New Perspectives in Neuromorphometry and Computational Neuroscience

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Abstract. This paper discusses a series of new techniques for neuromorphometry, including Minkowski's sausages, influence histograms, normal and tangent vector fields, and orientation histograms and bending energy. The possibilities opened by these developments with respect to the better understanding and more realistic simulation of the behavior of neural structures is also discussed.

Keywords: neuromorphometry, computational neuroscience, area of influence, spatial coverage, complexity, fractals, receptive fields, distributed coding, orientation histograms, bending energy.

1 Introduction

The brain is the most complex structure known to man. Its remarkable emmerging behavior, responsible for all human accomplishments, is known to be defined by two principal factors: (i) the electrochemical processes in and outside the cell; and (ii) the cell morphology, which imposes constraints to the aforementioned processes. The influence of the cell morphology over the neural behavior can be understood in terms of a multiscale perspective [Costa (1997a)]: at the *more microscopic scales*, the diameter and size of dendritic segments define the electrotonic properties of the dendritic arborization; at *intermediate spatial scales*, the profusion of branches define the degree of spatial coverage of the cell, consequently strongly influencing the pattern of synaptic connections with other cells; at *larger spatial scales*, the overal size and position of each neural cell play an important role in stablishing not only the extension of the associated receptive field, but also the temporal behavior of the respective neural structures. The importance of neural shape is further supported by the large number (about 500) of types of neurons which have been identified in the mammals' cortex. It is thus important to devise effective methods for the analysis and classification of neural cells.

While the electrochemical aspects of neural structures have received great attention from neuroscientists, e.g. [Koch & Segev (1989)], the morphometric features of such structures have been relatively overlooked. In fact, the relatively few approaches reported in the literature have been largely restricted to global features such as fractal dimension, e.g. [Montague & Friedlander (1991)]; influence area, e.g. [Toris et al. (1995)]; and the number of dendritic branches, e.g. [Toris et al. (1995)]; as well as local features such as the length and diameter of the segments, represented by dendrograms, e.g. [Toris et al. (1995); Poznanski (1992); Cesar & Costa (1997b)]. Moreover, such measures and representations have rarely been characterized and assessed, in such a way that there are few sound guidelines for selecting a set of shape features for neuromorphometric analysis of cell classification. In short, neuromorphometry is still an incipient area.

The work reported in the current article presents several attempts at partially overcoming the above identified shortcomings. These approaches are part of a larger project being developed at the *Cybernetic Vision Research Group*, initiated and supervised by the author since 1993, which is aimed not only at neuromorphometry, but also at the generation of biologically more realistic neural structures. As it happens, it was precisely this latter objective that motivated a more comprehensive and careful approach to neural shape analysis, since it is only by having a good statistical description of real cells in terms of an effective set of shape features that it becomes possible to generate biologically realistic cells. The present paper starts by addressing the problem of defining and estimating the area of influence and the spatial coverage and complexity of neural cells, which is done in terms of convex hull, Minkowski's sausages and influence histograms [Costa (1995); Costa et al. (1997a,b)]. Next, a new approach to general contour analysis based on vector fields [Costa (1997b-d)] is described, which allows normal vector fields to be obtained by using a combination of laplacian-of-gaussian and vector field

estimators. This approach, which can be immediately extended to N-dimensional spaces, allows the direct determination of orientation histograms and normal fields, from which tangen fields and the contour curvature and bending energy can be derived. Finally, the above mentioned vector field framework is discussed as an underlying mechanism for effective orientation enconding in the mammals' cortex. The perspectives for future developments, including the generation of biologically realistic neural structures and their respective modeling are also discussed.
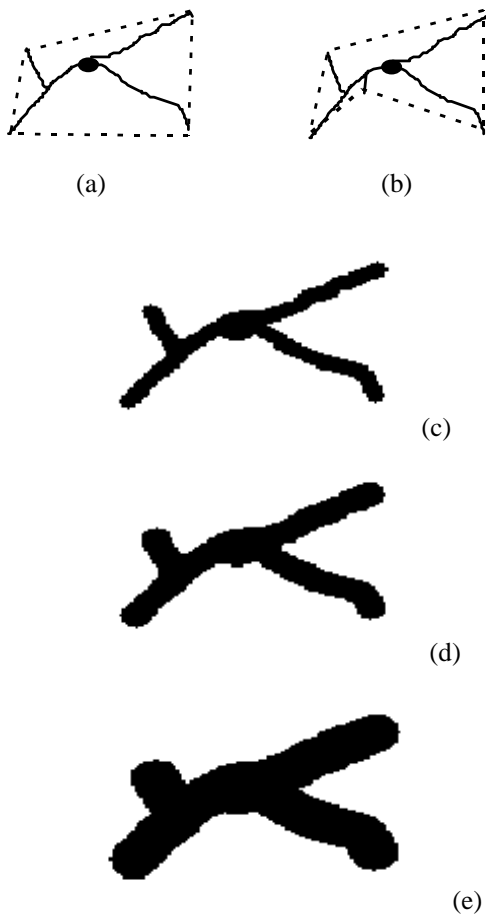

(a)   (b)

(c)

(d)

(e)

Figure (1): The estimation of the influence area in terms of the involving polygon defined by the dendritic extremities suffers from the serious problem that slightly distinct cells may yield rather different influence areas.

2 Area of Influence, Spatial Coverage, Complexity, Minkowski's Sausages and Influence Histograms

Though being a common concept in the specialized literature, there is no precise definition for what the *area of influence* of a neural cell actually is, or how it should be estimated. A typical approach to this problem consists in joining the extremities of the cell, in such a way as to form a polygon containing the cell (see Figure 1). However, as illustrated in Figure 1(a,b), slighly different neural cells can produce largely distinct involving polygons. In order to overcome such criticability, the definition of the influence area as the convex hull of the cell has been proposed in [Costa (1995, 1997a)]. Yet another possibility is to assume as the area of influence of a neural cell the set of points in the surrounding space whose distance to the neural cell (the minimal distance) does not exceed a fixed value L [Costa et al. (1997a,b)]], such as illustrated in Figure 1(c-e), with respect to L=3, 6, 9 and 12. The choice of L depends on the kind of physiological effect we are interested to analyse.

A concept that is closely related to the area of influence is the degree of spatial coverage exhibited by neural cells. Such as plants roots, dendritic and axonal arborizations are meant for optimizing the coverage of the surrounding space, in such a way that the estimation of the effectiveness of this process can provide valuable indication about the number of synaptic connections of a specific cell or structure. In the specialized literature, the spatial coverage has been often associated to the complexity of the cell. Typical approaches to the estimation of these characteristics include measures such as the number of branches divided by the area of influence, and fractal dimension. While the former alternative is simple and interesting, the fractal dimension is potentially more accurate, since it takes into account not only the number of branches, but also the complexity inherent to each dendritic segment (i.e. its roughness). The most frequently adopted approach to estimating the Bouligand-Minkowski fractal dimension of a neural cell or structure consists of the box-counting procedure, e.g. [Montague & Friedlander (1991)]. However, many problems affecting such an approach have been identified, e.g. [Coelho & Costa (1997)], including the dependence of the orientaton and position of the superimposed grid, the fact that neurons are not perfectly fractal objects, and the limitations imposed by the discrete representation of the cells in spatially quantized images. We have investigated an alternative method for estimating the Bouligand-Minkowski dimension that relies on the use on Minkowski's sausages [Tricot (1995)]. As illustrated in

Figure 1(c-e), these sausages are obtained by convolving the binary representation of the original cell with circular regions with monotonically increasing radius, and taking as result (a binary image) the non-null pixels. The respective fractal dimension can be obtained from the slope of the log-log representation of the curve *number of points* x *radius of circular region* in the region of fractality of the cell [Costa (1997a), Coelho & Costa (1997)]. The obvious advantage of this approach is that it does not depend on the orientation
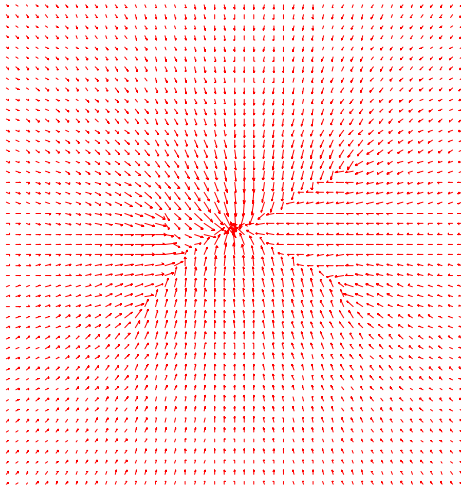

Figure (3): The electric field stablished around a neural cell, estimated in the Fourier domain.

and position of the superimposed grid that is implied by the box-counting procedure. Moreover, it provides a better conceptual understanding of the fractal dimension in biological terms: since the Minkowski sausage for a specific radius corresponds exactly to the area of influence as defined earlier in this section, the estimate fractal dimension indicate how well the surrounding space is being covered as the area of influence increases. In fact, this interpretation has motivated the extension of the Minkowski's sausages in order to quantify the profile of influence stablished by various biological processes. For instance, the stablishment of synaptic connections is known to be governed by a number of causes, including the distribution of chemoattractors and electric fields, which act by guiding the growth cones. Thus, if we are interested to investigate the area of influence of a specific neural cell or structure with respect to the distribution of electric potential field, we should obtain the distribution of the field along the surrounding space, which can be done by convolving the pictorial representation of the cell with

the point-spread function defined by a single charge (i.e. pixel) [Costa (1997b-d)]. Perhaps the most interesting feature of such an approach to the characterization of the spatial coverage by a neural cell is that it explicitly takes into account the fact that the spatial coverage is always relative to a specific biologically relevant factor (e.g. the electric field in the above example). However, such a definition of area of influence involves every pixel suffering a non-negligible influence from the cell. In order to provide more compact and global measures, it is possible to use the histogram of the intensity of the influence at each affected pixel, or even the respective entropy. Such histograms, which have been experimentally verified [Costa et al. (1997a,b)] to provide a global and yet rich description of the spatial coverage by neural cells with respect to specific biological factors, have been called *influence histograms*. Figure 2 presents two neural cells (a,b), the areas of inlfluence obtained with respect to a gaussian point-spread-function (c,d), and the respective influence histograms (e).

3 Fourier-Transform-Based Vector Fields, Normal Fields, Tangent Fields, Curvature and Bending Energy

As commented in the previous section, chemoattractors and electrical fields present immense importance in defining the interconnection patterns among neural cells. Furthermore, ionic and electrical gradients are also known to strongly and continuosly influence typical neural behavior. Consequently, in order to analyse and simulate neural structures, it is extremely important to have effective ways for calculating scalar and vector fields in 2 and 3-D spaces in real-time. As described in the previous section, scalar fields can be obtained straightfordly by convolving the neural shape with the point-spread-function, an operation that can be effectively implemented in the Fourier domain because the point-spread-function typically implies a large support area. It has been shown by the author [Costa (1997d)] that this approach can be extended also for the calculation of vector fields. In this case, two scalar point-spread-functions, each corresponding to the x- and y-components of the field, respectively, are convolved with the neural shape in order to determine the x- and y-components of resulting influence vector field, in such a way that the convolution can be performed through Hadamard porducts in the Fourier domain. Figure 3 shows an example of the determination of a vector field of influence of the neural cell in Figure 1(a) with respect to a exponentially decaying vector field (equivalent to electrical field in 2D spaces).

Such an approach also allows the trajectory of development of a growth cone, simulated in terms of differential equations assuming that the arc-length of the growth cone progresses at constant speed, to be accurately predicted.

In addition to its inherent value for simulation

straightforwardly obtained from the normal fields, providing an interesting representation of the distribution of orientations exhibited by the neural processes. In addition to orientation histograms, tangent fields can also be extracted from the respective normal fields. Since the point curvature along the contours is

(a)   (b)

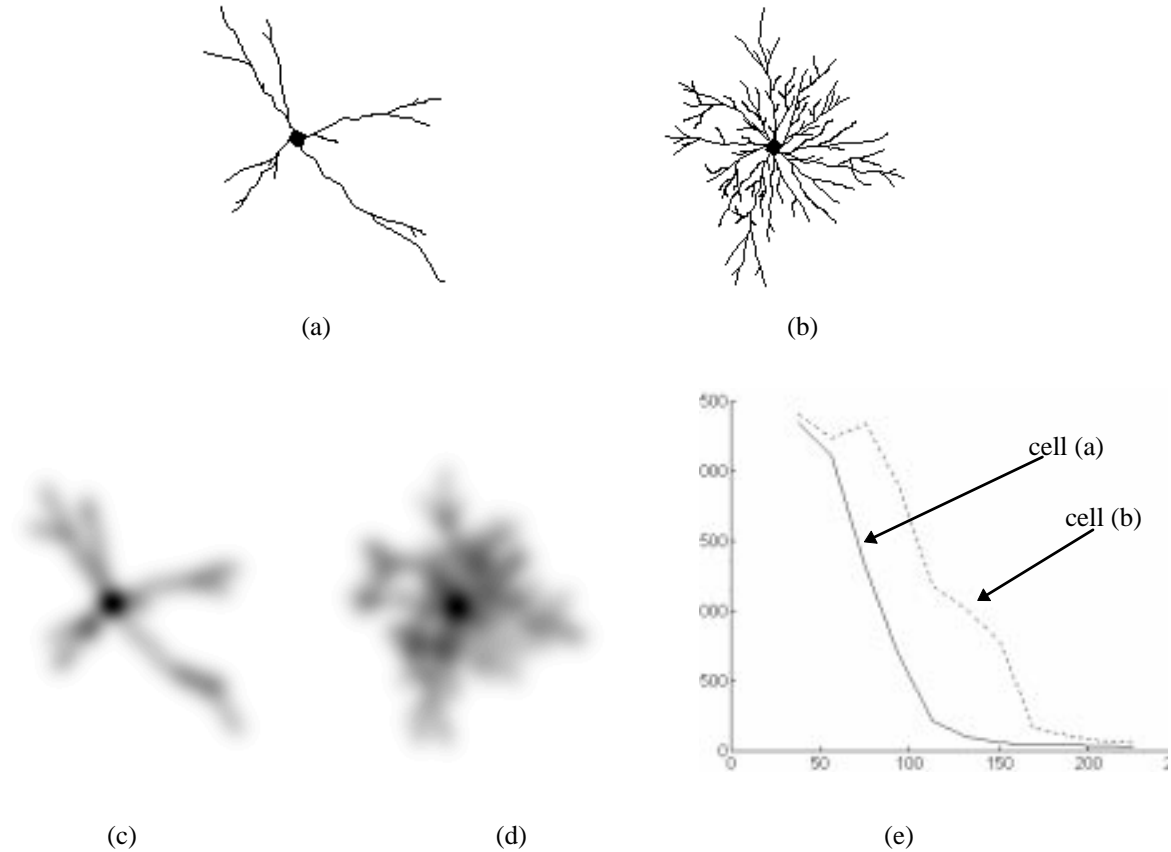(c)   (d)   (e)

Figure (3): Two neural cells (a,b) and their respective influence areas with respect to gaussian point-spread-functions (c,d), and the respective influence histograms (e). Being more complex, the cell (b) yields a broader influence histogram than that for cell (a).

of the development of neural structures, the effective numerical calculation of vector fields also allows us to estimate the normal field along the contours of general objects in the image. This can be done by having the the image first to undergo a laplacian-of-gaussian filtering, the result of this operation been used for estimation of a vector field with exponentially decaying magnitude. The underlying idea is that the laplacian-of-gaussian defines distributions of negative and positive values at each side of the image contours, thus making the field to orthogonally cross such contours.

The normal field obtained for the cell in Figure 1(a) is depicted in Figure 4(a). Orientation histograms, usually visualized in polar form, can be

defined as the derivative of the angle between the tangent vectors and the x-axis [Stoker (1969)], it is possible to use the derivative property of the Fourier transform and the total derivative theorem to estimate the point curvature, which provides important information for the detection of critical points in the contours, directly from the 2D representation of the tangent field. Morever, the normalized multiscale bending energy of the contours, which has been shown [Cesar & Costa (1996,1997a)] to represent an important subsidy for the classification of neural cells, can be obtained by adding the squares of the point curvature values. Since the determination of the curvature in this process does not depend on the previous segmentation
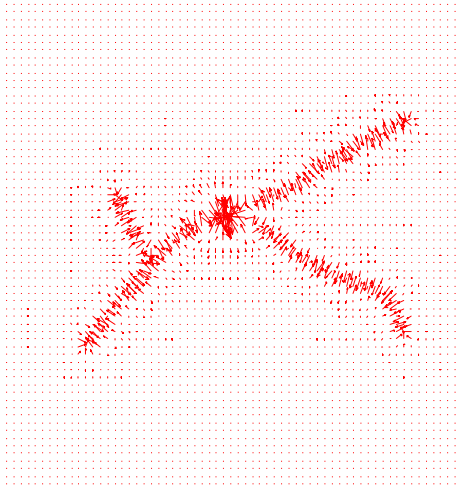
Figure (5): The normal vector fields obtained for the neural cell in Figure 1(a).

of the contours, the proposed method can be used for the treatment of even cluttered images such as textures .

5 Concluding Remarks and Future Developments

This article has presented a series of new concepts and methods for the morphometric analysis and simulation of neural cell and structures. The concept of influence area, spatial coverage and complexity of neural cells have been defined in a way that is biologically sound and which can be effectively calculated in terms of convex hulls, Minkowski's sausages, and influence histograms. The idea of influence area has been extended to include vector fields, such as those obtained from conservative fields, which provide an interesting alternative for the stactic and dynamic simulation of the physiological processes, such as the development of growht cones and electrotonic potential distribution, in neural structures. It has also been shown that, by estimating vector fields with exponentially decaying magnitude over images first processed by laplacian-of-gaussian, it is possible to estimate the normal and tangent fields along the image contours, from which orientation histograms, point curvature, and normalized multiscale bending energy can be determined. All these concepts and techniques can be easily extended to higher dimensional spaces. The Fourier-based approach and scalar decomposition used in the numerical approach to the estimation of such vector fields have also yielded interesting possibilities for

explaining orientation encoding at the primate visual cortex in terms of orthogonal orientation channels, corresponding to the x- and y-components of the point vector field [Costa (1997b,c)]. In fact, this hypothesis is supported by the fact that the receptive fields of simple cortical cells bear a substantial similarity with the point-spread-functions defined by the combination of laplacian-of-gaussian and exponentially decaying vector fields.

We are currently developing a framework for generation and simulation of biologically-realistic neural structures, and investigating the use of linear and non-linear variational methods in order to obtaining better localization of the contours dufing the blurring process implied by the laplacian-of-gaussian.

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