Definition of a model-based detector of curvilinear regions

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Abstract. This paper describes a new approach for detection of curvilinear regions. These features detection can be useful for any matching based algorithm such as stereoscopic vision. Our detector is based on curvilinear structure model, defined observing the real world. Then, we propose a multi-scale search algorithm of curvilinear regions and we report some preliminary results.

Introduction

Detecting specific features has been shown to be useful in many computer vision applications such as stereoscopic vision [1, 2] or object recognition [3], image retrieval [4]. A number of feature detectors [1, 2, 5-9] have been proposed in the literature. As these detectors can be combined in order to improve the recognition performances, it can be useful to add new features.

We propose in this paper to define a new model of such features, based on the extraction of curvilinear regions, often simply named: line extraction. There are a huge number of application fields where curvilinear structures extraction is used. In photogrammetic and remote sensing tasks, it is used to extract roads, railroads or rivers from satellite or low-resolution aerial imagery [10-12], which can be used for the capture or update of data for geographic information systems. Moreover, it is useful in medical imaging for the extraction of anatomical features or simply for the segmentation of medical images from CT or MR devices [13-15].

A few models [12, 14, 16-18] have been described for curvilinear structures detection, often application specific (for roads, vessels). Our aim is to define here a superset of these models, which can be used in the general case of object recognition allowing building an affine-invariant detector.

Steger [18] classified previous work in curvilinear detection into three families. The first approach detects lines by considering the gray values of the image only and uses purely local criteria. The second approach regards lines as object having parallel edges. The last family is to regard the image as a function Z(x,y) and extract lines from it by using differential geometric properties. The basic idea behind these algorithms is to locate the positions of ridges and ravines in the image function.

Steger described in his paper an explicit model for lines and line profile models. A scale space analysis is carried out for each of the models. This analysis is used to derive an algorithm in which lines and their widths can be extracted with subpixel accuracy. The algorithm uses a modification of the differential approach to detect lines and their corresponding edges.

In this paper, we propose an extension of Steger’s model, which allows detecting lines using all criteria of three families described above. Observing the real world, we give in the first section the definition of the curvilinear structure. The section 2 presents the detector which can be seen as a minimization problem. The components of the cost function are detailed. Using the approach of Steger, we defined two main steps of detection: the profile detection and the whole curvilinear structure detection. The main new criteria we introduce are texture attributes inside and around the shape, and information about line profile symmetry and local curvature. In the last section, we present some results concerning the profile detection and some preliminary results concerning the whole detector.

Curvilinear structure definition

Geometry

We could define a curvilinear region as a set of pixels delimited by left and right boundaries $\vec{l}(t)$ and $\vec{r}(t)$. In the continuous case, it can be defined by $\{\vec{a}(t), w(t)\}$ as shown by fig. 1. In the discrete case, it can be defined by the following set: $c = \{(\vec{a}_i, w_i), i = 0,\cdots,L\}$ where L is the length of the curvilinear region,

$\vec{a}(t)$ is a vector defining the axis between the boundaries: $\vec{a}(t) = \frac{\vec{l}(t) + \vec{r}(t)}{2}$

and $w(t) = \left\|\vec{l}(t) - \vec{r}(t)\right\|$.

Appearance

On a 1D view a curvilinear region could be defined by $\vec{v}(t)$ (the “crossection”) is the vector of pixel values on a linear segment centered at and to $\vec{a}'(t)$ and of length $w(t)$. $\vec{v}_l(t)$ (resp. $\vec{v}_r(t)$) is the vector of pixel values on a linear segment perpendicular to $\vec{a}'(t)$, and of length $k(t)$, with $k(t) < w(t)$.

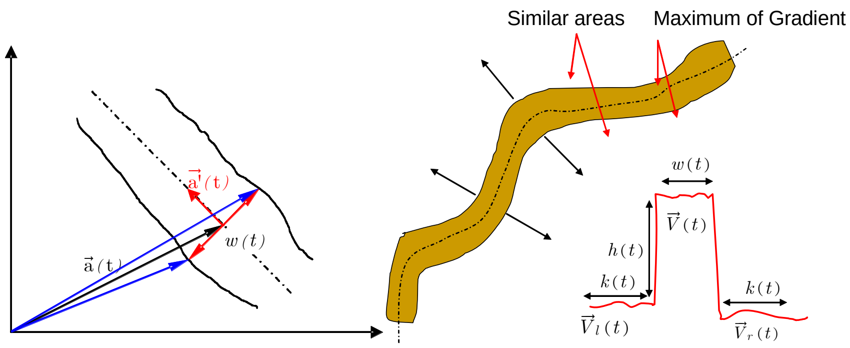

Fig. 1. Geometric and appearance attributes

Detection of lines in 1D

The problem of curvilinear detection using the previous model can be posed as a minimization problem, defining a cost function for which it is necessary to find a local minimum for over the space of all $\vec{a}, w$. We could then define the following cost function: $J(I, \vec{a}(t), w(t))$

where : I is the input image. The output will be a set S of N curvilinear regions defined by:

$S = \{c_j, j = 0,\ldots,N\}$, and $c_j = \{(\overrightarrow{a_{ij}}, w_{ij}), i = 0,\ldots,L_j\}$,

where L_j is the length of the j^{th} of the curvilinear region.

Cost function components

Our cost function is composed by different constraints, chosen using some observations of real pictures (Fig . 2). Observing a 1D profil (Fig. 3) we could see that a curvilinear structure has a high difference between the exterior (left and right) of the region and the “crossection”. This constraint can be defined as follow:

$$\left[1-m\left(\vec{V},\vec{V}_l\right)\right]\left[1-m\left(\vec{V},\vec{V}_r\right)\right]\approx 0,$$

where m is for example the normalized Euclidian distance computed in Fourier space, defined by :

$$m(f_l(t), f_r(t)) = \frac{\sqrt{\sum_u \left(\left|\hat{f}_l(u)\right| - \left|\hat{f}_r(u)\right|\right)^2}}{m_{\max}}$$

This distance allows taking the local texture into account. Another simplified distance could be the normalized module of luminance gradient.

Considering the value of left and right side should be similar that satisfied the following relation:

$$m\left(\vec{V}_l,\vec{V}_r\right)\approx 0$$

Moreover, we can observe (Fig. 2 and Fig. 3) that the texture in the crossection is constant along the curvilinear region and defined by :

$$m\left(\vec{V}(t),\vec{V}(t+dt)\right)\approx 0$$

Observing 2D signal (Fig. 3), we could add some 2D constraints on width and curvature: the width of curvilinear region is constant along the axis, implying:

$$\frac{dw(t)}{dt}\approx 0$$

Moreover the local curvature $\gamma(t)$ should be also constant along the axis, and the boundaries are locally parallel and symmetric about the central axis :

$$\frac{d\gamma(t)}{dt}\approx 0 \text{ and } \frac{d\vec{r}(t)}{dt}\approx\frac{d\vec{l}(t)}{dt}.$$

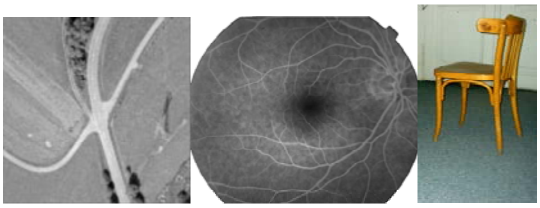

Fig. 2. Example of images containing curvilinear regions

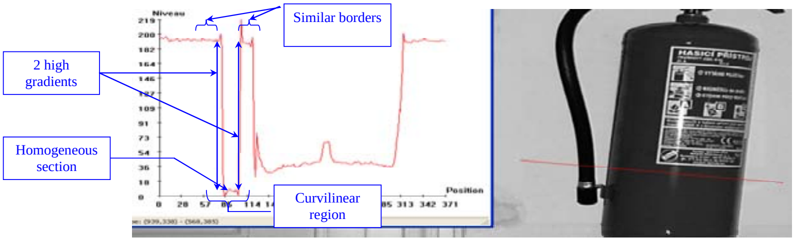

Fig. 3. Observations on 1D section

1D search algorithm

Along the 1D profile of length i_{max}, we have to minimize Q:

$$Q=1-\left(m\left(\vec{V},\vec{V}_l\right)m\left(\vec{V},\vec{V}_r\right)\left(1-m\left(\vec{V}_l,\vec{V}_r\right)\right)\right) \tag{1}$$

Since we want to detect the crossection for different scales, we have to compute Q for all the possible widths of crossection. In the case that there is only one curvilinear crossection along the profile, the pseudo code of the multi-scale algorithm work as follows:

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❖ For $i_1$=0 to $i_{max}$
  ➢ For $i_2=i_1+\Delta$ to $i_{max}$
    ▪ Compute FFT on left and right vectors of width Δ near $i_1$
      and $i_2$.
    ▪ Compute the complex distances in Fourier space.
    ▪ Normalize distances.
  ➢ Compute $Q(i_1,i_2)$ according eq. 1.
❖ Find minimum: $Q_{min}(Ia)=\min(Q(i_1,i_2))$ for i2 : i1 -> $i_{max}$ and for i1
  : 0 -> $i_{max}$ with $Ia=(i_1+i_2)/2$
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Experiments

Results of crossection detection

In order to validated the 1D model using some artificial and real signals. We have applied some previous presented algorithm on particular picture. We depicted on the following figures the original signal and the value of $Q'(i)=1-Q_{\min}(i)$.

This value should maximum when i=Ia, where Ia is the abscise of the axis.
The first particular signal simulates two textures of different frequencies and magnitude. The detector response is maximum for the center of the central texture (fig. 4). We compared the result of our own to the result of the usual correlation with a “gate” signal[1]. It is clear that localisation of the Q’(i) maximum is more precise using our own detector (since the correlation function gives multiple maxima in the area of the theoretical maximum).

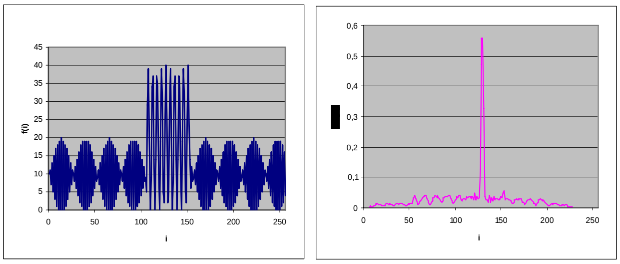

Fig. 4. Original textured signal and detector response

The detector response for a 1D selection of retina-vessel image is depicted fig.5. This signal has a low contrast; indeed all original values are between 95 and 127. Moreover the edges of the vessel are not clearly defined. Despite these constraints, the maximum value of our detector is obtained at the centre of the vessel and with a high value which is near the value obtained for the standard “gate” signal. The last example presented fig.6 example is a selection of a road in an aerial picture. The

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[1] (of the central texture width)

selection has made inside a part of a forest. Despite woods around the road, the value of the maximum is high (0.57) and is well localised on the centre of the road.

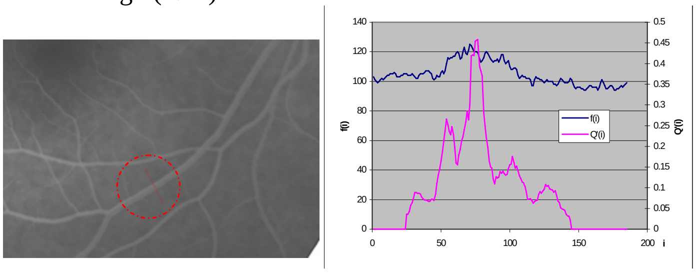

Fig. 5. Detector response in the case of retina vessel

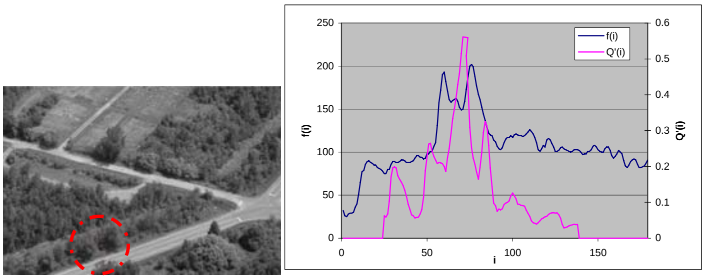

Fig. 6. Detector response in the case of road detection

1 D repeatability Study

Fig. 7. Example of images used for repeatability study

In order to validate our detector, we have realized a repeatability study. The robustness is evaluated against point of view change (4 sets of images, each made of 14 points of view of the same scene) and against natural noise introduced by camera sensor when increasing sensibility from 25 to 1600 ISO (one set of 20 images of one scene). Some examples are depicted on Fig. 7. For each image, 2 sections have been analyzed by a human expert and our algorithm in order to determine the centre position and the width of section. The errors introduced by our method (absolute value of differences between human measurements and filter responses) are presented in the Table 1 and Table 2. The error measured on the axis position and the curvilinear region width is from 1 to 2 pixels in many cases. The width values were from 8 to 180 pixels.

Table 1 : Repeatability study: robustness against point of view change

Scene	***Absolute axis position error (pixels)***	***Absolute width error (pixels)***
Exterior scene	1.5	1.69
White cable on textured flat	1.46	3
Grey cable on textured flat	1.46	1.61
White cable on wood-make table	2.04	1.92

Table 2 : Repeatability study : robustness against natural noise

Scene	***Absolute axis position error (pixels)***	***Absolute width error (pixels)***
Interior scene	1.5	4.08

2D detection preliminary results

We applied a preliminary version of the 2D algorithm to real images. On the following figures, the segments of curvilinear regions are depicted using colors, and the axis is depicted in white. In the case of the picture of the retina (Fig. 8), depending on parameters tuned by the user, it is possible so select a few families of regions (using with and minimal length of curvilinear region, for example). As presented in Fig. 9, it is also possible to use the algorithm for matching. The two original pictures are taken from near opposite points of view. However, some common parts are detected in both cases (branches, part of leafs), and thus could be used for a stereo matching process.

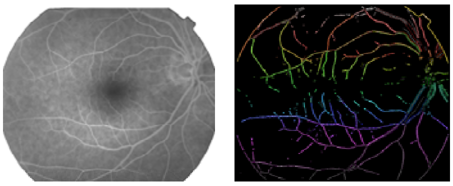

Fig. 8. Blood vessel segmentation (retina)

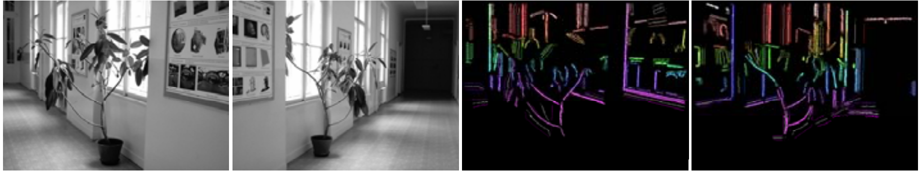

Fig. 9. Example of use of detector for stereo analysis

Conclusion

In this paper, we proposed a model for curvilinear structure detection, useful for objects recognition, matching or image retrieval. Our approach is based on an extension of Steger's model, introducing some texture based attributes and some new constraints on the shape of the region to be detected. After the segmentation step, it is also possible to use the features of the model to classify the curvilinear regions available in the images. We proposed a first filter allowing detecting the profile of curvilinear regions taking into account textures. We validated the filter using real images. However the full detector consumes high computing time. We planned thus to implement a simplified version of the method, for which the cost function will be computed only for a sampled set of pixels, belonging for example to the edges.

References

[1] T. Tuytelars and L. V. Gool, "Matching widely separated views based on affine invariant regions," International journal of computer vision, vol. 59, pp. 61-85, 2004.

[2] J. Matas, O. Chum, M. Urban, and T. Padjla, "Robust wide baseline stereo form maximally stable extremal regions," presented at British Machine Vision Conference (BMVC), pp 384-393, 2002.

[3] S. Belongie, J. Malik, and P. J., "Shape matching and object recognition using shape context," IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 24, pp. 509-522, 2002.

[4] A. W. M. Smeukers, M. Woming, S. Santini, A. Gupta, and J. Hamesh, "Content-based Image retrieval at the end of the early years," IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 22, pp. 1349-1380, 2000.

[5] T. Kadir, A. Zisserman, and M. Brady, "An affine invariant salient region detector," presented at European conference of computer vision, Prague, pp 228-241, 2004.

[6] C. Harris and M. Stephens, "A combined corner and edge detector" presented at Alvey vision conference, pp 147-151, 1998.

[7] K. Mikolajczyk, T. Tuytelars, C. Schmid, A. Zisserman, J. Matas, F. Schaffalitzky, T. Kadir, and L. V. Gool, "A comparaison of affine region detectors," International journal of computer vision, vol. 65, pp. 43-72, 2005.

[8] P. Moreels and P. Perona, "Evaluation of features detectors and descriptors based on 3D objects", International conference of computer vision, pp 800-807, 2006.

[9] K. Mikolajczyk and C. Schmid, "A performance evaluation of local descriptors", IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 27, pp. 1615-1630, 2005.

[10] A. Baumgartner, C. Steger, H. Mayer, and W. Eckein, "MultiResolution semantic and context for road extraction," in Semantic Modeling for the acquisition of topographic from images and maps, S. Verlag, Ed. Basel - Switzerland, 1997, pp. 140-156.

[11] M. A. Fisher, J. M. Tenebaum, and A. C. Wolf, "Detection of roads and linear Structures in low resolution aerial imagery using a multisource knownledge integration technique," Computer graphics and image processing, vol. 15, pp. 201-223, 1981.

[12] D. Geman and B. Jadynak, "An active testing model for tracking roads in satelite image," IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 18, pp. 1-14, 1996.

[13] Walter, Klein, Massin, and Zana, "Automatic segmentation and registration of retinal fluorescing angiographies," presented at CAFIA, 2000.

[14] T. Géraud, "Segmentation of curvilinear objects using watershed-based curve adjacency graph", presented at Iberian conference on Pattern Recognition and Image Analysis (IBPRIA), pp 279-286, 2003.

[15] M. E. Martinez-Perez, A. D. Hughes, A. V. Stanton, S. A. Thom, A. T. Bharath, and K. H. Parker, "Segmentation of retinal blood vessels based on the second derivative and region growing", presented at International Conference on Image Processing, Kobe (Japan), 1999.

[16] F. Deschènes and D. Ziou, "Detection of line junctions in Gray-Level Images" presented at International conference on Pattern Recognition (ICPR), 2000.

[17] D. Ziou, "Optimal line detector" presented at International conference on Pattern Recognition (ICPR), pp 3762, 2000.

[18] C. Steger, "An unbiased detector of curvilinear structures", IEEE Transaction on Pattern Analysis and Machine Intelligence, vol. 20, pp. 113-125, 1998.