Finding Line Patterns in Synthesized Image

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***Abstract*— The orientation space representation is constructed by treating the orientation parameters, which Gabor filters can be turned, as a continuous variable. The problem of multiple orientation line segmentation is dealt with by thresholding 3D images of the orientation space and then detecting the connected components therein. In this way, X-junctions and T-junctions are able to be separated effectively. Experimental results are presented using synthesized image.**

***Index Terms*— Image features, Thresholding, Filtering.**

I. INTRODUCTION

WIDTH and orientation are the predominant feature parameters that characterize a line. In addition, to detect and separate intersections and branches, it is necessary to analyze lines at X-junctions and T-junctions. At local regions such as X-junction or T-junction intersections, lines exist at multiple orientations. Koller et al [1] have proposed using a nonlinear combination of linear multiple scale filters to detect lines of various widths, and selecting only a single orientation for each pixel; however, multiple orientations were not considered in their method. In this paper, we first focus on line orientation, and then on multiple orientation line segmentation. There are a considerable number of studies in the literature dealing multiple orientation feature dealing with multiple orientation feature analysis, mainly relating to the detection of X-junction and T-junction edges [2]~[8]. Perona proposed detecting junction edges by searching for the local maximal orientation-selective filtering response with respect to continuous orientation [5,7,8]. Here, we employ the concept of continuous orientation set out by Perona [5], extending it to formulate a simple yet powerful method for segmenting multiple orientation lines. We propose a novel representation in the form of a three-dimensional orientation space, which is derived by adding the orientation axis to the abscissa and the ordinate of the image. The problem of multiple orientation segmentation is then formulated as an analysis of 3D images of the orientation space. The orientation space representation is constructed by treating the orientation parameter, to which Gabor filters can be tuned, as a continuous variable. In this way, the real component of a complex Gabor filter, which is characterized by an even symmetric receptive field function, can be used to enhance the lines in an image. Multiple orientation line segmentation is achieved by thresholding 3D images in the orientation space and then detecting the connected components therein. In constructing the orientation bandwidth for the Gabor filters is important. If the orientation bandwidth is small, the orientation selectivity is high, while the response of a line having a high degree of curvature is low, that is, the sensitivity of the line is low. We therefore need to achieve a good trade-off sensitivity and selectivity for optimum multiple orientation line segmentation.

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II. ORIENTATION SPACE REPRESENTATION BASED ON GABOR FILTER

To extract lines that have an even symmetric structure, we use as our tunable filter the real component of a complex Gabor filter [9], which is characterized by an even symmetric receptive field function. The filter, which is tuned to an arbitrary orientation to represent lines at multiple orientations, is given by

$$f^{\theta}(\mathrm{x},\mathrm{y};\sigma,\lambda,\omega)=\frac{1}{2\pi\sigma^2\lambda}\exp\left\{-\frac{\lambda^2\mathrm{x}'^2+\mathrm{y}'^2}{2\lambda^2\sigma^2}\right\}\cos(2\pi\omega\mathrm{x}') \tag{1}$$

where $(\mathrm{x}'+\mathrm{y}')=(\mathrm{x}\cos\theta+\mathrm{y}\sin\theta,-\mathrm{x}\sin\theta+\mathrm{y}\cos\theta)$, θ is a preferred orientation parameter by which the filter can be tuned, ω is the radial center frequency, and λ is the aspect ratio of the standard deviation along y to σ, which is the standard deviation along x.

Orientation space representation is a special type of multiple orientation representation that comprises a continuous orientation parameter and preserves the same spatial sampling at all orientations. Let I(x, y) represent any given image. Then, based on the filter $f^{\theta}(\mathrm{x},\mathrm{y};\sigma,\lambda,\omega)$, the orientation space representation $O(\mathrm{x},\mathrm{y},\theta)$ is defined as follows:

$$O(\mathrm{x},\mathrm{y},\theta)=\iint f^{\theta}(\mathrm{x}-\xi,\mathrm{y}-\eta;\sigma,\lambda,\omega)\,\mathrm{I}(\xi,\eta)d\xi d\eta \tag{2}$$

III. MULTIPLE ORIENTATION LINE SEGMENTATION IN ORIENTATION SPACE

In order to enhance a line characterized by width and orientation, we begin by tuning the filter to the optimum scale corresponding to the width of the line, and then deal with the orientation using the filter tuned to fit the width. Let us consider a profile having the Gaussian shape given by

$$I(x,y;\sigma_L) = \exp\left(-\frac{x^2}{2\sigma_L^2}\right) \tag{3}$$

where σ_L is the standard deviation of the profile. The response $R(x,y;\sigma,\lambda,\omega,\sigma_L)$ is given by

$$R(x,y;\sigma,\lambda,\omega,\sigma_L) = \frac{\sigma_L}{\sqrt{\sigma_L^2+\sigma^2}}\exp\left\{-\frac{x^2+4\pi^2\sigma_L^2\sigma^2\omega^2}{2(\sigma^2+\sigma_L^2)}\right\}\cos\left(\frac{2\sigma^2\pi\omega x}{\sigma^2+\sigma_L^2}\right) \tag{4}$$

We assume the following constraint condition:

$$\sigma\omega = C,\ C \in R \tag{5}$$

where C is a constant.

The condition under which $R(x,y;\sigma,\lambda,\omega,\sigma_L)$ is maximum at $x = 0$ for a fixed σ_L is then

$$\sigma_{opt} = argmax R(0,0;\sigma,\lambda,\omega) = \sqrt{4\pi^2C^2-\sigma_L} \tag{6}$$

when $C > 1/2\pi$.

The filter having the optimum scale corresponding to the line width is thus obtained by Eq.(6).

We assume that the filter is tuned so as to have the optimal scale as described below. Fig. 1 shows two filter responses in an orientation space, one of which is at the profile center of a given line, and the other at the intersection of given intersecting lines; the scale parameter σ of the filter is tuned so as to be optimum for the width of the lines in the figure. Fig. 1(c) shows the filter response along the orientation axis at the center of the line profile of the oblique line in Fig. 1(a), while Fig. 1(d) gives the filter response along the orientation axis at the center of the X-junction intersection in Fig. 1(d). If we let $R_{x,y}(\theta)$ be the filter response along the orientation axis θ at the image point (x,y), $R_{x,y}(\theta)$ can be considered as a function of the orientation θ that is,

$$R_{x,y}(\theta) = o(x,y,\theta) \tag{7}$$

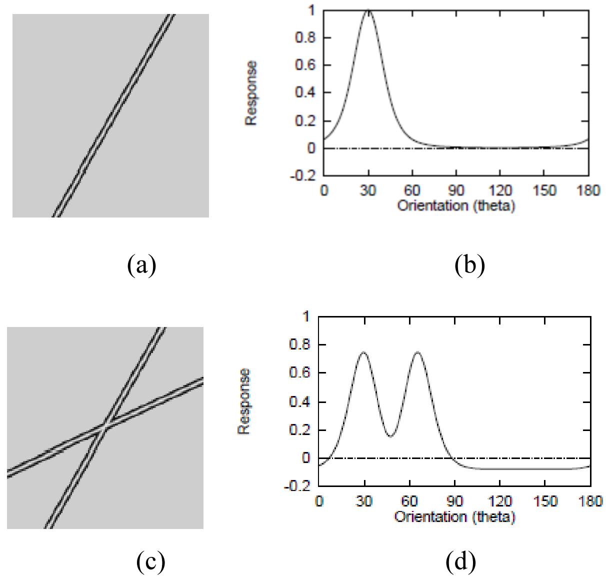


Fig. 1. Synthesized images of (a) a line inclined at 30° to the vertical axis and (b) two lines, one of which is inclined at 30° and the other at 65°. (c) Filter response along the orientation axis at the center of the line profile in (a). (d) Filter response along the orientation axis at the center of the intersection in (b). Here, the filter responses can be considered as functions of the orientation.

As shown in Fig. 1(d), there may be more then than one maximum in the filter response $R_{x,y}(\theta)$ at a line intersection. In such a case, the maxima correspond to multiple orientations at the intersection.

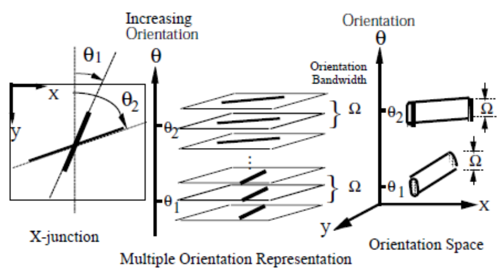


Fig. 2. Outline of the concept of orientation space filtering.

Fig. 2 gives outline of the concept of orientation space filtering. As illustrated in Fig. 2, if a given line is inclined at an angle θ_1 to the vertical axis, the filter response in the orientation space should have a local maximum at θ_1 along the orientation axis; also, the responses of filters tuned to the orientation $\theta_1 \pm \Omega/2$, where Ω is the orientation bandwidth, give relatively large magnitudes. Therefore, each line enhanced by filtering in the orientation space forms a connected component in that space, and there is a one-to-one correspondence between each connected component in the orientation space and each line. As shown in Fig. 1(d), there is a local minimum midway between two local maxima and the difference between the minimum and maxima is large. As a result of their strong connectivity, as well as the orientation selectivity of the filter, the connected components in the orientation space are easily separated by using a threshold whose range is between the local minimum and local maxima. Consequently, we can treat the problem of multiple orientation line segmentation as one of detecting the connectivity in the orientation space. The implementation of the proposed method for segmenting and separating multiple orientation lines can be summarized as follows;

(I) After filtering the image in the orientation space, thresholding is performed to obtain the connected components. The result of thresholding is represented by

$$O_T(x,y,\theta) = \begin{cases} S(O(x,y,\theta) - T_1), \mathit{light} \\ S(T_1 - O(x,y,\theta)), \mathit{dark} \end{cases} \qquad (8)$$

where T_1 is the threshold, and $S(x)$ is defined as $S(x) = 1$ for $x > 0$, otherwise $S(x) = 0$. The connected components in $O_T(x,y,\theta)$ can be considered to correspond to each segmented line.

(II) Labeling is then carried out for the connected components in $O_T(x,y,\theta)$. Let the labeling result be $O_L(x,y,\theta)$. While noise components can be suppressed by orientation space filtering, some noise components may still remain. However, these components will be removed by thresholding because their volume should be small. Let l^i be the set of the pixels in an image that compose a line i. Then, each l^i is segmented by mapping the points with the same label in the orientation space to a 2D image plan. That is,

$$l^i \in (x,y) \mid (O_L(x,y,\theta) = i), \text{and } V_i > T_2 \qquad (9)$$

where i denotes the number of connected components labeled in $O_L(x,y,\theta)$ corresponding to l^i, V_i is the number of voxels of the connected components labeled I, and T_2 is the threshold.

The performance of our method depends on the orientation bandwidth of the filter. The orientation bandwidth Ω depends on the parameters σ, ω, and λ. Since we assumed that $\sigma\omega = C$ (we used C=0.5 in our experiment), Ω is inversely proportional to λ. That is, if λ is large, Ω is small, which means that the orientation selectivity is high. Fig. 3(a) shows three filter responses for $R_{xc,yc}(\theta)$ (see Eq. (7)) at the intersection center (xc, yc) of X-junctions at which angles between two lines are 19°, 25°, and 31°, where λ=2. As shown in the figure, two local maxima were detected. The difference between the local maxima and the local minimum between them is directly related to the separability of the lines. If the difference is relatively large, two peaks corresponding to two lines can be separated using the wide range of T_1 (shown in Eq. (8)). Although two local maxima exist when the angle is 19°, the difference is small, that is, the separability is low. In this case, the selection of the threshold T_1 is quite difficult, Fig. 3(b) shows two plots. The continuous line is a plot of the minimal angles between two lines at the intersections of X-junctions having two local maxima when λ is varied; the broken line is a plot of the minimal angles between two lines at the intersections of X-junctions at which the local minimum is less than half of the local maxima. As shown in Fig. 3(b), when λ becomes large, the orientation selectivity becomes sharp, and hence the minimal angle of an X-junction that can be separated and segmented becomes small.

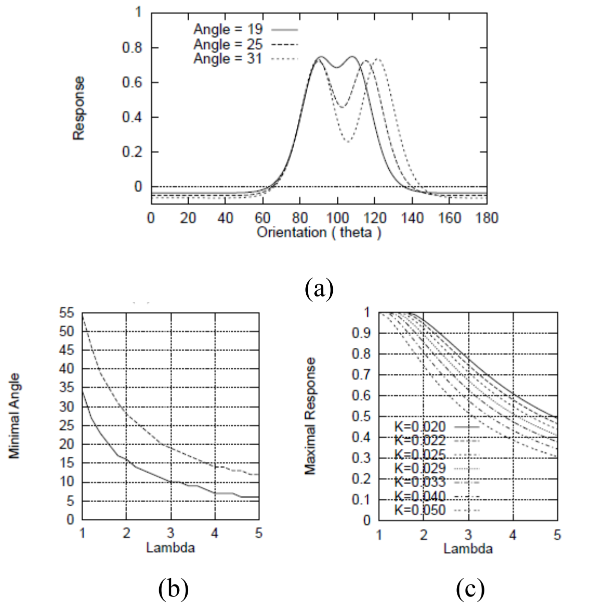
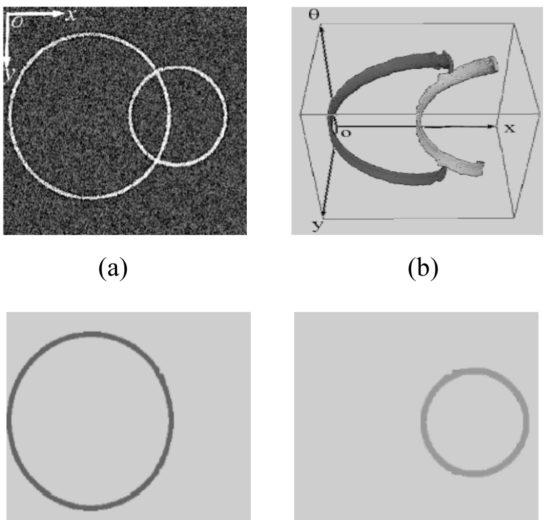


Fig. 3. Filter response for $R_{xc,yc}(\theta)$.

Fig. 3(c) shows maximal filter responses at the profile centers of circumferences corresponding to the normalized curvature k, when λ is continuously varied from 1 to 5. The maximal filter response corresponding a high degree of normalized curvature is markedly less than that corresponding to a low degree of normalized curvature. As shown in the figure, the maximal filter response becomes small as λ becomes large, that is, the sensitivity of the curve becomes low. The maximal filter response at λ=2 is slightly less than the maximum at λ=1. On the other hand, as shown in Fig. 3(b), when λ=2, the minimal angle between two lines at the intersection of X-junction at which the local minimal filter response is less than half of the local maximal filter response is 27°. Taking account of the behaviors of the minimal angle between two lines at the intersection of X-junction and the maximal filter response, in our subsequent experiments, we employed λ=2 to achieve a good tradeoff between sensitivity and selectivity.

IV. EXPERIMENTAL RESULTS

We synthesized an image consisting of two intersecting circles, and then imposed added Gaussian noise to the image. Fig. 4(a) depicts the synthesized image, and 4(b) the result of orientation space filtering. As shown in Fig. 4(b), two connected components corresponding to the two circles were extracted in the orientation space, following which the two circles were segmented out (Fig. 4(c) and (d)).



(a) (b)

(c) (d)

Fig. 4. (a) added Gaussian noise image, (b) Two connected components were extracted and labeled in the orientation space, (c) and (d) The two circles were then segmented and labeled.

V. CONCLUSIONS

The sensitivity limits of the method with respect to X-junction segmentation were demonstrated. The trade-off between sensitivity and selectivity was considered and illustrated. Experimental results using synthesized images illustrate the effective performance of the method for multiple orientation line segmentation. In order to represent multiple orientation features, an orientation space is constructed by treating the orientation parameter as a continuous variable. The problem of multiple orientation segmentation is formulated as one of finding the connectivity in the 3D orientation space by virtue of the continuity of lines and their orientation. Multiple orientation line segmentation is achieved by thresholding 3D images of the orientation space and then detecting the connected components therein without employing any extra tracking algorithms.

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