The Contour Specialization of Cyvis-I: An Effective Framework for Intermediate Visual Representation

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Abstract. This paper reports on how the determination of comprehensive visual representations has been allowed by a novel approach to digital orientation and curvature estimation. The reported approach is strongly supported on solid concepts from differential geometry and can be effectively implemented by using the Fourier transform and its inverse. The developed framework allows not only multiple important representations of the image contours to be obtained, but also effectively supports multiscale operation, that is allowed through selective low-pass Gaussian filtering. The overall computational effort is proportional to O(N.Log(N)). Experimental examples are included that substantiate the potential of the described approach respectively to a real image.

1 Introduction - Back to Nature

That vision is an activity much more complex than typically acknowledged by us humans is promptly verified by whoever starts working toward the development and implementation of powerful and versatile computer vision systems. However, there is virtually no doubt that such systems are possible, as it has been proved by so many biological visual systems, and especially the primate visual system, that have been presenting outstanding real-time performance under the most demanding and difficult conditions. It should thus be hardly surprising that insights from nature provide one of the most promising subsidies for the development of more versatile and powerful artificial visual systems. Such an interplay between natural and artificial vision has been the principal underlying philosophy adopted by the Cybernetic Vision Research Group at the IFSC-USP [Costa (1993); Costa *et al.* (1994)]. One of the projects that have been developed in this group consists of a biologically-inspired versatile computer vision system, called Cyvis-1 [Costa *et al.* (1994)]. Based on a series of biological insights, Cyvis-1 includes a series of processing streams dedicated to the analysis of some specific image attribute such as color, texture and edges. Each of these specialized streams possesses a modular and hierarchical architecture, communicating actively with the other streams in order to improve visual analysis performance [Costa (1994)]. A particular important aspect of Cyvis-1, as well as in many other approaches to computer vision, concerns how the visual information is encoded and represented at each of its hierarchical levels. By the way, one of the most important lessons nature has to teach us with respect to the design of more powerful vision systems concerns the adoption of effective visual representations of the visual scenes to be analyzed. By reducing the redundancy that is typical in real images, such representations allow a substantially more compacted codification of the original visual stimulus, thus allowing the recognition processes to proceed faster and more effectively [Barlow (1994)]. It should be however observed that compactness is only one of the requirements that should be conciliated by adequate representational frameworks. Another exceedingly important issue concerns the meaningfulness provided by the representation, for such a feature greatly influences the design of better and more effective recognition algorithms. Although the choice of a suitable representation framework should generally be made considering the characteristics of the recognition algorithms and scenes to be processed, nature again has an important lesson to teach us. It is a well-known fact that the mammals' retina implements some kind of edge-detection of the boundaries of contrasting objects in the original scene, thus contributing to a drastic reduction of the amount of visual data [Barlow (1994); Marr (1982)]. What is more, such clear and conceptually meaningful representations of the image objects in terms of their contours has been acknowledged to encode great part, if not the whole, of the original visual information [Marr (1982)]. The next important representation scheme adopted at the cortical level of the primate visual system is characterized by the piecewise linear representation of the contours. Such a representation provides not only a further degree of compactness of the visual information, which is achieved by representing straight sections of the edge-detected image in terms of the respective line parameters (e.g. orientation and position), but also provides the basic structure from which more sophisticated representations in terms of curvature can be derived. It is important to note that (from the perspective of the neurophysiological point of view) there are controversies about the existence of 'curvature detectors' in human vision system [Guez *et al.* (1994); Haan (1995)] while the extraction of orientation information is somewhat more accepted [Zucker (1985); Blasdel & Salama (1986)]. Therefore, it would be desirable to develop a model that could estimates the curvature from the orientation information. These latter representational frameworks possess a solid mathematical embasement and presents paramount importance as a means of effective shape characterization. The power of shape analysis through curvature can be illustrated by the fact that circles and straight lines can be identified by searching for contour sections presenting constant curvature. Moreover, curvature is rotation and translation invariant, and orientation can successfully support scale invariance with minimum additional effort by normalizing the ordinate-axis. At a higher abstraction level we have the complementary representations provided by the first and second derivatives of the curvature parametric function, as well as its power and phase spectra. Such additional representations provide a wealth of useful information that can be used for segmentation and detection purposes. For instance, the first and second derivatives can be used as a means to detect critical contour segmentation points. The spectra can supply subsidies for texture characterization.

This paper presents a framework that matches all these requirements. The major representation elements such as orientation and curvature are implemented based on the solid background of Differential Geometry. The digital implementation of these concepts is done by signal processing techniques. One particular problem in extending Differential Geometry concepts to digital implementations conserns the spatially sample nature of the latter. This problem has been circumvented through the use of the Derivative Theorem of the Fourier Transform (FT) and the Gaussian low-pass filtering scheme.

The hierarchy and interdependency between the various representational structures discussed above is summarized in Figure 1. Provided a computer vision system is capable of effectively deriving all such representations according to a multiscale fashion, shape analysis and recognition can be substantially eased and made more effective. The principal problem that has constrained such a comprehensive approach consists in the fact that accurate curvature estimation has been an exceedingly difficult endeavor [Cesar & Lotufo (1993); Worring and Smeulders (1993)], which has been characterized by errors ranging from 1% to 1000%. By developing a sound technique for curvature estimation, which is based on signal processing techniques [Cesar & Costa (1995)], we have been able to implement an accurate and effective framework for estimating orientation and curvature, as well as their derivatives and spectra of these. Another important issue concerning visual representations consists in the fact that it is desirable to have reversible representations in order to reduce the complexity and storage requirements respectively to the many databases that have to be implemented at the various hierarchical levels of a computer vision system such as the Cyvis-1 [Costa *et al.* (1994)].

This paper starts by describing our approach to estimate the derivatives of digital curves (outlined in [Cesar & Costa (1995)]) as well as its extension in order to provide a direct link between orientation and curvature. The application potential of the thus obtained framework is then exemplified respectively to a real contour.

2 Tangent Orientation and the Fourier Transform

The approach adopted in this work uses the basic concepts of differential geometry applied to planar curves. The tangent orientation of a curve is defined as follows. Let $C(t)=(x(t),y(t))$, $t\in [a,b]$, be a planar curve represented in the parametric form. The curve $C(t)$ is said to be differentiable if $x(t)$ and $y(t)$ are differentiable with respect to the parameter t [Stoker (1969)]. The derivative of the curve $C(t)$, denoted by $C'(t)$ is defined as:

$$C'(t)=\frac{dC(t)}{dt}=(x',y') \qquad (1)$$

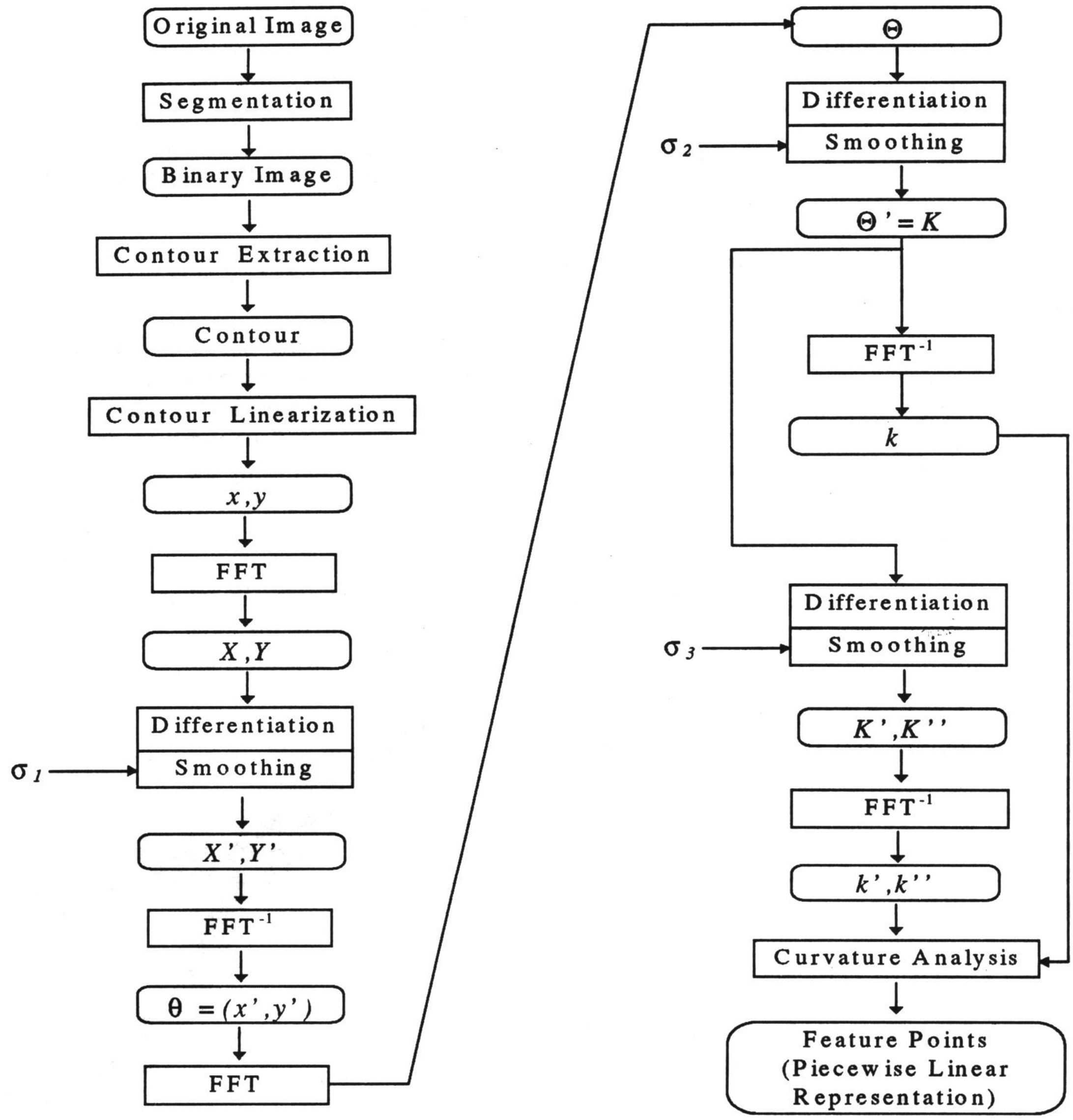

Figure 1: The processes (rectangles) and representations (round corner boxes) in the proposed framework.

where

$$x' = x'(t) = \frac{dx}{dt} \qquad y' = y'(t) = \frac{dy}{dt} \quad (2)$$

The vector $C'(t)$ applied to the point $t_0 \in [a,b]$ i.e. $C'(t_0)$ is located at the origin and has its direction parallel to the tangent line of $C(t_0)$. The tangent vector function $\phi(t)$ of the curve $C(t)$ is obtained by locating the vectors $C'(t)$ at the respective points on the curve $C(t)$ (in other words, by a parallel translation of vector $C'(t)$). The function $\phi(t)$ defines a field vector over the curve $C(t)$, which can be used for research involving orientation [Zucker (1985)]. Because of computational reasons, the calculus of the derivatives of $x(t)$ and $y(t)$ is unfortunately no easy endeavor, for the analytic expressions of these signals are rarely known. Furthermore the noise present in contours obtained from real images can seriously corrupt the results, since the differential operation can enhance the signal high frequency components. The solution proposed in this work for the calculation of $x'(t)$ and $y'(t)$ consists in using a differentiation scheme based on the derivative property of the Fourier Transform [Cesar & Costa (1995)]. To avoid the noise enhancement that would otherwise be introduced, the differentiation is carried out jointly with smoothing, which is accomplished through Gaussian low-pass filter. Let $X(s)$ and $Y(s)$ be the Fourier Transform of the signals $x(t)$ and $y(t)$

respectively. Denoting the FT of $x'(t)$ and $y'(t)$ by $X'(t)$ and $Y'(t)$, it can be shown that [Castleman (1979)]:

$$x'(t) = F^{-1}\{X'(s)\} = F^{-1}\{i2\pi\ sX(s)\} \quad (3)$$

$$y'(t) = F^{-1}\{Y'(s)\} = F^{-1}\{i2\pi\ sY(s)\} \quad (4)$$

where $F^{-1}\{\}$ stands for the Inverse Fourier Transform (IFT). The smoothing is done by defining the Transfer Function $G(s)$ of the low-pass filter as:

$$G(s) = \frac{1}{\sigma\sqrt{2\pi}} exp(\frac{-s^2}{2\sigma^2}) \quad (5)$$

As mentioned, the earlier filter is defined by a Gaussian of standard deviation σ. The filtered spectra $X_f(s)$ and $Y_f(s)$ can be calculated as:

$$X_f(s) = G(s)X(s) \quad (6)$$

$$Y_f(s) = G(s)Y(s) \quad (7)$$

and the smoothed derivatives of $x(t)$ and $y(t)$ can be obtained by substituting $X(s)$ and $Y(s)$ in Equations 3 and 4 by $X_f(s)$ and $Y_f(s)$ (Equations 6 and 7). The resulting expressions can be used to calculate function $\phi(t)$. Once the function $\phi(t)$ is specified in terms of the FT, the tangent orientation of a curve can be defined as follows [Stoker (1969)].

DEFINITION 1 (*Tangent Orientation of a curve*): Let $C(t)=(x(t),y(t))$ be a parametrized curve of the parameter $t\in [a,b]$, and let $\phi(t)$ be the tangent vector function of the curve C. The tangent orientation $\theta(t)$ of the curve $C(t)$ at a point $t_0\in [a,b]$ is defined to be the angle between the vector $\phi(t_0)$ and the X-axis.

The tangent orientation of a curve has already been used in shape representation and recognition [Marshall (1989); Gonzalez & Wintz (1987)] and is a useful tool in many Computer Vision tasks. The next section shows how the tangent orientation can be used as a subsidy for curvature evaluation.

3 Digital Curvature Evaluation

The curvature of a contour is one of the most important concepts in shape analysis, both from the human and machine vision perspectives [Attneave (1954); Pavlidis (1977)]. From the literature in Differential Geometry it is known that the curvature can be calculated from the tangent orientation of a curve, as expressed by the following definition.

DEFINITION 2 (*Curvature of a curve*): Let $C(t)=(x(t),y(t))$ be a parametrized curve of the parameter $t\in [a,b]$, and let $\theta(t)$ be the tangent orientation of $C(t)$, as was defined in definition 1. Then, the curvature $k(t)$ of the curve $C(t)$ can be defined as the first derivative of the tangent orientation $\theta(t)$, i.e.:

$$k(t) = \theta'(t) \quad (8)$$

Although the above definition of curvature depends on the arc length parametrization of the curve, it has led to good practical results, as illustrated in Section 4. Equation 8 provides an analytical tool for curvature evaluation using the tangent orientation of a curve. However, this expression also depends on the differentiation of a function whose analytical form is unknown. Further, as it was explained in Section 2, the differentiation process can enhance the noise added by the discrete nature of the input. The procedure to solve these problems is analogous to that explained in

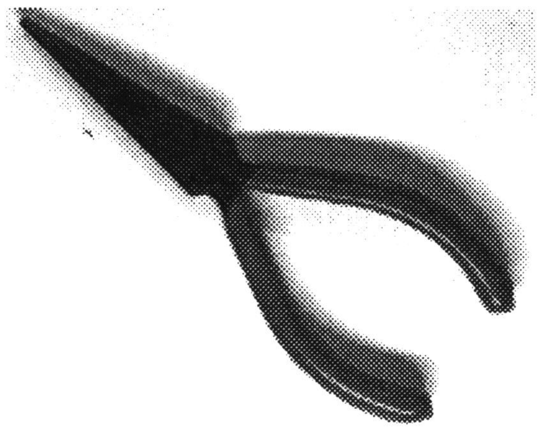

Figure 2: Original image

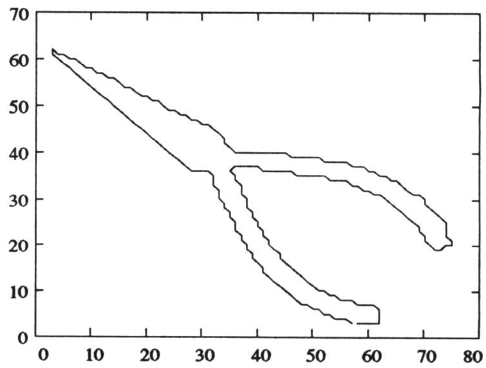

Figure 3: Contour

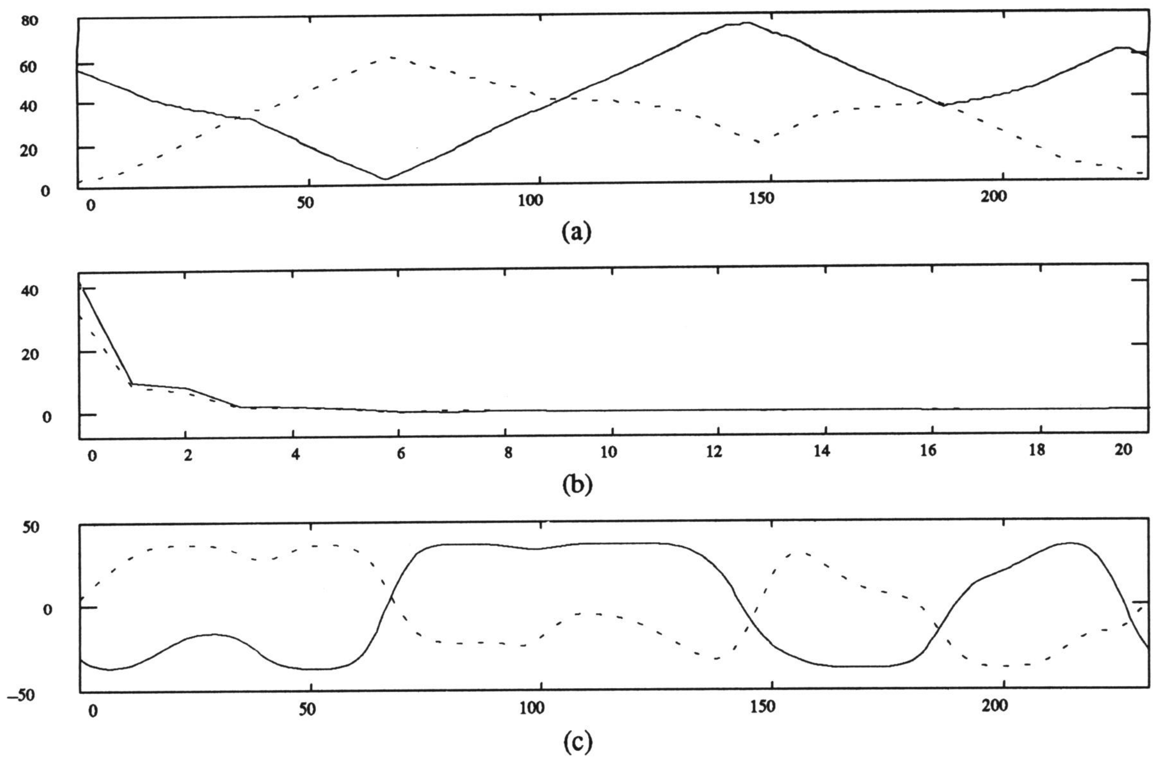

Figure 4: Signals x (solid) and y (dash) (a) , their respective Fourier Magnitude (b) and derivatives (c).

Section 2, i.e. by using the derivative property of the FT jointly with Gaussian low-pass filtering. Let $\Theta(t)$ be the FT of the tangent orientation $\theta(t)$. By using the Derivative Theorem (Section 2) the derivative $\theta'(t)$ can be evaluated as given by expression 9:

$$\theta'(t) = F^{-1}\{\Theta'(s)\} \qquad (9)$$

Equation 9 can be substituted in equation 8 to yield the final curvature expression given below.

$$k(t) = F^{-1}\{\Theta'(s)\} \qquad (10)$$

It should be finally observed that the overall described framework presents a computational demand of $O(N.Log(N))$, which is determined by the Fast Fourier Transform and its inverse. The next section illustrate the performance of these tools in experimental situations.

4 Experimental Results

This section illustrates the representations developed in Sections 2 and 3 with respect to a contour of a tool (pliers). Figure 2 shows the original image as acquired by a conventional camera. The image was captured under non-uniform illumination, which led to a noisy contour after the pre-processing steps (i.e. thresholding and median filtering). Figure 3 shows the contour extracted from the original picture. This contour, which has been poorly sampled (231 points), has led to good results as shown in the rest of this section. Figure 4(a) presents the signals x and y linearized from the contour of Figure 3. These signals were obtained by following the contour in a clockwise manner from the starting point located at the discontinuity of the contour. The magnitude $|X|$ and $|Y|$ of the FT of signals x and y are presented in figure 4(b). The latter presents only the first 20 harmonics, since the remaining components vanish rapidly. The derivatives of signals x and y are obtained by using the differentiation method presented in Section 2 are presented in Figure 4(c). Note that although the differentiation enhances the high frequencies of the signals, the resulted x' and y' are smoothed due to the Gaussian low-pass filtering.

The tangent orientation of the pliers contour is obtained using Def. 1 and showed in figure 5(a). The abrupt change of the tangent orientation corresponds to the extremity of the pliers. Figure 5(b) shows the curvature signal (absolute value) of the pliers which was calculated by using Def. 2. The largest peak of

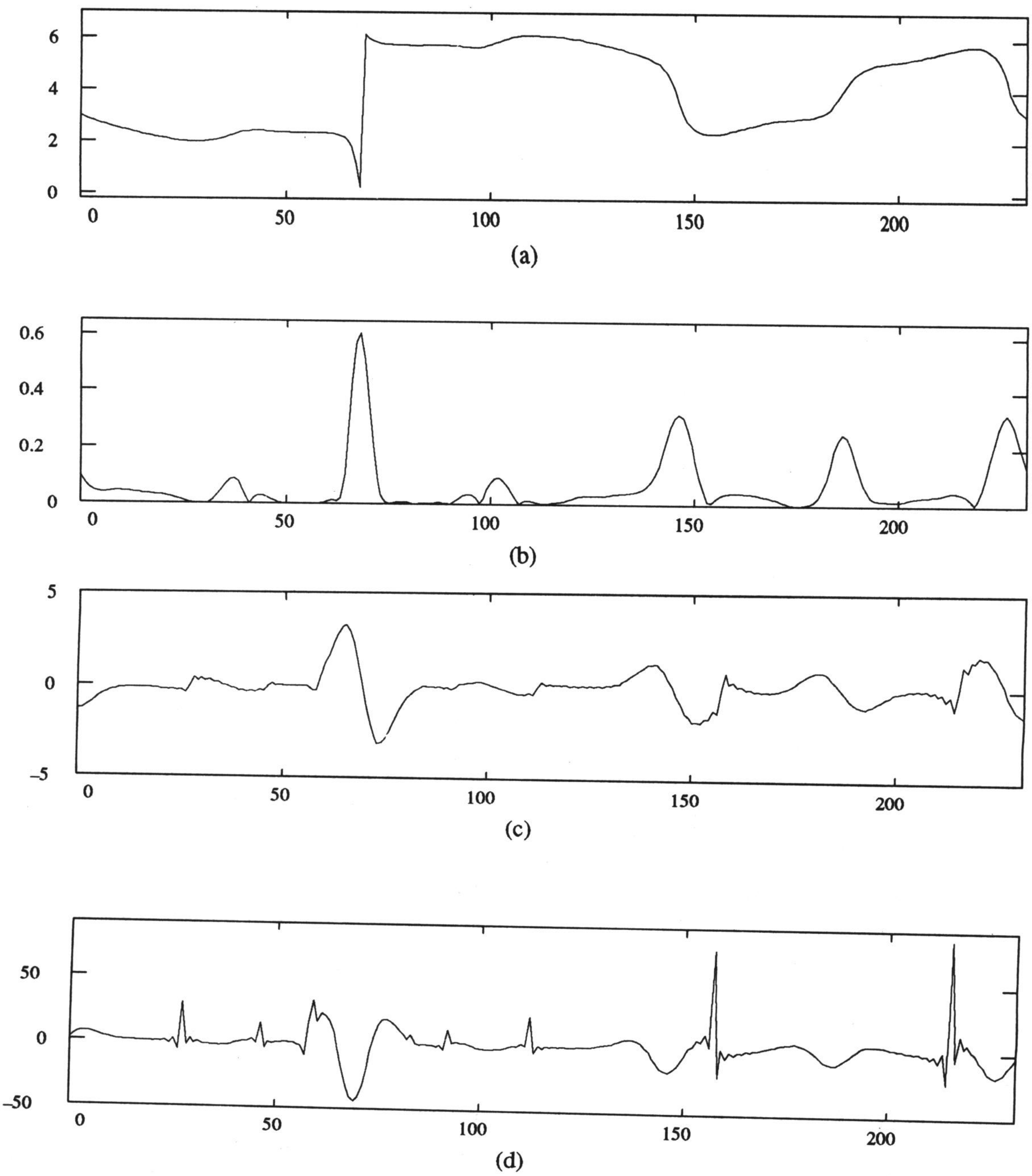

Figure 5: Tangent orientation (a) of the contour (Fig.3), curvature (b) and its first (c) and second (d) derivatives.

this signal corresponds to the steep change in the tangent orientation function.

In order to obtain the points of maxima curvature (absolute value), this signal was differentiated twice to obtain k' (figure 5(c)) and k'' (figure 5(d)). The feature points are identified by the application of the three following criteria: the point must be a zero-crossing of k'; it must have $k''<0$; and finally it must have $k > T$, i.e. the curvature at that point must exceed a given threshold T. This last condition is necessary for the elimination of the false maxima curvature points created by unwanted oscillation near the x-axis baseline. The points of maxima curvature are marked as bars and showed in Figure 6. The calculated feature points (piecewise linear representation) are presented in Figure 7. These points were marked over the smoothed reconstructed version of the original contour, by using the IFT of the low-pass filtered spectra X_f and Y_f (Equations 6 and 7). In this example it was assumed that the standard deviation σ = *8* and that *T=0.03*. Figure 8 shows the feature points for σ = *16* and *T= 0.015*. These points

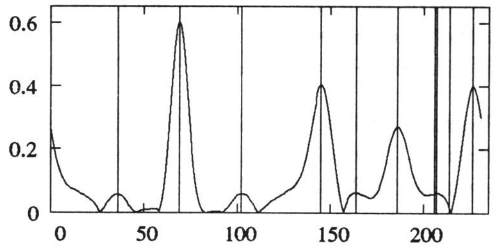

Figure 6: Curvature maxima

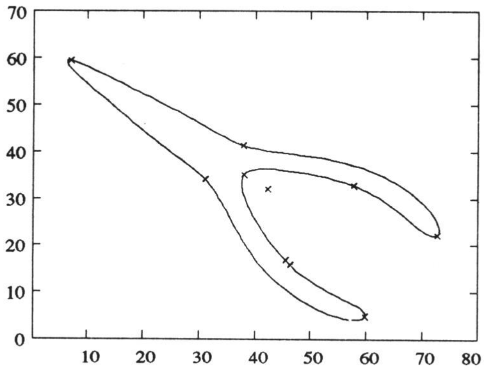

Figure 7: Feature points *(σ=8, T=0.03)*.

were marked over the smoothed reconstructed version of the original contour, by using the IFT of the low-pass filtered spectra X_f and Y_f (Equations 6 and 7). In this example it was assumed that the standard deviation σ = *8* and the *T=0.03*. Figure 8 shows the feature points for σ = *16* and *T=0.015*. The central point (marked with an 'x' shows the center of mass of the contour).

5-Concluding Remarks and Future Work

A framework capable of effectively providing a comprehensive set of visual representations has been described and exemplified with respect to a real image. Although presenting potential for applications on its own, the described framework has been conceived as a major part of Cyvis-1, a biologically-inspired versatile computer vision system that is under development at the Cybernetic Vision Research Group, IFSC-USP. By using effective and fast algorithms from digital signal processing, the reported framework is capable of producing a wealth of visual representations from the digital contours of the objects in the image, including the linearized contours (x and y), the respective Fourier descriptors, the first and second derivatives of x and y, the contour orientation and curvature, as well as the first and second derivatives and spectra of the latter. Such diverse representations provide a rich background

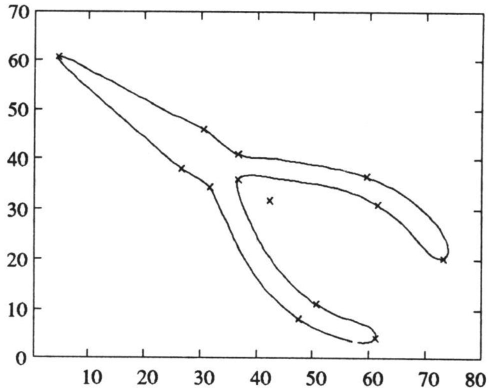

Figure 8: Feature points *(σ=16, T=0.015)*.

upon which effective and versatile image analysis systems can be built upon. When considered jointly with the its first and second derivatives, the contour curvature provides an important subsidy for piecewise linear contour segmentation. What is more, by adopting as its major building block the Fourier transform and its inverse, the proposed framework has proven to be especially suitable for multiscale processing, as allowed by selective low-pass filtering through Gaussian blurring. Further efforts are being currently conducted towards investigating the effects of the adopted parametric representation as well as applying the reported tools in order to conduct more comprehensive and accurate psychophysical experiments in humans.

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