

Image Edge Detection Applying the Toll Set and Entropy Concepts

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ABSTRACT

An image edge detection method based on the toll set concept is proposed. Initially the edge structure is established for an image following human perception model. Then toll set membership values are computed and the toll set intersection and union operators are applied to them. The final toll set membership values are normalized to get the vagueness degrees and the thresholding operation based on entropy concept is performed on them to determine the edge of an image.

톨연산과 엔트로피 개념에 기초한 화상의 경계선 추출

조 동 옥[†]

요 약

본 논문에서는 톨연산에 기초한 화상의 경계선 추출 방법을 제안 한다. 첫째로 3×3 window내 에서 경계라고 고려 할 수 있는 구조를 고려하여 톨 멤버십 함수를 계산 한다. 이후 볼 교집합연산과 합집합 연산을 행하며 계산의 편의를 위해 정규화를 행한다. 최종적으로 엔트로피 개념에 기초한 thresholding을 행함으로써 경계를 추출 하고자 한다.

1. Introduction

Identifying and locating the object boundaries in a scene from its 2-D projection (the image data) is a crucial step toward the ultimate goal of computer vision. These object boundaries, as well as sharp variations in surface structure (e.g., texture) and illumination (e.g., shadow), manifest themselves as sharp changes in image intensities.

The goal of edge detection is to obtain a complete and meaningful description from an image by characterizing these intensity changes in terms of their phy-

sical origins. Since the performance of the higher level processes such as object recognition using this description relies heavily on the accuracy of the detected edges, the edge-detection problem has become a central area of research in computer vision. Despite considerable work and progress made on this subject, edge detection is still a challenging research problem due to the lack of robust and efficient general-purpose algorithms. In the past few years, a large number of papers on this subject focus on edge detection based on the mathematical models[1~4]. Each of these method is very good in the special intended circumstances. However, as they are not universal, each method has its own peculiarities and limitations, such as widely applied optimal step edge detector is very

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논문접수: 1995년 4월 13일, 심사완료: 1996년 5월 1일

inefficient in ramp edge detection. Furthermore, all mathematical models have a common drawback, i.e. they all require some prior information about input image for proper parameter value selection.

To overcome the limitations of mathematical models, different approaches based on human knowledge type are proposed and the application of the toll set concept presented here is one of them. Toll sets are a new set concept introduced by Dubois and Prade[5] at IFSA'91. In a toll set each element shares the cost for its membership participation. In this article the pixels in an image pay the appropriate amount of the toll set membership cost to be adopted into an edge. To perform various toll set operations with pixels, the possible edge structures are established into 16 types on a 3x3 window frame. Then, the proposed membership function is used to compute the membership cost for the chosen pixels for the window frame to the toll set in their degree of edge structure participation. The computed toll membership values undergo the toll intersection and union operations with each of 16 edge structure types, the results of which reveal the most appropriate types for the chosen pixels of windows. In the final stage of thresholding operation, the entropy concept is utilized, which has resulted the edge detection very robust and general.

2. Brief Introduction of Toll Sets[5]

Toll sets are in a sense a modified version of fuzzy sets. The former differs from the latter in that membership of a toll set is characterized by the cost, while membership of a fuzzy set is the grade of relevance. While the grade of a fuzzy set takes a value in the unit interval, the membership of a toll set take any nonnegative real value. Moreover, it may take the value of infinity.

In the universal set U, a toll set T is defined as $\psi_t(x)$, where the membership value of an element, x, in a toll set $\psi_t(x) = 0$, and it is defined as a free membership. When $\psi_t(x) = +\infty$, i.e., x is said to be forbidden

from joining with T. Primary operation on toll sets are as follows:

[inclusion]

For toll sets S and T, $S \leq T$ iff

$$\psi_s(x) \geq \psi_T(x)$$

[complement]

$$\bar{\psi}_T(x) = \begin{cases} +\infty & \text{if } \psi_T(x) = 0 \\ 0 & \text{if } \psi_T(x) > 0 \end{cases}$$

[Union and intersection]

The union operator are the following

$$\psi_{S \cup T}(x) = \min [\psi_s(x), \psi_T(x)]$$

While, intersection can not be defined uniquely, but must satisfy

$$\max [\psi_s(x), \psi_T(x)] \leq \psi_{S \cap T}(x) \leq \psi_s(x) + \psi_T(x)$$

Note that the intersection means the cost to pay obtaining two memberships represented by S and T. The above relation implies that the cost for S and T should be between the two extreme cases of $\max[\psi_s(x), \psi_T(x)]$ and $\psi_s(x) + \psi_T(x)$. The former means the maximum discount that higher fee of ψ_s and ψ_T is sufficient for obtaining the both memberships, whereas the latter means no discount: we should pay $\psi_s + \psi_T$ for the both memberships.

3. Application of Toll Set Theory in Edge Detection

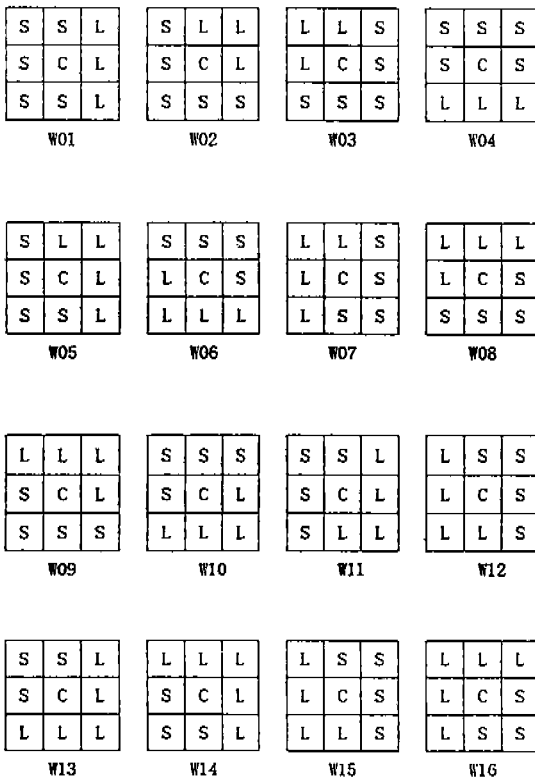
In this section, it is described how the toll theory, which was briefly introduced in Section 2, has been applied to edge detection.

The existing edge detection methods have mainly performed assuming in a certain specified environment [9, 10] as an image which usually has a case de-

pendent image structures is hardly collectively dealt with by any of those methods: Character edge detection from tires [9], and an attempt to find an optimal thresholding value [10] are some of those main trends.

In this paper, a method to efficiently extract meaningful edges from a case dependent image is proposed by applying the toll theory.

Edges in an image occur where intensity or range changes its value abruptly. So if we construct all the possible edge structure into a 3×3 window, their cases are as shown in Figure 1, where S represents "small" gray level or range values compared to the center pixel (C) and L represents "large" values.



(Fig. 1) Edge Structures

We define the toll membership value for "small" and "large" as shown below. Also the figure 2 (a) & (b) show the "small" toll membership value and

"large" toll membership value respectively.

$$\psi_{small}(x) = -\lg[-(1/255) \times (x - 255)] \quad (1)$$

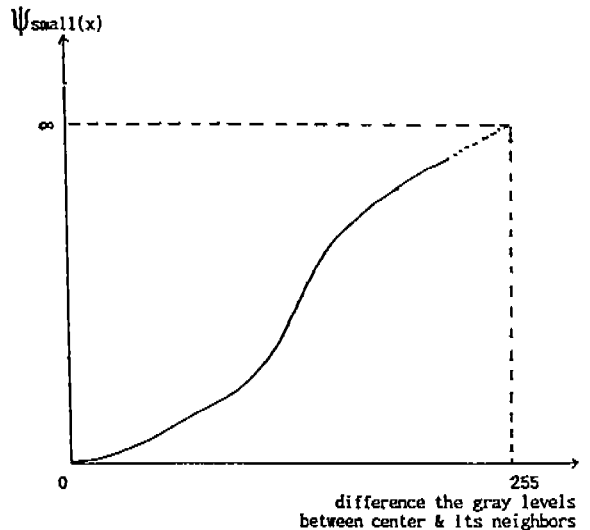
where $x = |C - S|$

$$\psi_{large}(x) = -\lg((1/255) \times x) \quad (2)$$

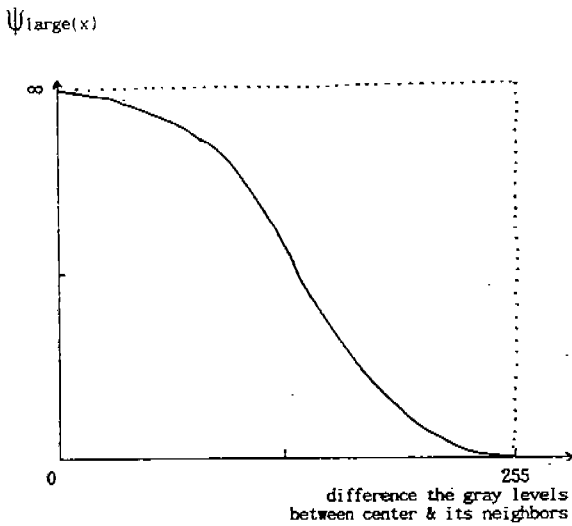
where $x = |C - L|$

The lg function $f(x) = -\lg x$ is used to calculate the toll membership values. The reasons are following. When $x=0$, the corresponding $f(x)$ value has $+\infty$; when $x=1$, $f(x)$ value has 0. Therefore, the lg function $f(x) = -\lg x$ with values ranging from $x=0$ to $x=1$ can be defined as an toll membership values. For example, expression(1) shows that, if $x = |c - s| = 255$, its value becomes $-\lg 0 = +\infty$, i.e., if the gray level difference is 255, it is forbidden to participate in the "small" toll set. Likewise, expression(2) is for the "large" toll set.

To determine the edgeness for the image window, toll intersection & union operations are performed between the image window and each of windows given in Figure 1. For example, if we apply toll intersection



(a) "small" toll membership value



(b) "large" toll membership value

(Fig. 2) "small" & "large" toll membership value

operation to the window of Figure 3, it becomes

$$\max \{ Da, Db, Dc, Dd, Df, Dg, Dh, Di \} \tag{3}$$

where Da is the gray level or range value difference between a and e applied to $\psi_{small}(x)$ operation.

a	b	c
d	e	f
g	h	i

(Fig. 3) 3x3 window

Now, toll union operation is performed for entire image window, i.e.

$$\min \{ W1, W2, \dots, W16 \} \tag{4}$$

The reason for performing the toll set intersection and union operations in sequence is to decide the

most appropriate type out of 16 edge structure types to which given pixels in a window must belong. After these operations we get a transformed pixel value array which contains edgeness information. Final thresholding process determines the existence of an edge.

4. Calculation of the Threshold Values

Finally the edgeness values obtained by the above process undergo the thresholding operation. For this, each toll membership value is normalized as

$$N(T_{ij}) = 1 - \exp(-T_{ij}) \tag{5}$$

where $N(T_{ij})$ value denotes the grade of some edgeness property possessed by the (i, j)th pixel. Since the edge operation is performed within 3x3 window, an image X with size 256x256 is reduced to 254x254 edge image. Therefore the vagueness of the edge value is computed as,

$$A(N) = - \frac{\sum_{i=1}^{254} \sum_{j=1}^{254} [N(T_{ij}) \lg N(T_{ij}) + (1 - N(T_{ij})) \lg (1 - N(T_{ij}))]}{254 \times 254} \tag{6}$$

Expression (6) measures the degree of entropy [6]~[8] for the edgeness of a pixel in an image of 256x256 resolution.

The mean of the edgeness values for a given 256x256 resolution image is obtained by

$$Na(T) = \frac{\sum_{i=1}^{254} \sum_{j=1}^{254} N(T_{ij})}{254 \times 254} \tag{7}$$

In the thresholding operation, when the above A(N) value is below 0.3, the pixels of N(T) value below 0.3 are regarded as an edge and when $A(N) > 0.3$ the pixels of edge value less than $Na(T)$ are selected to form an edge.

5. Experimental Result

An image of 256×256 resolution and 256 gray levels are used in the experiments. Figure 4 & 5 are the original images. Figure 6 and 7 are the edge detected images by the Sobel operation (threshold value =7). Also the edge detected images processed by the proposed method are shown in Figure 8 and 9. Comparing the edge detection results in Fig. 6(Sobel operation), for the objects in Fig. 4, with the ones in Fig. 8 (the proposed method), the edge information within the face image in Fig. 6 is hardly recognizable (lowering the threshold value to solve this problem results in no edge information) whereas the one in Fig. 8 appears to be clearly extracted. In the Whole images, the extracted edges in Fig. 8 are found to be significantly more meaningful than the ones in Fig. 6.

Also comparing the processed results in Fig. 7 (sobel operation) and the ones in Fig. 9(the proposed method), the edges for the eye, nose and mouse in the face have been accurately extracted in Fig. 9 while few edges have appeared to be extracted in Fig. 7. As the experimental results have shown, the proposed method is a method which is robust against noise and efficiently extracts meaningful edges.

It is also to be noted that the reason to select a face image with the background as the object image for the experiment was because a face image equally encompasses both the area of small gray-level-difference and the area of large difference, and hence is suitable for the experimental image object for the edge detection algorithms.

At this stage, we carry on a research work for edge extraction, in which noise removal is performed if in the noise region, and edge extraction while removing noise is performed for edges. We also work a method to understand the edge structure without thresholding for edge extraction, which is to find the meaningful edge efficiently. This work will be presented as the supplemental paper for this paper in the near future.



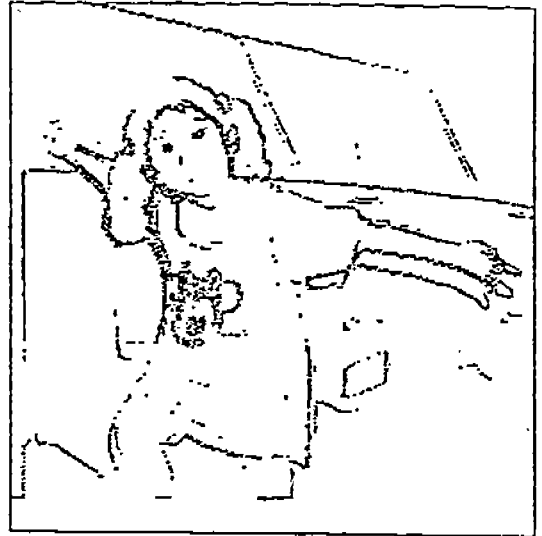
(Fig. 4) original image



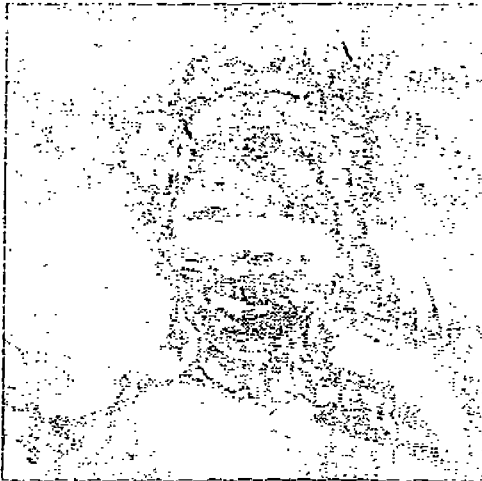
(Fig. 5) original image



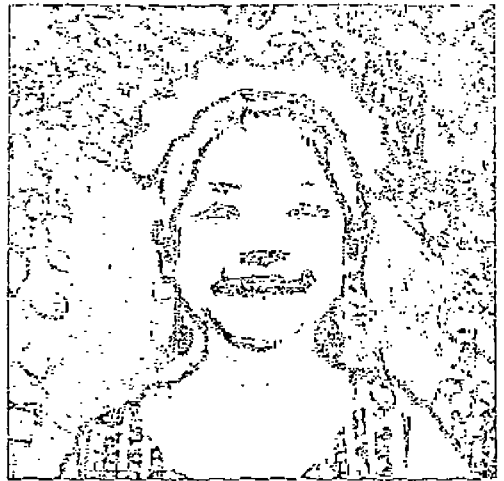
(Fig. 6) Edge detection of Figure 4 by Sobel operation



(Fig. 8) Edge detection of Figure 4 by the proposed method



(Fig. 7) Edge detection of Figure 5 by Sobel operation.



(Fig. 9) Edge detection of Figure 5 by the proposed method

6. Conclusion

A new edge detection approach is tried in an effort to bring the higher degree of human perception into the image processing. We found the application of the toll set concept is very useful and robust in edge detection. We expect more experiments using various kinds of images so that the characteristics of the proposed method becomes clear and further research especially in relation with other human perception based methods. We also expected the toll set concept may find other areas of application. Finally I am thankful for Teag-Gu Lim for his fine data processing job.

REFERENCES

[1] M. Petrou & J. Kittler, "Optimal edge detectors for ramp edges," IEEE Trans. PAMI, Vol-13, pp. 483~491, May, 1991.

[2] S. Sarkar & K.L. Boyer, "On optimal infinite impulse response edge detection filters," IEEE Trans. PAMI, Vol-13, pp.1154~1171, Nov., 1991.

[3] W.H.H.J. Lunscher & M.P. Beddoes, "Optimal edge detector design I:Parameter selection and noise effects," IEEE Trans. PAMI, Vol-8, pp. 164~177, Mar., 1986.

[4] W.H.H.J. Lunscher & M.P. Beddoes, "Optimal edge detector design 2:Coefficient quantization," IEEE Trans. PAMI, Vol-8, pp.178~187, Mar., 1986.

[5] D.Dubois & H.Prade, "Toll Sets," Proceedings of IFSA '91, Brussels, Artificial Intelligence, pp.21~24, 1991.

[6] A. Shimizu, "An Attempt to Methods for Approximate Reasoning Based on Fuzzy Entropy's Theory," Proceedings of the 2nd International Conference on Fuzzy Logic and Neural Networks, Vol.1, pp.301~304, 1992.

[7] S.K. Pal & A. Rosenfeld, "Image Enhancement and Thresholding by Optimizing Fuzzy Compactness," Pattern Recognition Letters, Vol.7, pp.77~

86, 1988.

[8] X.Q. Li, Z.W. Zhao, H.D. Cheng, C.M. Huang & R.W. Harris, "A Fuzzy Logic Approach to Image Segmentation," Proceedings of ICIP, pp. 337~341, 1994.

[9] M.M. Kim et al, "Edge detection of characters on the rubber tire image using fuzzy α -cut set," Korean Signal Processing Conference, pp.688~692, 1993.

[10] Y. S. Choi et al, "Minimum-error thresholding using fuzziness," Korean Signal Processing Conference, pp.325~328, 1993.



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