**Resumo**

Resumo do trabalho. Morphological pattern spectra com- puted from granulometries are frequently used to classify the size classes of details in textures and images. An ex- tension of this technique, which retains information on the spatial distribution of the details in each size class is devel- oped. Algorithms for computation of these spatial pattern spectra for a large number of granulometries on binary im- ages are presented.

**1-Introdução**

A importância do assunto deve ser destacada resumidamente.

GRANULOMETRIES are ordered sets of morphological openings or closings, each of which removes image details below a certain size. These can be used for texture analysis through the use of pattern spectra, which show how the number of foreground pixels in the image changes as a function of the size parameter [3]. A drawback of the classical definition of pattern spectra is that spatial information is not included in a pattern spectrum as shown below. In this paper, spatial pattern spectra are developed which retain information on the distribution of these details at different scales.

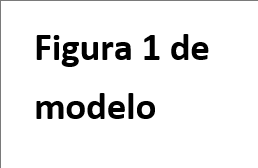


Figure 1: Parts (a) through (c) show three images consisting of squares of different sizes; (d) shows the pattern spectra, denoting the number of foreground pixels removed by openings by reconstruction by λ × λ squares. No granulometry is capable of separating the patterns, because the only differences between the images lie in the distributions of the connected components.

**2-Objetivos**

Dar uma ideia compacta da metodologia ou forma de abor-dagem da pesquisa, bem como o projeto foi desenvolvido. Let binary images X and Y be defined as a subset of the image domain M ⊂ Zn or R n(usually = 2).

Definition 1 - A binary granulometry is a set of operators {αr} with r from some ordered set Λ (usually Λ ⊂ R or Z), with the following three properties.

Exemplo de fórmula (1)

Exemplo de fórmula (2)

Exemplo de fórmula, (3)

for all r,s ∈ Λ.

Definition 2 - The pattern spectrumsα(X)obtained by applying granulometry {αr} to a binary image X is defined as

Exemplo de fórmula (4)

in which A (X) is a function denoting the Lebesgue measure in Rn.

In the case of discrete images, and with r ∈ Λ ⊂ Z, this differentiation reduces to

Exemplo de fórmula (5)

Exemplo de fórmula (6)

with r += min {r′∈Λ|r′> r}, and # (X) the number of elements of X.

The opening transform [5]ΩXof a binary image X for a granulometry αr is:

Exemplo de fórmula (7)

The pattern spectrum of a binary image X using granulometry {αr} is the histogram of Ω X obtained with the same size distribution [5], disregarding the bin for grey level 0.

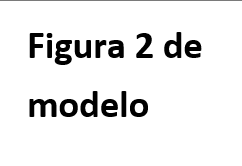


Figure 2: Opening transform with{αr}as in Fig. 1: (left)original image; (right) opening transform (contrast stretchedfor clarity).

**3-Metodologia**

Dar uma ideia compacta da metodologia ou forma de abor-dagem da pesquisa, bem como o projeto foi desenvolvido. Pattern spectra only retain the amount of detail present at scaler. This can be amended by computing some parameterization of the spatial distribution in an imageαr(X)\αr+(X) as a function of r.

Definition 3 – Let M(X) be some parameterization of the spatial distribution of detail in the image X. The spatial pattern spectrum S M, αis then defined as.

Exemplo de fórmula (8)

An obvious parameterization of the spatial distribution isthrough the use of moments. Focusing on the case of 2-D binary images, the momentmijof orderijof an imageXis given by.

Exemplo de fórmula (9)

The spatial moment spectrum Smij,αof orde is

Exemplo de fórmula (10)

Fori= 0andj= 0we obtain the standard pattern spec-trum. For eachr,(Smij,α(X))(r)is just the moment of an im-age, therefore, derived parameters such as coordinates ofthe centre of mass, (co-)variances, skewness and kurtosisof the distribution of details at each scale can be computedeasily. We can then define pattern mean spectra, pattern(co-)variance spectra, pattern kurtosis spectra, etc. Thepattern mean-xand variance-xspectra (S ̄x,αandSσ(x),α)are defined as:

Exemplo de fórmula (11)

and:

Exemplo de fórmula (12)

These two are shown in Figures 3 and 4. Note that thesedefinitions hold only where(Sm00,α(f))(r)6= 0. For all othervalues ofrthey will be defined as zero. Further post-processing can be done to compute central moments andmoment invariant from pattern moment spectra [1, 2].

**4-Resultado e Discussões**

Verificar os principais resultados obtidos de acordo com osobjetivos propostos. Nacken [5] derived an algorithm forcomputation of pattern spectra for granulometries based onopenings by discs of increasing radius for various metrics,using the opening transform. After the opening transformhas been computed, it is straightforward to compute thepattern spectrum:

* Item um
* Item dois

To compute the patternmomentspectrum, the only thingthat needs to be changed is the wayS[ΩX(x)] is incre-mented. As shown in Algorithm 1.

* Item um
* Item dois

This algorithm can readily be adapted to other granulome-tries, simply by computing the appropriate opening trans-form. Pattern spectra only retain the amount of detail present at scaler. This can be amended by computing some parameterization of the spatial distribution in an imageαr(X)\αr+(X) as a function of r.

Definition 3 – Let M(X) be some parameterization of the spatial distribution of detail in the image X. The spatial pattern spectrum S M, αis then defined as.

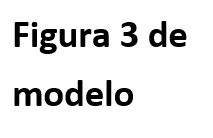


Figure 3: The opening transform using city-block metric:(a) opening transform of Fig. 1(c); (b) pattern spectrum; (c)pattern variance-x; (d) variance-yspectra.

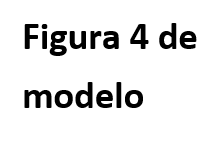


Figure 4: Pattern mean-x(top) and variance-x(bottom)spectra: the three collumns show spectra for Fig. 1(a), (b)and (c) from left to right respectively. Unlike the standardpattern spectra, these spatial pattern spectra can distin-guish the three images

**5-Conclusão**

Conclusão do trabalho. Sitting on a corner all alone, staringfrom the bottom of his soul, watching the night come in fromthe window.

It’ll all collapse tonight, the fullmoon is here again In sick-ness and in health, understanding so demanding It has noname, there’s one for every season Makes him insane toknow

Running away from it all ”I’ll be safe in the cornfields”, hethinks Hunted by his own, again he feels the moon rising onthe sky

Find a barn which to sleep in, but can he hide anymoreSomeone’s at the door, understanding too demanding Can this be wrong, it’s love that is not ending Makes him insane to know

She should not lock the open door (Run away, run away, runaway) Full moon is on the sky and He’s not a man any more sees the change in him but can’t (Run away, run away, runaway) See what became out of her man Fullmoon Swimming across the bay, the night is gray, so calm today She doesn’t wanna wait. ”We’ve gotta make the love complete tonight...”

In the mist of the morning he cannot fight anymore Hundredmoons or more, he’s been howling Knock on the door, an dscream that is soon ending Mess on the floor again She should not lock the open door (Run away, run away,run away) Full moon is on the sky and he’s not a man any-more She sees the changes in him but can’t (Run away, runaway, run away) See what became out of her man. She should not lock the open door (Run away, run away, runaway) Full moon is on the sky and he’s not a man anymoresees the changes in him but can’t (Run away, run away, runaway) See what became out of her darling manShe should not lock the open door (Run away, run away, runaway) Fullmoon is on the sky and he’s not a man anymoreSee what became out of her man.

**Refêrencias**

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