Visual Pathways for Detection of Landmark Points

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Abstract. We describe a neuron multi-layered architecture that extracts landmark points of high curvature from 2d shapes and resembles the visual pathway of primates. We demonstrate how the rotated orientation specific receptive fields of the simple neurons that were discovered by Hubel and Wiesel can perform landmark point detection on the 2d contour of the shape that is projected on the retina of the eye. Detection of landmark points of high curvature is a trivial task with sophisticated machine equipment but we demonstrate how such a task can be accomplished by only using the hardware of the visual cortex of primates abiding to the discoveries of Hubel and Wiesel regarding the rotated arrangements of orientation specific simple neurons. The proposed layered architecture first extracts the 2dimensional shape from the projection on the retina then it rotates the extracted shape in multiple layers in order to detect the landmark points. Since rotating the image about the focal origin is equivalent to the rotation of the simple cells orientation field, our model offers an explanation regarding the mystery of the arrangement of the cortical cells in the areas of layer 2 and 3 on the basis of shape cognition from its landmark points.

Keywords: Visual cortex, Landmark points, Shape encoding, Curvature detection.

1 Introduction

Our first knowledge about cortical neurons and their receptive fields we owe to Hubel and Wiesel. The Nobel Prize winners made a remarkable progress during their 25 years of collaboration in elucidating the responses of cortical neurons by using stimuli of great relevance to vision. In their papers they define the ways in which area VI receptive fields differ from LGN receptive fields. The qualitative methods they used for studying the cortex continue to dominate experimental physiology (Hubel and Wiesel, 1959, 1962, 1968, 1977; Hubel, 1982).

Hubel and Wiesel recorded the activity of cortical neurons while displaying patterned stimuli, mainly line segments and spots, on a screen that was imaged through the animal's cornea and lens onto the retina. As the microelectrode penetrated the visual cortex, they presented line segments whose width and length could be adjusted. First, they varied the position of the stimulus on the screen, searching for the neuron's receptive field. Once the receptive-field position was established, they

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measured the response of the neuron to lines, bars and spots presented individually. From Hubel's Nobel lecture we quote:

"Our first indication of the beauty of the arrangements of cell groupings came in 1961 in one of our first recordings from striate cortex of monkey, a spider monkey named George. In one penetration, which went into the cortex at an angle of about 45° and was 2.5 mm long, we were struck right away by something we had only seen hints of before: as the electrode advanced the orientations of successively recorded cells progressed in small steps, of about 10° for every advance of 50 μm. We began the penetration around 8:00 p.m.; five hours later we had recorded 53 successive orientations without a single large jump in orientation. During the entire time, in which I wielded the slide projector and Torsten mapped the fields, neither of us moved from our seats. Fortunately our fluid intake that day had not been excessive!" Hubel, Nobel Lecture, December 1981.

In this paper we show how these specific arrangements of the cortical cell groupings can lead to the extraction of landmark points of high curvature on a 2d shape contour that is projected on the retina of the eye. We describe an artificial neural architecture that abides to the described by Hubel arrangements of cell groupings and achieves landmark points extraction, we therefore imply that the specific arrangements of the cell groupings in the visual cortex of primates perform landmark point extraction in a way similar to our artificial model. Our purpose in this paper is to describe how what we know about the cortical cells of the primates can be used to perform landmark extraction from shapes.

The rest of the paper is organized as follows: First we present related work from both fields of neuropsychology and computer science that support the concept of landmark points in shape perception. Our specific layered architecture is presented in the next section where first we properly define the term "landmark point' and "landmark region" that will be used hereinafter and then we explain how our proposed architecture simulates the way the specific arrangements of the cortical cells are likely used to extract landmark points and regions.

2 Related Work

The concept of landmark points for shape summarization has been appreciated by many researchers in many different areas of neuropsychology and computer science. The importance of landmark points of high curvature in the way that humans perceive shapes is apparent in the work of Goodale et al [Goodale, 1994], [Goodale 1991]. In this study patients with unilateral or bilateral lesions of the visual cortex are "*unable to calibrate their grasp according to the best "grasp lines" made up from points of maximum convexity or concavity along the boundary of an object where the most stable grip should be expected"*. Other patients with damages in the visual cortex are unable to discriminate from different shapes and orientations. Goodale concludes that "*The brain damage that the patient suffered as a consequence of anoxia appears to have interrupted the normal flow of shape and contour information into her perceptual systems*".

Leslie G. Ungerleider et al [Ungerleider, 1998] report that the visual processing pathways in primates:

"*….appear to be organized hierarchically, in the sense that low-level inputs are transformed into progressively more integrated representations through successive stages of processing. Within the ventral stream, for example, the processing of object features begins with simple spatial filtering by cells in V1, but by the time the inferior temporal cortex (area TE) is activated, the cells respond to global object features, such as shape …. Thus, much of the neural mechanism for both object vision and spatial vision can be viewed as a bottom-up process subserved by feed-forward projections within a pathway*".

A. Dobbins, S.W. Zucker and M.S. Cynader presented evidence that the curvature detection is related to *end-stopping neurons*, they also presented a supporting mathematical model [Dobbins, 1987]. Our work is very similar to theirs but our model is faster since it calculates the curvature in terms of simplest parallel calculations.

In the field of human cognition systematic work has been done in systems of human psychology and learning [Drigas, 2005]. Further research has revealed that the extraction of landmark points is a critical process in human perception and the basis for potential mechanisms of shape identification and recognition [Biederman, 1987], [Kayaert, Biederman 2003].

In biology biometrics Bookstein was among the first to define landmark points on various biological shape for species classification [Bookstein 1996].

At the same time many researchers in various fields of computer science have been studying shape representation techniques and many have appreciated the use of landmark points as the most compatible to the human cognition method of representing and encoding shape information. Berreti introduces a decomposition of the shape into primitives based on the curvature [Berreti, 2000]. Attneave et al and Pomerantz et al notice that the curvature of a curve has salient perceptual characteristics [Attneave, 1954], [Pomerantz, 1977] and has proven to be useful for shape recognition [Pavlidis, 1980]–[Wang, 1999]. Asada and Brandy have developed the "curvature primal sketch" descriptor [Asada, 1986], a multiscale structure based on the extraction of changes in curvature. From curvature features, a description of the contour in terms of structural primitives (e.g., ends, cranks, etc.) is constructed. Mokhtarian and Mackworth [Mokhtarian, 1986], [Mokharian, 1992] showed that curvature inflection points extracted using a Gaussian scale space can be used to recognize curved objects. Dudek and Tsotsos [Dudek, 1997] presented a technique for shape representation and recognition of objects based on multiscale curvature information. Another technique based on the landmark points of high curvature, is also introduced by [Super, 2004].

In this paper we realize an inherit advantage of the similar to [Shams,1997] and [Fukusmima, 1982] neuron based architectures in implementing the allocation of landmarks on shapes by proposing a hierarchical model that incorporates visual acquisition and landmark allocation in distinct layers emulating the visual pathway of primates.

3 Detection of Landmark Points

David H. Hubel mentions in his Nobel lecture:

"Orientation-specific simple or complex cells "detect" or are specific for the direction of a short line segment. The cells are thus best not thought of as "line detectors": they arc no more line detectors than they are curve detectors. If our perception of a certain line or curve depends on simple or complex cells it presumably depends on a whole set of them, and how the information from such sets of cells is assembled at subsequent stages in the path, to build up what we call "percepts" of lines or curves (if indeed anything like that happens at all), is still a complete mystery." Hubel, Nobel Lecture, December 1981.

Simple cells have oriented receptive fields, and hence they respond to stimuli in some orientations better than others. This receptive field property is called orientation selectivity. The orientation of the stimulus that evokes the most powerful response is called the cell's preferred orientation. Orientation selectivity of cortical neurons is a critical receptive-field property. LGN and retinal neurons have circularly symmetric receptive fields, and they respond almost equally well to all stimulus orientations. Orientation-selective neurons are found throughout layers 2 and 3, though they are relatively rare in the primary inputs within layer 4C.

In the rest of this paper we will present our model for shape encoding from landmark points. We will show that continuous successive orientations by 10 degrees of an orientation selective filter, like the ones discovered by Hubel and Wiesel in the visual cortex of primates, can be a mechanism of landmark point detection. We will describe the mechanism and the neuron connectivity model that under the above assumptions encodes the shape of a 2d contour on the basis of connected landmark points of high curvature.

3.1 The Proposed Landmark Points

Let X be a planar curve parameterized on the scalar t, the parametric representation of X is then $\vec{c}(t) = (x(t), y(t))$, where x(t) and y(t) the coordinate functions. We need a way to identify landmark points of high curvature on the curve X and be consistent to the functionality of the cortical cells. We know from Hubel and Wiesel that the cortical cells in layers 2 and 3 have orientation selective receptive fields and that this orientation changes direction continuously in successive layers. We show now that with successive rotations of an orientation selective filter we can indeed measure the curvature at every point on the curve. The idea is to use the orientation selectivity to locate the direction which is tangent to the curve at a specific point and at the same time measure the curvature at this point by accumulating the firings of the successive layers in which the rotated field keeps being close to the direction of the tangent. This way we use the rotation operation that we know happens in the visual cortex cells in successive layers and the orientation selectivity to perform curvature detection in a way that is compatible to our best knowledge regarding the functionality of the visual cortex cells of layers 2 and 3. Let $\vec{c}(t) = (x(t), y(t))$ a point on the curve.

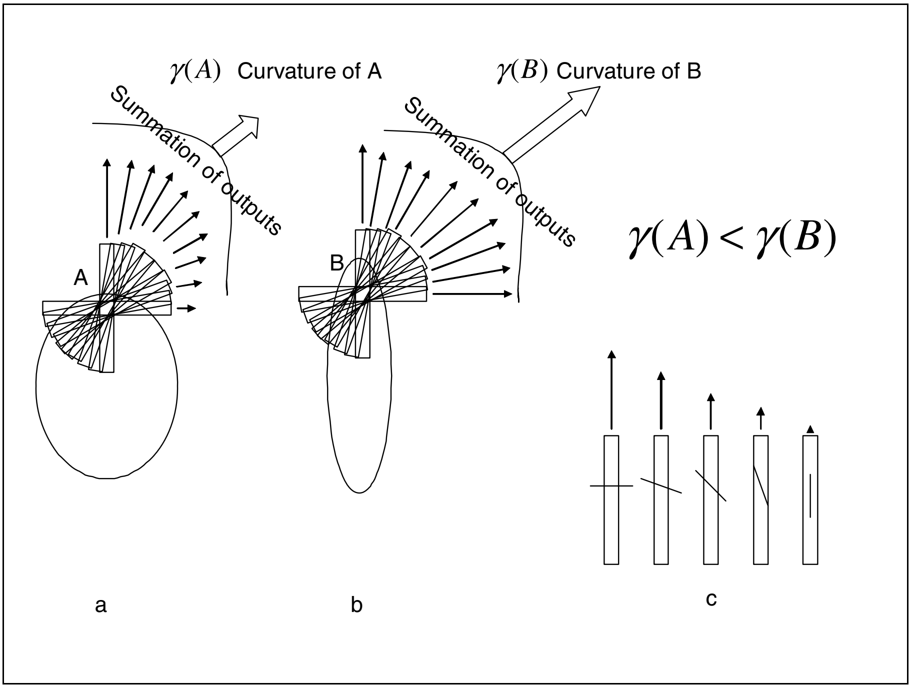

Fig. 1. Curvature detection by rotating an orientation selective receptive field. The curvature is proportional to the sum of the outputs of the rotated receptive fields. In (c) we see the orientation selective receptive field as a rectangular area and the respective outputs as arrows for several orientations from 0 to 90 degrees. The length of the arrow is proportional to the output strength for the given orientation. In (a) and (b) we illustrate the calculation of the curvature for two points A and B. In both cases the orientation selective receptive field is rotated form 0 to 90 degrees with step 10 degrees and the output for each step of rotation is proportional to the degree of the approximation of the curve on the direction permitted by the receptive field for this rotation. The outputs in case (b) will be stronger than the outputs in case (a) for most of the rotations since the change of the orientation of the receptive field approximates better the change of the direction of the tangent of the curve at the neighborhood of B.

If we rotate the axis this point will become $\vec{c}_R(t) = (x_R(t), y_R(t))$ where $x_R(t) = y(t)\cos(\theta) - x(t)\sin(\theta)$, $y_R(t) = y(t)\sin(\theta) + x(t)\cos(\theta)$ and θ the angle of rotation.

Let us look now at the second coordinate function $y_R(t)$. Its first derivative is $\dot{y}_R(t) = \dot{y}(t)\cos(\theta) - \dot{x}(t)\sin(\theta)$ and when it becomes zero we get

$$\dot{y}_R(t) = 0 \Leftrightarrow \dot{y}(t)\cos(\theta) - \dot{x}(t)\sin(\theta) = 0 \Leftrightarrow \dot{y}(t)\cos(\theta) = \dot{x}(t)\sin(\theta) \Leftrightarrow \tan(\theta) = \frac{\dot{y}(t)}{\dot{x}(t)} \quad (1)$$

This result is consistent to our intuition that the derivative of the second coordinate function at some point t becomes zero when the axis are rotated at an angle equal to the angle of the tangent to the curve at the point $\vec{c}(t)$. An orientation selective receptive field will emit the strongest output at this angle since the direction of the tangent best approximates the curve at this point. Now recall that the curvature at this point is defined as $\frac{d\theta}{ds}$, the rate of change of the angle of the tangent to the curve at the specific point per unit arc length. A rotation of the orientation selective receptive field corresponds to a step in tangent direction and arc length. If therefore we rotate the orientation selective receptive field and the respective neurons keep firing it means that we are still approximating the curve by being on the direction of the tangent even if we have moved by a unit of arc length. The more we keep approximating the curve by rotating the tangent direction and moving on the arc by a unit of length, the more is the curvature at the specific point and we can measure this curvature by accumulating the firings of all the layers, each layer corresponding to a rotation of the receptive field by 10 degrees. Just to illustrate the simplicity of the just described method we recall that in analytical terms the curvature is calculated as: $\frac{d\theta}{ds} = \frac{\frac{d\theta}{dt}}{\frac{ds}{dt}}$ where $\frac{d\theta}{dt}$ can be calculated by (1) where:

$$\tan(\theta(t)) = \frac{\dot{y}(t)}{\dot{x}(t)} \Leftrightarrow \theta(t) = \arctan\frac{\dot{y}(t)}{\dot{x}(t)} \Leftrightarrow \dot{\theta}(t) = \frac{\dot{x}(t)\ddot{y}(t) - \dot{y}(t)\ddot{x}(t)}{\left\|\dot{\vec{c}}(t)\right\|^2}$$

and $\frac{ds}{dt} = \left\|\dot{\vec{c}}(t)\right\|$ thus the curvature of the curve at the point $\vec{c}(t) = (x(t), y(t))$ is given by:

$$\gamma(t) = \frac{\dot{x}(t)\ddot{y}(t) - \ddot{x}(t)\dot{y}(t)}{\left\|\dot{\vec{c}}(t)\right\|^3} \quad (2)$$

We see that the analytical calculation of the curvature at each point on the curve involves the first and second derivatives of the coordinate functions but we manage to describe the calculation of the curvature of a planar curve through a series of operations that are consistent to our knowledge regarding the functionality of the cortical cells. In fact we explain that rotating an orientation selective two dimensional receptive field is the nature's suggestion for measuring the curvature at each of the points of a planar curve. In Fig. 1 we can see an orientation selective receptive field and its successive rotations in two scenarios of different curvatures. In the case of high curvature the field approximates better the direction of the tangent to the curve for several successive rotations.

We call each one of these rotations, a *view* from that angle of rotation. We call *interesting point*, a point on the contour at which the first derivative of $y_R(t)$ becomes zero. We call *strength* of an *interesting* point the curvature at this point. We call *landmark point,* an *interesting* point on the contour that has strength more than a given threshold S.

A *Landmark region* is made out of *interesting* points (on the contour) that fail to qualify as landmark points according to the definition above thus a landmark region is a collection of neighboring points on the contour that have strength less then S. The term landmark for the region can be justified if we think that quantity can compensate for quality. We call *width* of the landmark region the number of points included in the region.

Landmark points and regions partition the contour in a morphological meaningful way while at the same time they are defined through native quantitative methods. Notice that according to our definitions above the property of a point in being a landmark for the contours shape is defined through local measures. A higher layer in which landmark points and regions are combined to provide a global descriptor that depends on the contours whole shape is described in the extended version of this paper.

3.2 The Proposed Architecture

We propose a layered architecture as a visual pathway model for detecting landmark points of high curvature. The idea that we are going to implement here is the successive rotations of the orientation selective receptive field as was explained in the previous section.

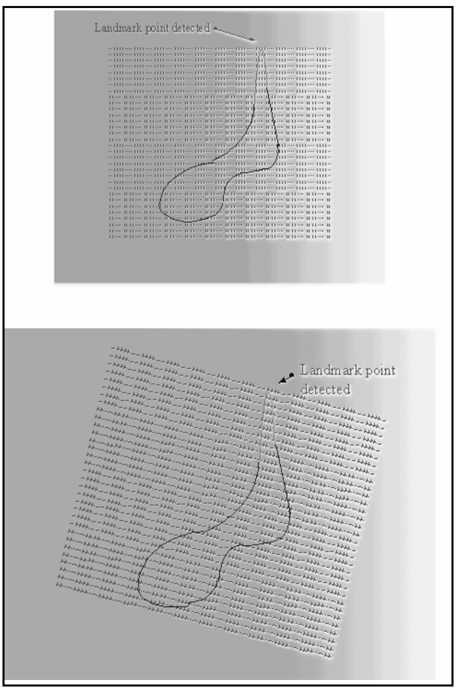

Fig. 2. The pictures above demonstrate landmark detection for the presented shape in two L1-sublayers. The same receptive field is rotated by 10° in the second image. The landmark point is detected in both the sub-layers, despite the rotation of the receptive field.

The lowest layer L0 is made out of perceptual units that we call L0-neurons and will play the role of the retinal photosensitive cells. These neurons receive the image intensity input and they become active on large intensity changes. We use these L0-neurons to detect the contour that outlines the shape of the presented object. The L0-neurons feed the inputs of the L1-neurons in layer 1.

The L1-layer is consisted of a pack of sub-layers. Every L0-neuron sends its output to the corresponding L1-neuron in each L1-sub-layer. We can imagine all the layers staggered and aligned and the connections are only across neurons that correspond to the same coordinates in their respective layers. An image containing a given random shape is captured through the sensitivity of the L0-neurons to the image's intensity differences. When a L0 neuron is adequately stimulated sends an active output to all the corresponding staggered neurons in layer L1, this way once an image is presented to layer L0 after a while all of the L1 sub-layers receive an active input from the L0 neurons that happened to be located on the boundary contour of the shape.

The L1-sublayers in our architecture act as directional oriented *interesting* point detectors. Recall that *landmark* points are *interesting* points above a threshold and they are defined through local shape characteristics of curvature. In this layer, we will detect the contour's landmark points of high curvature. Each L1-sublayer consists of neurons with the necessary receptive field to detect *interesting* points for a given orientation. The orientation bias of the receptive field of the neurons varies smoothly form L1-sublayer to the next and spans a complete angle of at least 90 degrees of rotation. Our L1-sublayers are the analogous to the hyper-columns of the human visual cortex [Hubel, 1981].

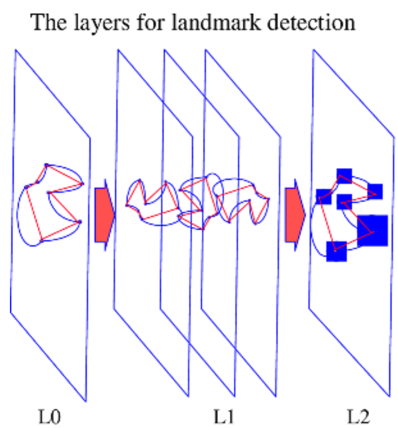

Fig. 3. The proposed layered architecture for extracting landmark points. The layers together with a graphical high level description are shown.

L1-neurons fire whenever an *interesting* point is present at their receptive field. The receptive field necessary to cause firing under *interesting* point conditions can be constructed by combining simple orientation specific receptive fields. The computational equivalent of this is a two dimensional filter with adjusted weights so as to penalize non horizontal straight segments. For the other directions the same receptive field rotated to the appropriate angle can be assumed. In figure 2 you can see a landmark-receptive field for two different L1-sublayers detecting *interesting* points on a given shape.

The same *interesting* point will cause firing in some L1 sub-layers but not in others, depending on the rotation of the receptive field of the layer's L1-neurons, but the bigger the strength of the *interesting* point is, the more are the L1-sublayers it will be visible from, where visibility of point A form layer B is defined as the fact of at least one neuron firing at sub-layer B because of the *interesting* edge point A.

The L2-cells receive the firings that were caused from contour's *interesting* points at layer L1. A strong *interesting* point will be *visible* after many consecutive rotation steps and will therefore cause a series of L1-firings in subsequent L1-sublayers that will drive the same L2-neuron. The magnitude, therefore of the input of an L2-neuron resembles the strength of the respective *interesting* point. Since every point is an *interesting* point from one view, the L2-layer will receive a *complete copy* of the contour but with different input magnitude for each point depending on the point's landmark potential. Morphological properties of the closed contour have been therefore transformed to equivalent differences in the stimulation of the L2-neurons, without loosing the spatial correspondence of the respective L0-neurons.

The functionality of the L2-neurons just described is consistent to the curvature detection observed in higher layer cortical neurons since it is clear that the magnitude of the input signal of the L2-neurons indicate *interesting* points of the analogous strength while the location of the landmark neurons describe the relative location of the landmark points on the contour.

Table 1. A landmark filter. It detects horizontal high curvatures on the boundary. The amount of locality that we accept for the formation depends on the size of the filter.

0	0	0	0	0
−4	−4	−4	−4	−4
−1	1	1	1	−1
−1	1	1	1	−1
1	1	−4	1	1

A landmark on the contour will cause firings in several consecutive L1-sublayers at the same location and therefore will accumulate a stronger stimulus to the respective L2-neuron. On the other hand a landmark region made of weaker points will cause many neighboring L2-neurons to receive weaker input. The wider the landmark region is the more neighboring L2-neurons will be stimulated because to its increased visibility at different neighboring locations across several rotations.

The task for the L2-layer is to collect the firings caused by the landmark points and regions on the contour and encode the shape from the strength of its landmark features. In figure 3 the layered architecture for curvature detection is illustrated graphically.

4 Experimental Results

We have described a biological inspired neural architecture that performs landmark point detection on the closed contour of an arbitrary shape. Here we demonstrate experimental results by using the above described methodology to detect points of high curvature.

The L0-layer that performs capturing and edge detection is trivial to implement with a capturing device and a direction-less edge detector, applied on the captured raster image. The resulting edge image plays the role of the signals sent from the L0-layer to all the L1-sublayers. The directional oriented, *interesting* and landmark point detection for each L1-sublayer corresponds to a filtering with the appropriately rotated landmark filter. A receptive field for the L2-neurons suitable to detect *interesting* points on the shape's boundary can be implemented by an actual digital filter that we call *landmark filter*. Instead of rotating the landmark filter, we equivalently use the same filter but rotate the edge image for each step. The result of the landmark detection for each step of rotation above corresponds to the task of a single L1-sublayer. These results, if superimposed, correspond to the Layer-L2 input coming from the L1-layer. In Figure 4 we use the landmark filter defined by the stencil shown in Table 1 to demonstrate the detection of a landmark point and its morphological strength, on a simple ellipsoidal shape.

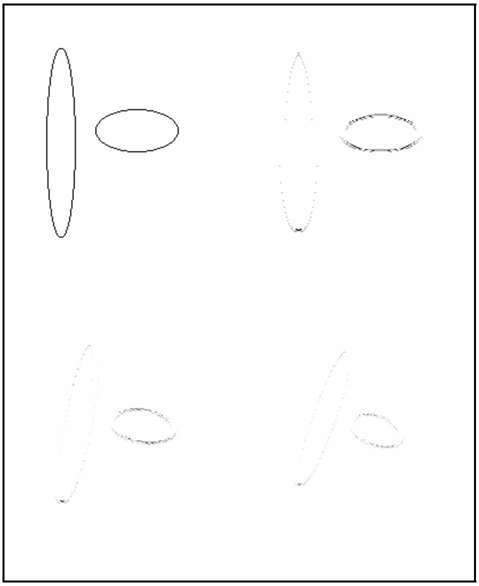

Fig. 4. In this picture we demonstrate the persistence of a landmark point to be detected by the landmark filter despite successive rotations of the image. In the upper left corner we have the original image of two ellipses that we want to detect the landmark points of their shape. The rest of the pictures correspond to the original image rotated by 0°,10°,20° respectively (left to right first) and filtered by the landmark filter that is defined in Table 1. We see that for this range of rotation the same strong landmark points of the left ellipsis are detected by the same filter in all the rotated images. On the other hand the detected points on the right ellipsis depend strongly on the rotation of the image a fact that indicates their low landmark potential.

By super-positioning the interesting point images we accumulate the strength of these points in the intensities of a single image. Points with high intensity values correspond to morphological significant (landmark) points on the contour where clusters of points of low intensity correspond to regions that connect the landmark points. A ranking therefore of the contour points according to their intensity at this stage, corresponds to their morphological significance on the contour.

A significant contribution in our approach of measuring and detecting curvature is that it can be performed with rotated filters on a single image simultaneously and in parallel, therefore the curvature detection can be performed in just the time it takes to filter a single curve image, assuming that the superposition of the filtering results happens instantly.

Further treatment regarding shape recognition and classification is not the intention of this paper but it is apparent that our representation not only abides to the physical and psychological discoveries regarding the perceptional tasks in primates but also presents a feature extraction technique that combined with standard computational techniques leads to state of the art performance and recognition capability.

5 Conclusion

We have offered an explanation regarding the rotated orientation selective receptive fields of the cortical neurons in layers 2 and 3 of the visual cortex of primates that were first discovered by Hubel and Wiesel. We have shown that by means of this specific arrangement of neurons it is possible to perform detection of landmark points of high curvature. We appreciated the completeness and performance superiority of our approach compared to other curvature detection methods since our model provides the fastest possible mechanism for curvature measurement of planar curves.

References

[Asada, 1986] H. Asada and M. Brady, “The curvature primal sketch,” IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 1, pp. 2–14, Jan. 1986.

[Attneave, 1954] F. Attneave, “Some informational aspects of visual perception,” Psychol. Rev., vol. 61, pp. 183–193, 1954.

[Berreti, 2000] Stefano Berretti, Alberto Del Bimbo and Pietro Pala, “Retrieval by Shape Similarity with Perceptual Distance and Effective Indexing”, IEEE Trans on Multimedia, vol. 2, no. 4, pp. 225-239, Dec. 2000.

[Biederman, 1987] Biederman, I. (1987). Recognition-by-Components: A Theory of Human Image Understanding. Psychological Review, 94, 115-147.

[Bookstein, 1996] F.L. Bookstein. Landmark methods for forms without landmarks: morphometrics of group differences in outline shape. Med. Im. Anal., 1(3):225–243, 1996.

[Brenner, 1996] Brenner, E. & Smeets, J.B.J. (1996). Size illusion influences how we lift but not how we grasp an object. Experimental Brain Research, 111, 473-476.

[Dudek, 1997] G. Dudek and J. K. Tsotsos, “Shape representation and recognition from multiscale curvature,” Comput. Vis. Image Understand., vol. 68, pp. 170–189, 1997.

[Drigas, 2005] S. Drigas, G. Koukianakis and V. Papagerasimou, “A System For Hybrid Learning And Hybrid Psychology”, 2nd International Conference on Cybernetics and Information Technologies, Systems and Applications: CITSA 2005, Orlando, Florida..

[Fukushima, 1982] K. Fukushima, S. Miyake: "Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition", Competition and Cooperation in Neural Nets, Lecture Notes in Biomathematics 45, eds.: S. Amari, M. A. Arbib, pp. 267-285, Berlin, Heidelberg, New York: Springer-Verlag (1982).

[Goodale, 1994] Goodale, M.A., Meenan, J.P., Buelthoff, H.H., Nicolle, D.A., Murphy, K.J., & Racicot, C.I. (1994b). Separate neural pathways for the visual analysis of object shape in perception and prehension. Current Biol., 4, 604-610.

[Goodale 1991] Goodale, M.A., Milner, A.D., Jakobson, L.S., & Carey, D.P. (1991). A neurological dissociation between perceiving objects and grasping them. Nature, 349, 154-156.

[Hubel, 1981] David H. Hubel, Evolution of ideas on the primary visual cortex, 1955-1978: A biased historical account, Nobel lecture, 8 December 1981, Harvard Medical School, Department of Neurobiology, Boston, Massachusetts, U.S.A., Nature, 299:515-524.

[Hubel D.H, Wiesel T., 1990] Brain mechanisms of vision, In I. Rock (ed.) The Perceptual world , pp. 3-24. W. H. Freeman NY.

[Hubel D.H, Wiesel T., 1968] Receptive fields and functional architecture of monkey striate cortex, J. Physiol., 195:215-243.

[Hubel D.H, Wiesel T.N., Stryker M. 1978] Anatomical demonstration of orientation columns in macaque monkey, J. Comp. Neurol., 177:361-380.

[Jalba, 2006] Andrei C. Jalba, Michael H. F. Wilkinson, Jos B. T. M. Roerdink, “Shape Representation and Recognition Through Morphological Curvature Scale Spaces” IEEE Trans. Image Proc., vol. 15, no. 2,pp. 331-341 ,Feb. 2006.

[Kayaert, 2003] Greet Kayaert, Irving Biederman and Rufin Vogels, “Shape Tuning in Macaque Inferior Temporal Cortex”, the Journal of Neuroscience, April 1, 2003 • 23(7), pp. 3016 –3027.

[Milner, 1993] Milner, A.D. & Goodale, M.A. (1993). Visual pathways to perception and action. In T.P. Hicks, S. Molotchnikoff & T. Ono (Eds.) Progress in Brain Research, Vol. 95 (pp. 317-337). Amsterdam: Elsevier.

[Mokhtarian, 1986] F. Mokhtarian and A. K. Mackworth, “Scale-based description and recognition of planar curves and two-dimensional shapes,” IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 1, pp. 34–43, Jan. 1986.

[Mokharian, 1992] , “A theory of multiscale, curvature-based shape representation for planar curves,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 14, no. 6, pp. 789–805, Jun. 1992.

[Pomerantz, 1977] J. R. Pomerantz, L. C. Sager, and R. J. Stoever, “Perception of wholes and their component parts: Some configural superiority effects,” J. Exp. Psychol., vol. 3, pp. 422–435, 1977.

[Pavlidis, 1980] T. Pavlidis, “Algorithms for shape analysis of contours and waveforms,” IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-2, no. 3, pp. 301–312, Mar. 1980.

[Shams, 1997] Soheil Shams, "Affine Invariant Object Recognition through Self Organization", Hughes Research Laboratories, 1997.

[Super, 2004] B.J Super. Fast correspondence-based system for shape-retrieval. Patt. Recog. Lett., 25:217–225, 2004.

[Ungerleider, 1998] L. G. Ungerleider, S. M. Courtney and J. V. Haxby, “A neural system for human visual working memory”, Proc. Natl. Acad. Sci. USA, vol. 95, pp. 883–890, Feb. 1998.

[Wang, 1999] S. L. Y.-P. Wang and K. T. Lee, “Multiscale curvature based shape representtation using b-spline wavelets,” IEEE Trans. Image Process., vol. 8, no. 10, pp. 1586–1592, Oct. 1999.