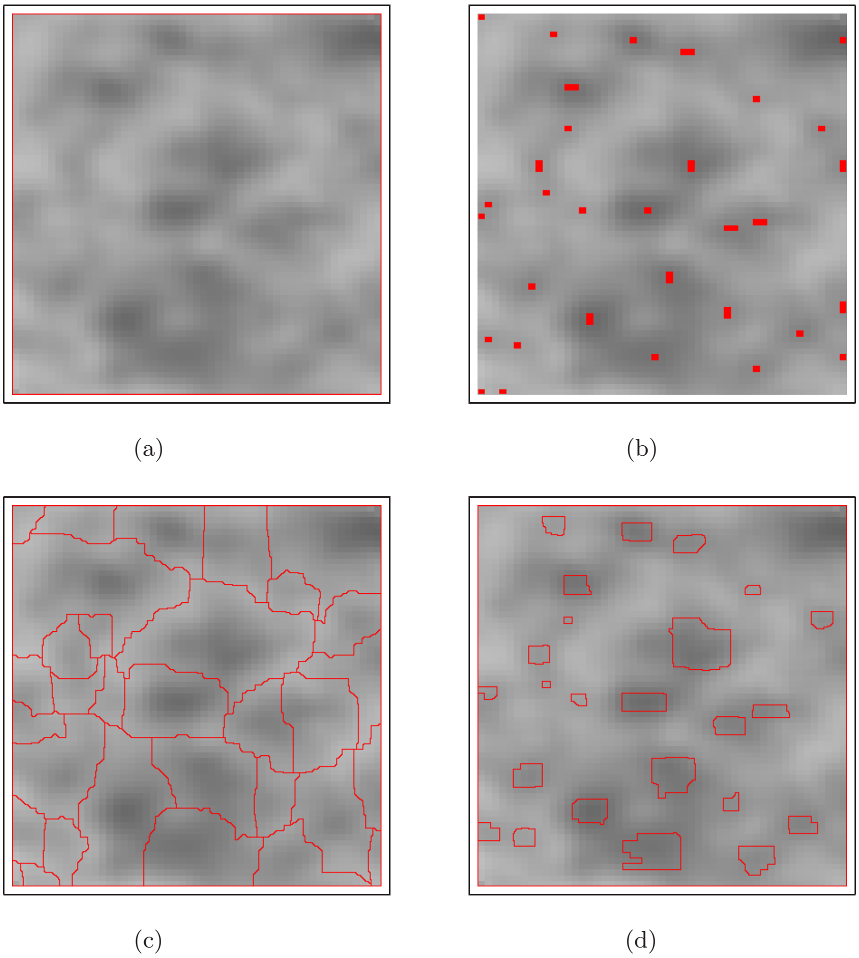

Fig. 1. The blob detector: (a) original image; (b) inner markers — dynamics exceeding some scale value; (c) outer markers — watershed of inner markers; (d) final result – marker based watershed of the gradient image.

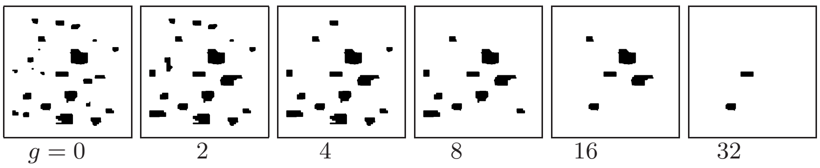

Fig. 2. An image decomposed into a sequence of binary images by the proposed operator Φ_g depending on grey-scale parameter g

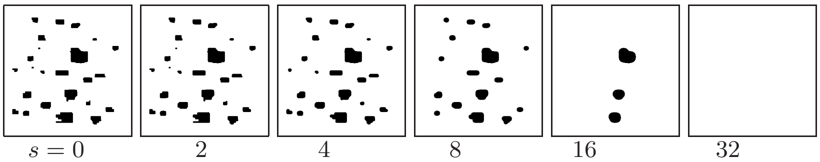

Fig. 3. A binary image decomposed into a sequence of binary images by the proposed operator Ψ_g depending on spatial scale parameter s

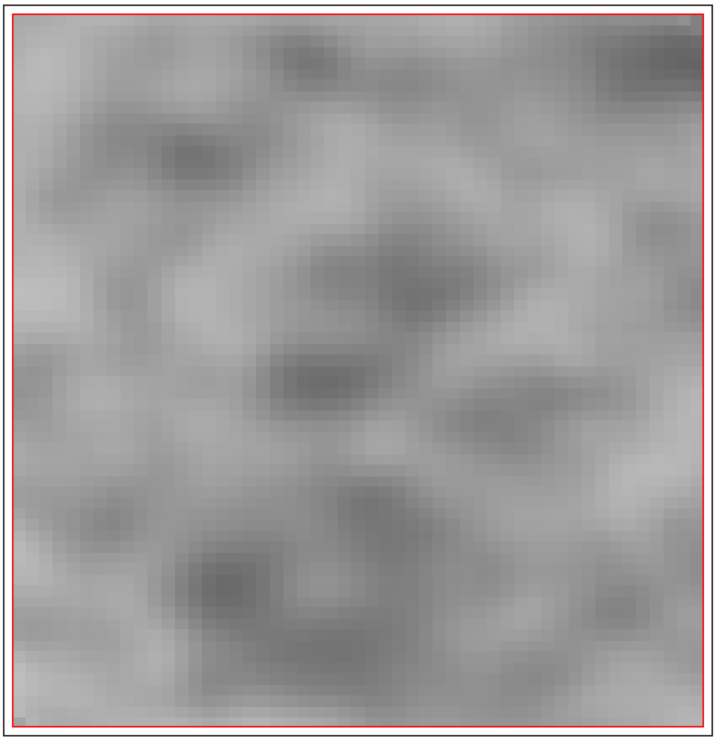

Fig. 4. Demonstration image. Part of the "texture" within the nucleus of an epithelial cell from the uterine cervix, prerepared with Papanicolaou stain and imaged under oil at 100x magnification.

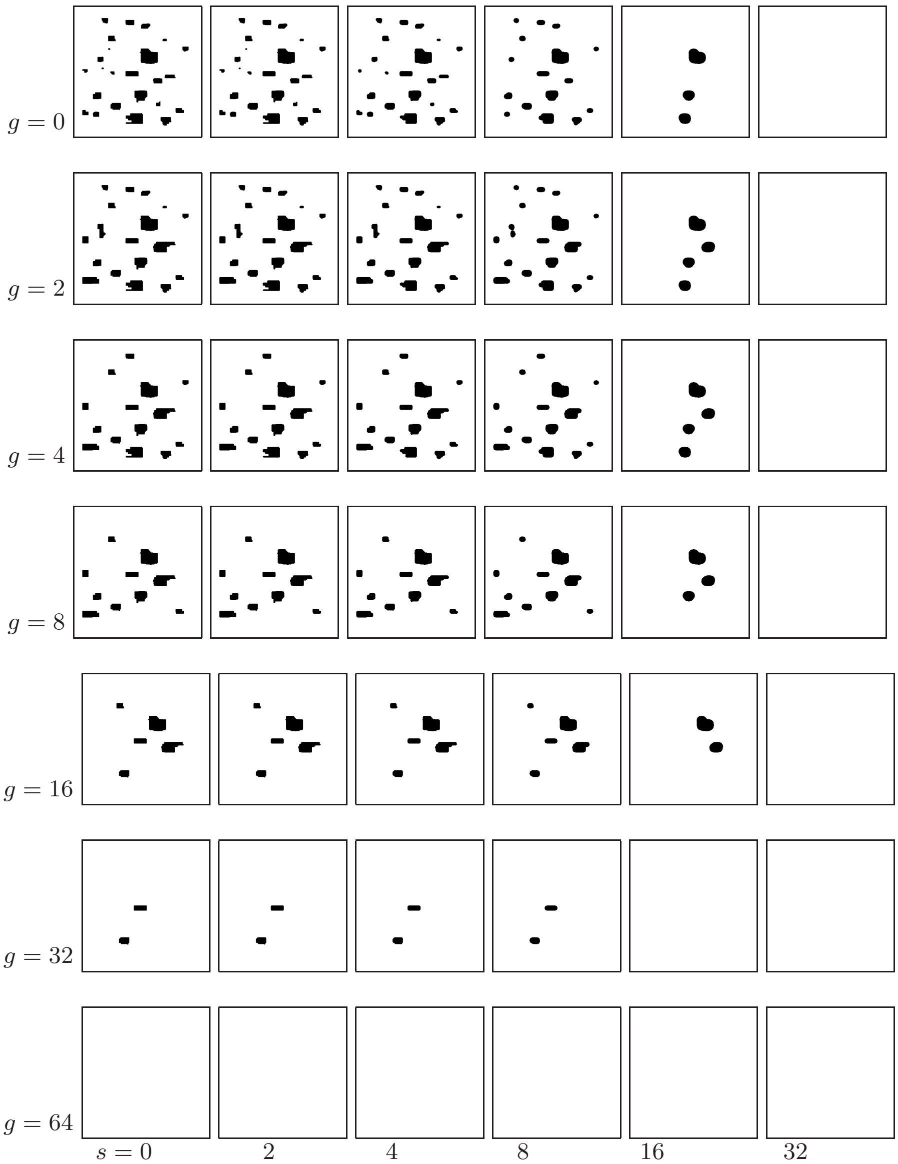

Fig. 5. Selected points in the bi-scale-space analysis of the image in figure 4