# MORPHOLOGICAL DOMINANT POINTS DETECTION FOR MOTION ANALYSIS ON PROGRAMMABLE RETINA

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**ABSTRACT**

This paper presents the first results of my PhD thesis, which addresses the problem dominant points detection for motion analysis on programmable retina. The goal of this research is to develop new algorithmical concepts to implement efficient image processing tools over the massively parallel cellular array of processors of the programmable retina, in order to perform effective motion analysis tasks.

*Key words:* dominant point, level set, scale-space, thinning algorithm, parallel cellular machine

## 1. INTRODUCTION

The programmable retina [1] is a CMOS array sensor in which a Boolean elementary processor has been integrated inside every pixel, so it is a cellular SIMD machine with optical input. This architecture has been shown [4] to be well suited for non-linear (Boolean) and level-by-level processing, thanks to an analog-to-digital conversion by multiple thresholding, that allows data processing during the acquisition. These reasons have led us to consider the mathematical morphology framework for dominant points computation.

The dominant points (interest points or key points in literature) is location in the image where the signal changes in several directions, thus carrying more information. Examples includes corners and T-junctions, as well as locations where texture varies significantly [8]. References for a quasi exhaustive survey are [3] and [8].

Mathematical morphology is a nonlinear image processing framework developed by G.Matheron and J.Serra [7]. Level sets represent a natural way to extend the morphological operator from binary to gray-level images.

We present in this paper a new algorithm to compute dominant points on a grey level image. It is founded on mathematical morphology, and is adapted to SIMD cellular, level sets based Boolean computation. It is also compliant with the morphological scale-space framework. Then, we give some idea to how we use our dominant points detector as part of motion analysis.

## 2. MORPHOLOGICAL DOMINANT POINTS DETECTION

Let $E$ be any set. A binary image $X$ is an subset of $E$. Let $K$ be an interval $[0, n]$ of $\mathbb{N}$. A grayscale image is a function $I$ from $E$ to $K$. Such grayscale image $I$ can be represented by its level sets $\{I_t\}_{t\in[1,n]}$ defined as follows:

$$I_t = \{p \in E | I(p) \geq t\} \tag{1}$$

For the binary image one natural interest function is provided by the local curvature. The curvature is reciprocal of the radius of the maximal inscribed circle tangent to point $p$.

The skeleton was introduced by H.Blum [2] as the medial axis which is the union of the centers of the maximal inscribed balls. According to H.Blum, the highest curvature points are located on the maximal inscribed circles which centers are the extremities of branches of the skeleton. Furthermore, this curvature is reciprocal of the distance between the contour and the extremal point of the skeleton.

So, the skeleton algorithm used in our dominant point detector ( see Figure 1) is the 8-connected MB1-Hybrid thinning algorithm detailed in [5]. The advantages of this algorithm are: (1) it has a certain rotation invariance; (2) it produces few spurious branches; (3) its computational cost is low.

In order to obtain the positive high curvature points on a binary image, we compute one complete iteration of the MB1-Hybrid skeleton then we calculate the *extremal points* of the skeleton (those which have one neighbor only in the image). In the same way, the negative high curvature points are computed thanks to the exoskeleton (skeleton of the complementary of the image). Figure 1 shows an example of this process.

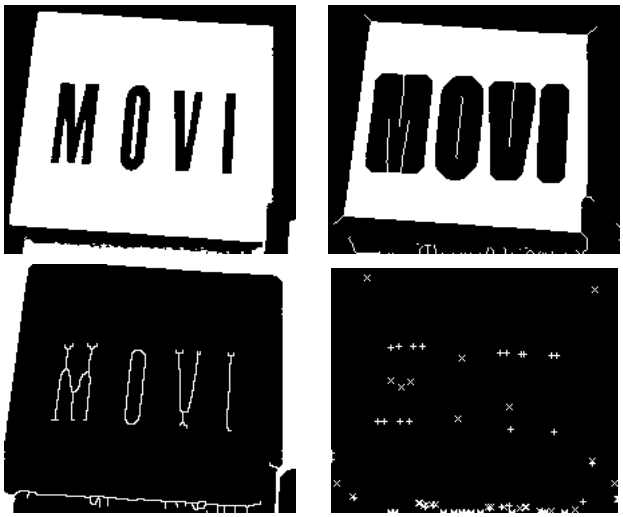

Figure 1: The original binary image, 8-connected skeleton (5 iterations), 4-connected exoskeleton (5 iterations) and union of the extremal points of the skeleton (points marked “x”) and the exoskeleton (points marked “+”).

This procedure will be performed on every level set of the gray-level image in order to obtain the interest function by summing the results.

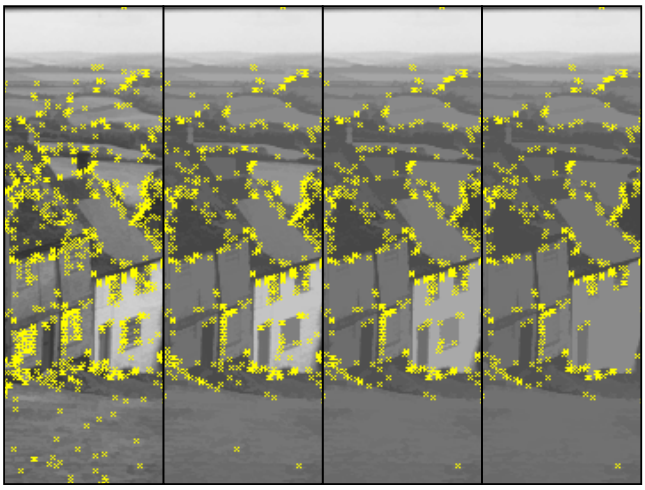

Figure 2: Dominant point detection over a morphological scale-space on a detail of the ”goldhill” image

A hierarchical selection of the level sets defines a morphological scale-space [6]. As our interest function is a sum over the level sets, it is necessarily decreasing as the morphological scale increases. Then, our detector is compliant with such morphological scale-space as no new dominant point appears as the scale increases.

The algorithm can be executed in parallel cellular machine like the programmable retina very efficiently. The MB1-Hybrid thinning algorithm is a good trade-off between rotation invariance, efficiency and robustness. The number of dominant points can be tuned according to the contrast thanks to the thresholding and according to the size of the level sets through the scale-space framework.

## 3. OPTICAL FLOW AND MOTION ANALYSIS

The dominant points detection is the first step involve in correlation to match different images on a sequence. Actually, after matching results of the dominant points detection on several successive images, we compute the optical flow. We are also able to deduce some other properties like distance between objects, between us and an object, the speed of an object and the speed of the image sensor.

As we work with a scale-space by choosing the level sets, we have certain possibilities to modulate the computation of optical flow in some regions of the image. That’s allow us not to compute redondant information due for example to the background of the image.

This study is part of our current research in the field of motion analysis. In following works, we will automatically detect and study motion on a video system based on artificial retina.

## 4. REFERENCES


[1] T.M. Bernard, ”Des rétines artificielles intelligentes”, *phD Thesis*, Université Paris-Sud, 1992.

[2] H. Blum, *A transformation for extracting new descriptors of shape, Symposium Models for Perception of Speech and Visual Form,* Weiant Whaten-Dunn Ed., MIT Press, Cambridge, MA, 1967.

[3] R. Deriche and G. Giraudon, ”A computional approach for corner and vertex detection”, *IJCV*, vol. 10(2), pp. 101-124, 1993.

[4] A. Manzanera, ”Vision artificielle rétinienne”, *phD Thesis*, ENST, 2000.

[5] A. Manzanera and T.M. Bernard, ”Metrical properties of a family of 2D parallel thinning algorithm”, IWCIA, *Electronic Lecture Notes on Discrete Applied Mathematics*, Elsevier Science, Palermo, May 2003.

[6] F. Meyer and P. Maragos, ”Morphological scale-scale representation with levelings”, *Scale-space’99*, LNCS, pp. 187-198, Spinger-Verlag, 1999.

[7] J. Serra, *Image analysis and mathematical morphology*, New York, Academic Press, 1982.

[8] C. Schmid et al., ”Comparing and evaluating interest points”, *ICCV* Bombay, January, 1998.