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New Approaches to Robust Corner Point Detection Using Constrained Regularization and Mean Field Annealing Techniques

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Constrained Regularization과 Mean Field Annealing 방법을 이용한 새로운 코너 찾기 방법에 관한 연구

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ABSTRACT

In this paper, we propose two approaches to consistent boundary representation for solving the corner point detection problem for computer vision applications: a constrained regularization(CR) approach and a mean field annealing(MFA) approach. The curvature function computed on the preprocessed smooth boundary, which is obtained by either the CR approach or the MFA approach, is consistent. Thus, we can consistently detect corner points in this curvature function space. Ideal corner points rarely exist for a real boundary. They are often rounded due to the smoothing effect of the preprocessing. In addition, a human recognizes both sharp corner points and slightly rounded segments as corner points. Thus, we establish a criterion, called "corner sharpness", which is qualitatively similar to a human's capability of detecting corner points. We use corner sharpness to increase the robustness of the proposed algorithms.

要　　約

본 논문에서는 컴퓨터비전 응용을 위해 코너점을 찾는데 있어 발생하는 문제점을 해결하기 위한 물체의 boundary를 견고하게 표현하는 두 가지 접근방법 즉 constrained regularization을 이용하는 방법과 mean field annealing을 이용하여 코너점을 견고하게 찾는 방법을 제안한다. constrained regularization 또는 mean field annealing으로 전처리된 boundary로부터 구한 곡률 함수는 견고하며, 따라서 그 곡률 함수 상에서 견고하게 코너점을 찾을 수 있게 된다. 실제 boundary 상에서 사실상 이상적인 코너점은 거의 존재하지 않는다고 볼 수 있다. 즉, 전처리 과정 등에 의해 어느 정도 마모될 수 있다. 또한, 인간의 시각은 아주 날카로운 코너점 뿐만아니라 약간 마모된 코너도 코너점으로서 인식한다. 따라서, 인간시각의 코너점을 찾는 능력과 유사한 능력을 갖도록 corner sharpness를 정의한다. 인간의 시각이 찾은 코너점과 제안한 두 접근방법에 corner sharpness를 적용하여 구한 코너점을 비교 분석한다.

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I. Introduction

The human visual system uses two-dimensional(2-D) boundary information to recognize objects since the shape of the boundary usually contains the pertinent information about an object. Thus, representing a boundary concisely and consistently is necessary for object recognition. There are two main categories in representing objects in general: global methods and local methods. The moment-invariants, the Fourier Descriptor, and the circular autoregressive model are commonly used global methods. They are often easy to obtain and easy to use in a matching problem. Features extracted using global methods are robust with regard to noise. In addition, global methods are invariant under rotation, scale, and translation. However, they do not provide local information on the boundary so that they cannot handle partially occluded objects.

In local methods, the boundaries need to be segmented in order to represent them analytically. In general, there are two possible approaches to the boundary segmentation problem. One is to detect corner points. This method mainly depends on a curvature function. Hence, computing the curvature function properly is very important for consistent corner point detection. There have been several corner point detection methods developed. However, the existing methods do not lead to consistent boundary representation since they inconsistently detect corner points. The other approach is to obtain a piecewise-linear polygonal approximation to the digitized boundary. The vertices found in the linear polygonal approximation are usually called break points. However, this method may cause different boundary segmentation with regard to the starting point. While this approach may work well for the boundary which has many line segments, it is not a good method for a smooth or curved boundary since a large number of line segments are necessary to represent them.

We use corner points for boundary representation since it is well known[1] that the information of the shape is concentrated at the points having high curvature. We propose two approaches to consistent boundary representation in this paper: a constrained regularization(CR) approach and a mean field annealing(MFA) approach. We can consistently detect corner points from the preprocessed smooth boundary obtained by either the CR approach or the MFA approach. Ideal corner points rarely exist for a real boundary. They are often rounded due to the smoothing effect of the preprocessing. A human recognizes both sharp corner points and slightly rounded segments as corner points. Thus, we establish a criterion, called "corner sharpness", qualitatively similar to a human's capability of detecting corner points, in which a little tolerance is given to recover slightly rounded corner points.

This paper is structured as follows: In section 2, problems of current methods to compute curvature function on a digitized boundary are discussed. Section 3 first introduces the theory of a regularization technique and a new method of boundary smoothing for curvature estimation using a constrained regularization technique. In addition, another boundary smoothing method using a mean field annealing technique is proposed. A new method of robust corner point detection using a criterion called corner sharpness is proposed in section 4. Finally, discussion of the proposed methods as well as concluding remarks are given in section 5.

Ⅱ. Problem Statement

There are two possible approaches to compute the curvature function on a digitized boundary curve: one is performed in a discrete domain and the other is performed in a continuous domain. Many researchers have developed several k-curvature methods to estimate curvature in a discrete domain using k-vectors on their leading and trailing curve segment of the point[2-3]. However, the common problem with them is determining a unique smoothing factor k. We have exploited the continuous domain by investigating several lowpass filtering techniques. Among other things, Mokhtarian and Mackworth[4] used Gaussian smoothing to compute curvature at varying levels of detail. They convolved $X(t)$ and $Y(t)$ with a one-dimensional(1-D) Gaussian kernel $g(t,\sigma)$ of standard deviation σ, *i.e.*, $X(t,\sigma)=X(t)*g(t,\sigma)$ and $Y(t,\sigma)=Y(t)*g(t,\sigma)$. By the derivative theorem of convolution, the discrete curvature using Gaussian smoothing becomes[4]:

$$\kappa(t,\sigma) = \frac{\dot{X}(t,\sigma)\,\ddot{Y}(t,\sigma) - \ddot{X}(t,\sigma)\,\dot{Y}(t,\sigma)}{[\ \dot{X}^2(t,\sigma) + \dot{Y}^2(t,\sigma)]^{3/2}} \qquad (2.1)$$

We encounter the same problem as we encountered with k-curvature methods in determining a unique smoothing factor. We must choose σ small enough to preserve valid high frequency shape information, yet sufficiently large to remove noise effects. Fig. 2-1 shows a gun boundary which is represented by an 8-neighbor Freeman chain code. The starting point is marked with '*' and the direction of tracing is counter-clockwise. Fig.

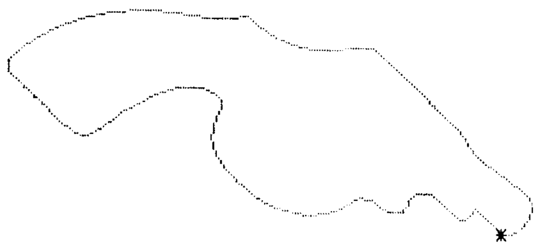
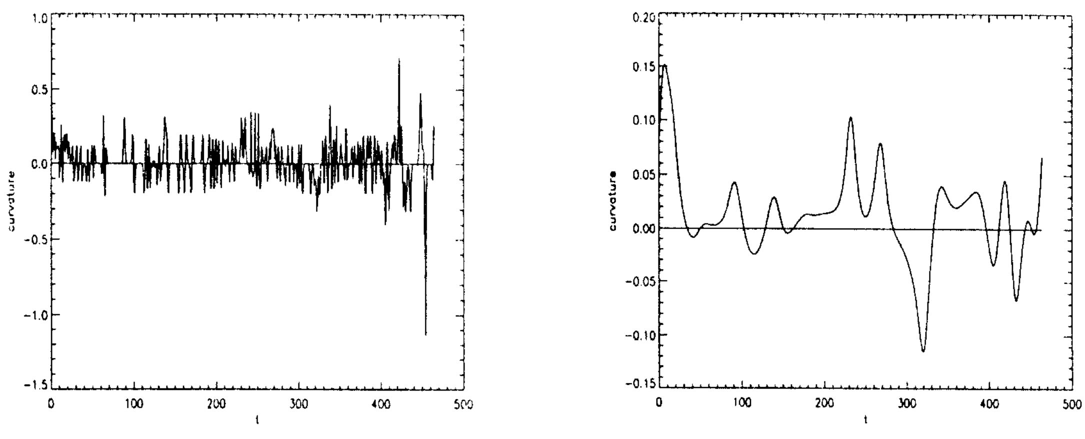


Fig. 2-1. A gun boundary



(a) (b)

Fig. 2-2. Gaussian smoothing: (a) σ=1; (b) σ=8.

2-2 shows the results after Gaussian smoothing. Varying σ produces results which range from too noisy(σ=1) to too smooth(σ=8). Thus, we can not consistently detect corner points in this curvature function space.

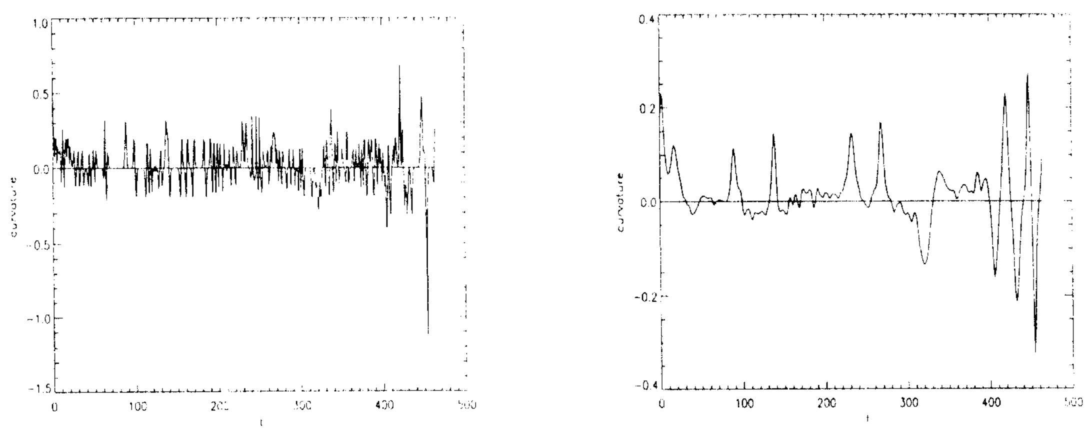
Ⅲ. New Approaches To Curvature Estimation

1. Constrained regularization approach

Regularization theory has been successfully applied to several image restoration and vision problems. The regularization technique transforms ill-posed problems into well-posed problems, providing consistent, unique, and stable solutions. The main objective in solving such ill-posed problems is the construction of a physically acceptable and meaningful approximation to the true solution that is sufficiently stable from a computational point of view.

Shahraray and Anderson[5] first applied the regularization technique for the measurement of the boundary curvature of a planar curve. They used the standard regularization method with generalized cross-validation(GCV) to find the optimal value of the regularization parameter from the data. GCV is a method for estimating a value of the regularization parameter which does not require knowledge of noise variance. However, it may fail catastrophically in some circumstances, producing either no positive smoothing parameter or a underestimated smoothing parameter[6]. In addition, the GCV method is mathematically intense due to many matrix decompositions and the requirement to obtain the inverse of large matrices.

We have knowledge about the quantization noise, which is the dominant noise. In addition, Reinsch[7] suggests that if the noise variance is roughly known, then the regularization parameter should be chosen so that the residual error is equal to the noise variance. By imposing the above noise constraint, we can obtain the desirable result which is appropriate for further processing in a shorter time and a simpler way than the method



(a) (b)

Fig. 3-1. Curvatures for the gun boundary: (a) before CR; (b) after CR.

proposed in[5]. Thus, we proposed a CR approach for consistent object representation in the previous paper[8]. It combines a regularization and a noise constraint to determine a unique smoothing factor.

We applied the algorithm to the gun boundary(Fig. 2-1) to see if the algorithm works well for the real images. Fig. 3-1(a, b) show the curvature functions before CR and after CR, respectively. The resulting curvature function was smooth enough to be used for further processing and preserved sufficient local information for corner point detection.

2. Mean field annealing approach

Problems involving the minimization of functions that have many local minima have been prominent in various engineering applications for a long time. The gradient descent method is a typical example of a minimization algorithm which may become stuck in a local minimum depending upon the starting point. Kirkpatrick et al.[9] developed the Simulated Annealing(SA) technique to overcome this problem.

Geman and Geman[10] used a Bayesian approach for image segmentation. They showed hat if the image can be modeled as a Markov Random Field(MRF), there is an equivalence between the MRF and the Gibbs distribution. They proposed a procedure called stochastic simulated annealing(SSA). It converges to a global minimum under certain conditions. However, it is extremely slow in practice.

Bilbro et al.[11] applied the MFA technique while they were trying to segment range images from a range sensor. They sought a way to smooth out the noise without eliminating the edges. They accomplished this by using a global process that combines consistent local measurements to infer global properties. MFA is an approximation to SSA which replaces the random search by deterministic gradient descents. This approximation makes the algorithm converge faster than SSA.

Since a data point is correlated to its neighbors in boundaries, we can model the boundary as a MRF. Thus, we can use the MFA technique for the problem of boundary smoothing. We pose the boundary smoothing problem as the minimization of the sum of a "noise" term and a "prior" term. Thus, we choose a Hamiltonian as follows:

$$H(\mathbf{f_e}, \mathbf{f_m}) = H_n(\mathbf{f_e}, \mathbf{f_m}) + H_p(\mathbf{f_e}) \qquad (3.1)$$

The noise Hamiltonian (H_n) is

$$H_n(f_e, f_m) = \sum_k \frac{[\ f_e(k) - f_m(k)]^2}{2\sigma^2} \qquad (3.2)$$

where σ^2 is a noise variance. The prior Hamiltonian (H_p) represents the measure of a certain local property. This can be written as

$$H_p(f_e) = -b\sum_k \frac{1}{\sqrt{2\pi T}} \exp\left(-\frac{\Delta_k^2}{2T}\right) \qquad (3.3)$$

Δ_k is the operator on the neighborhood of the kth element. We use a discrete form for the second derivative for Δ_k as in the CR approach because it represents the roughness of data. b is a weighting factor for the prior Hamiltonian against the noise Hamiltonian, and T is a control parameter known as "temperature".

The Hamiltonian, $H(\mathbf{f_e}, \mathbf{f_m})$ may have many local minima and behave poorly in other ways. Hence, instead of minimizing H, we approximate H with a simple convex function H_0 which is easy to minimize. H_0 must depend on a set of parameters to be similar to H. Then, we adjust those parameters in such a way that H_0 will be similar to H. We choose H_0

$$H_0(\mu, f_e) = \sum_{k=0}^{N-1} [\ \mu(k) - f_e(k)]^{\ 2} \tag{3.4}$$

The above H_0 has only one minimum since it is a paraboloid. Thus, minimizing H_0 is simple. We have a convex form and we can find the μ's which make H_0 similar to H.

To find μ, we minimize the expectation of the difference between H_0 and H_T with respect to μ to make two functions similar as follows :

$$E_{MF} = \langle\ \mathrm{H}(\boldsymbol{f_e},\ \boldsymbol{f_m}) - H_0(\mu,\ \boldsymbol{f_e})\rangle_\mu \tag{3.5}$$

Minimizing E_{MF} insures that $H_0(\mu,\ \boldsymbol{f_e})$ is similar to $H(\boldsymbol{f_e},\ \boldsymbol{f_m})$. It can be shown[11] that the minimization of E_{MF} is equivalent to the minimization of $\langle H(\boldsymbol{f_e},\ \boldsymbol{f_m})\rangle_\mu$. $\langle H_n\rangle$ is constant and $\langle H_p\rangle$ has the following asymptotic behavior:

$$\langle H_p\rangle \xrightarrow[T\to 0]{} H_p \quad \text{and} \qquad \langle H_p\rangle \xrightarrow[T\to\infty]{} 0 \tag{3.6}$$

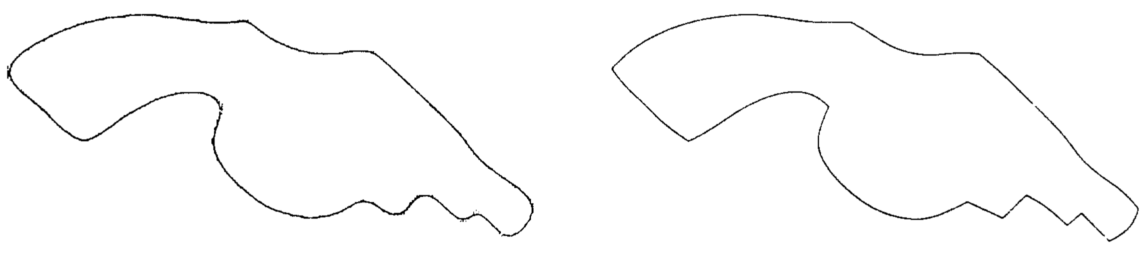
Thus, minimizing $\langle H(\boldsymbol{f_e},\ \boldsymbol{f_m})\rangle$ is equivalent to minimizing $H(\mu,\ \boldsymbol{f_m})$. Conclusively, we will minimize

$$H(\mu, \boldsymbol{f_m}) = \sum_k \frac{[\ \mu(k) - f_m(k)]^{\ 2}}{2\sigma^2} - \frac{b}{\sqrt{2\pi T}} \sum_k \exp\left(-\frac{[\ \mu(k+1) - 2\mu(k) + \mu(k-1)]^{\ 2}}{2T}\right) \tag{3.7}$$

We perform the minimization of Eq. (3.7) by annealing on T. That is, we begin with a large value foı T since $Hp \approx 0$ for large T and minimizing the H of Eq. (3.7) is equivalent to setting $\mu = \boldsymbol{f_m}$. Then, we start the algorithm with this initial condition, gradually reduce T, and at each new value of T, we minimize H by using gradient descent or other standard minimization methods.

From Eq. (3.7) and the above annealing procedure, we can see the algorithm is influenced by the following parameters: σ(the standard deviation of the noise), b(the relative magnitude of the prior term), T_i(the initial temperature), and T_f(the final temperature). The decrement factor in the annealing procedure is also important. However, it was empirically shown that a geometric annealing schedule: $T \leftarrow \alpha T (\alpha \langle 1)$ is good enough[12]. We applied the order-of-magnitude analysis to our parameter estimation and obtained the following estimated parameter values: $T_i \approx 6\sigma^2$, $T_f \approx 0.01$, and $b \approx 2.8\sigma$.

As shown in Fig. 3-2(a), the original gun boundary was smoothed well enough to be



(a) (b)

Fig. 3-2. (a) Result of CR; (b) result of MFA

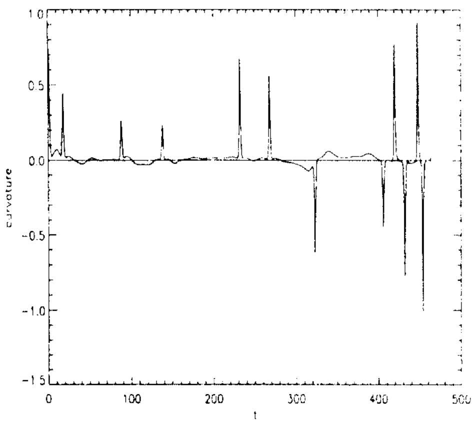


Fig. 3-3. Curvature after MFA.

used for further processing with the CR approach, but some corner points were not preserved well. We applied the MFA algorithm for the same boundary. Fig. 3-2(b) shows the smooth boundary obtained by the MFA approach based on the above estimated parameters.

Fig. 3-3 is the corresponding curvature function. We can clearly see that the MFA method gives better performance in a sense of corner preservation. Thus, we can detect corner points easier with the MFA approach than with the CR approach. However, it takes more time for detecting corner points due to the annealing procedure.

Ⅳ. Robust Corner Point Detection

A human recognizes slightly rounded segments and sharp corner points as corner points. Furthermore, corner points may be slightly rounded due to the smoothing effect of preprocessing. As the corner point is rounded, the corresponding curvature function is spread over the neighborhood, while the overall tangent angle change around that corner point remains the same. When the corner point is spread over a tolerably narrow number of neighbors, it still can be recognized as a corner point. However, when the corner is rounded too much, it should be recognized as a curved segment. We defined corner sharpness as a curvature change($\Delta\theta/\Delta s$, in a normalized curvature function space) within a unit perimeter(Δs) of a simply closed boundary. We also determined the threshold value(θ_{th}=20π) for the corner point detection in the normalized curvature function space[8].

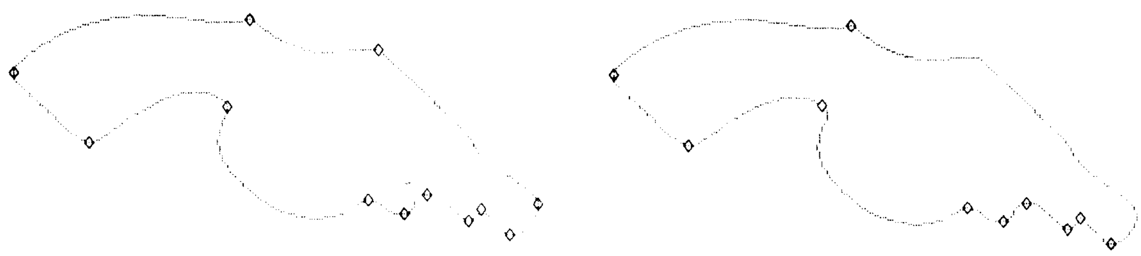
The CR method slightly smooths out corner points and the resulting curvature at corner points are spread over the neighbors. Unless we give a little tolerance when we detect corner points in this curvature function space, we may miss some corner points. Thus, we detect corner points based on the following empirically derived result when we use the CR approach[8]:

Each point on a boundary is considered as a corner point if one of the following conditions is satisfied:

$$(i) \int_0^{\Delta s} x\,ds \geq 20\pi \qquad (ii) \int_0^{2\Delta s} x\,ds \geq 30\pi$$
$$(iii) \int_0^{3\Delta s} x\,ds \geq 40\pi \tag{4.1}$$

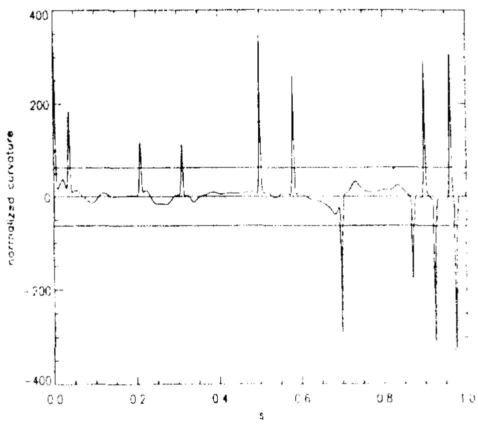
Only the points which satisfy one of the above conditions are considered as corner points in the CR approach. Fig. 4-1(a) shows corner points for the gun boundary detected by a number of human observers. Fig. 4-1(b) shows corner points detected by using condition(i) of Eq. (4.1) with the CR approach. As shown in the figure, two corner points were not detected. This was due to the smoothing effect at corner points with the CR approach.

However, we recovered the missing corner

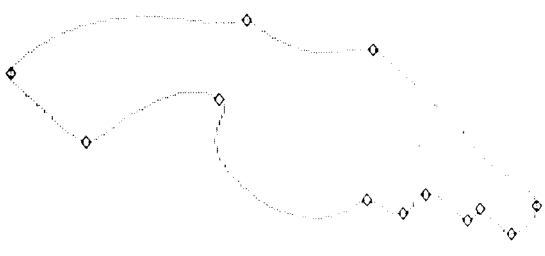


(a) (b)

Fig. 4-1. Detected corner points: (a) by human observers; (b) by CR with condition (i).



(a)



(b)

Fig. 4-2. Results of the MFA approach: (a) normalized curvature; (b) corner points.

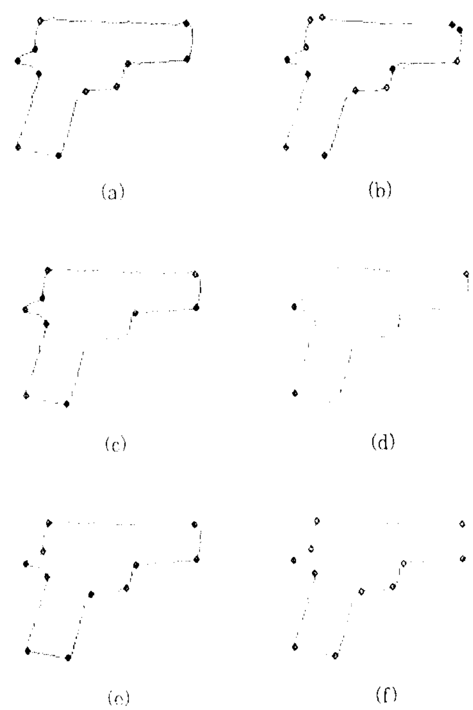


Fig. 4-3. Corner points detected in various methods(Model 1):
(a) Human; (b) Gaussian(σ=2); (c) Gaussian(σ=4); (d) Gaussian(σ=8); (e) CR; (f) MFA.

Table 4-1. The number of corner points detected in various methods.

	Gaussian smoothing			CR method	MFA method	Human
	σ=2	σ=4	σ=8			
Model-1	13	9	3	11	11	11
Model-2	10	8	4	8	8	8
Model-3	9	5	4	6	6	6
Input-1	17	11	3	15	12	13
Input-2	29	21	16	21	21	21

points by using condition (ii) and condition (iii). We were able to locate the same number of corner points as those detected by the human observers at almost the same positions by using corner sharpness in the CR approach.

We already have shown that the MFA method preserves corner points very well, and the resulting curvature function has large and sharp curvature extrema. Thus, the first condition of the above Eq. (4-1) is enough to detect corner points in the MFA approach. Fig. 4-2(a) is the normalized curvature function computed in the MFA approach. Fig. 4-2(b) shows the result of corner point detection in this normalized curvature function space. As shown in the figure, we obtained the same corner points as in Fig. 4-1(a). Thus, we can detect corner points easier with the MFA approach, while it provides the same results.

Table 4-1 shows the number of corner points detected in the various methods for three model boundaries and two input boundaries(Model-1: gun, Model-2: hammer, Model-3: wrench, Input-1: gun+hammer, Input-2: gun+wrench). We obtained the results of human observers in the table by asking several people to choose corner points in the given boundaries. Fig. 4-3 shows the corner points detected in various methods for Model-1. As shown in Fig. 4-3 and Table 4-1, we detected almost the same number of corner points using corner sharpness and the CR approach as human observers did. Our results using corner sharpness and the MFA approach gave equally good results.

Ⅴ. Conclusion

We presented several different issues in representing 2-D boundaries in this paper. We proposed new methods of boundary smoothing for curvature estimation and robust corner point detection for consistent boundary representation to overcome the common critical problem of current boundary representation methods.

We proposed two boundary smoothing methods: the CR method and the MFA method. The CR method resulted in slight unnecessary smoothing at corner points. However, it did not cause any serious problem in detecting corner points since we used corner sharpness to compensate for the unnecessary smoothing effect at corner points. On the other hand, the MFA method preserved corner points very well. Hence, we detected corner points easier with this approach than with the CR approach. However, it took more time to obtain the smooth boundary due to the annealing procedure. The performance of the CR method and the

MFA method in detecting corner points were as good as that of the human observers.

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