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Image Feature Extracting Operators Using DBAH/DBAG and its Implementation

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Abstract

Human psychovisual phenomena involved in extracting features is more sensitive in dark regions than in bright regions.

Therefore, feature extracting operators should be considered local intensities in order to perceive objects analogous to human vision system.

Generally, conventional feature extracting operators have some handicaps like an computational complexity or multivariable needs.

In this paper, a novel feature extracting operator is proposed to overcome these demerits. This operator could be implemented very simply and be proved good performances through experiments applied to synthetic and real images.

요 약

인간의 시각현상은 밝은 영역보다 어두운 영역의 특징점 추출에 더 민감하다. 그러므로 특징점 추출 연산자는 인간의 시각체계와 유사하게 물체를 인식하기 위해 국부적인 밝기를 고려해야 한다.

일반적으로 지금까지의 특징점 추출 연산자는 계산량이 많거나 다변수를 이용해야 하는 문제점을 가지고 있다.

본 논문에서는 이러한 단점을 극복하는 새로운 연산자가 제안된다. 이 연산자는 실현이 매우 간단할 뿐만 아니라 합성영상과 실영상에 적용한 결과 우수한 성능을 나타내었다

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Ⅰ. Introduction

Edge and valley are perceptually important features in gray level images. In case of projection of object space with non-uniform reflection, the features called edges occur at points which have abrupt changes in luminance and in case of projection of object space with uniform reflectance, the features occur at points which have local luminance minima called valleys. Since the major portion of the visual information of an image is contained in the edges and valleys, these features extracting process from digital images is very important. Despite their fundamental importance in digital image processing and analysis, there is no precise and widely accepted mathematical definition of these features.

In general, an observer's feeling associated with the edges in an image is more sensitive in dark regions than in bright regions. Hence human visual system has visual increment thresholds and converges asymptotically from the De Vries_Rose region to the Weber region as intensity increase [1]. Therefore, to extract the significant features as perceived by human beings, a good sketch feature operator should match the above mentioned human psychovisual phenomena as closely as possible.

In this paper, we propose a new operator called "DBAG" for extracting sketch features which is defined by the difference between the arithmetic mean and the harmonic mean. The DBAG depends on the local intensities as well as the rates of intensity change. In addition, the DBAG has a small response with small rates of intensity change in very dark regions and exhibits a trend converging asymptotically from the De Vries-Rose region to the Weber region as intensity increase. Experimental results revealed a good performance of the DBAG as expected in the present study.

Ⅱ. Conventional Operators

An approximation of the visual increment threshold was proposed by Kundu et al. They pointed out that the perceived intensity of a surface depends on its local intensities and classified the visual increment threshold differently according to the De Vries-Rose region, the Weber region and the saturation region as a function of local intensity. The visual increment thresholds in each region were proposed as follows:

$$\Delta B_T = \begin{cases} K_1\sqrt{B}, & \textit{De Vries-Rose region}, \\ K_2 B, & \textit{Weber region}, \\ K_3 B^2, & \textit{saturation region}, \end{cases} \qquad (1)$$

where ΔB_T, B, K1, K2, and K3 denote the visual increment threshold, local intensity and constants of the corresponding regions respectively.

Several operators have been emerged to improve the performance of the sketch feature extraction in images. These include Van Vliet's nonlinear gradient and nonlinear Laplacian [2], the logical Laplacian [3], the entropy operator [4], the DIP(difference of inverse probabilities) operator [5], etc..

The operators presented by Van Vliet et al. relate closely to the morphological gradient operator [6] and the implementation of these operators is very easy. The nonlinear gradient operator is relatively insensitive to noise and granularity but it extracts ramp edges often existing in real images as thick lines and does not depend on local intensities. The nonlinear gradient operator, NG, is defined as follows:

$$NG[f(i,j)] = f_{max}(i,j) - f(i,j), \quad (2)$$

where fmax(i,j) denotes the maximum intensity and f(i,j) the center-pixel intensity in a window.

The Laplacian edge operator produces a zero crossing at an edge location. It detects high frequency details accurately and its implementation is facilitated, but it is generally more sensitive to noise than other operators. This defect can be overcome to some extent by adopting its nonlinear versions. The nonlinear Laplacian, NL, is defined by the second-order derivatives as follows:

$$NL[f(i,j)] = f_{max}(i,j) + f_{min}(i,j) - 2f(i,j), \quad (3)$$

where fmin(i,j) denotes the minimum intensity in a window. The shifting effect of the edge locations which occurs in the nonlinear gradient operator does not occur in the nonlinear Laplacian because of its second-order derivatives. However, the nonlinear Laplacian does not depend on local intensities and creates several false edges, especially in the areas where the image variance is small, because small intensity perturbations tend to produce false zero-crossings.

The logical Laplacian operator, LL, is defined in a 3×3 window as follows:

$$\begin{aligned} LL[f(i,j)] = {} & L_1[f(i-1,j-1) - f(i,j)] \\ & + L_2[f(i-1,j) - f(i,j)] \\ & + L_1[f(i-1,j+1) - f(i,j)] \\ & + L_2[f(i,j-1) - f(i,j)] \\ & + L_2[f(i,j+1) - f(i,j)] \\ & + L_1[f(i+1,j-1) - f(i,j)] \\ & + L_2[f(i+1,j) - f(i,j)] \\ & + L_1[f(i+1,j+1) - f(i,j)], \end{aligned} \quad (4)$$

where $L_1(x)$ and $L_2(x)$ are nonlinear accelerated type functions for rejecting small differences and amplifying large differences. The logical Laplacian is less sensitive to noise than any other versions of the Laplacian but it also does not depend on local intensities.

The entropy operator, H, calculates the entropy at a center-pixel in a 3×3 window as follows.

$$H[f(i,j)] = -\sum_{i=-1}^{1}\sum_{j=-1}^{1} p_{ij} \log p_{ij} / \log 9, \quad (5)$$

where

$$p_{ij} = f(i,j) / \sum_{i=-1}^{1}\sum_{j=-1}^{1} f(i,j). \quad (6)$$

The entropy operator extracts the edges of dark regions quite well because of its dependence on local intensities. However, the edges are extracted as thick lines since it weights all pixels uniformly within the local region. It is noted that the entropy operator needs a large amount of computation due to the logarithmic operation.

The DIP operator calculates the difference of inverse probabilities in a 3×3 window as follows:

$$\begin{aligned} DIP[f(i,j)] = {} & [\sum_{i=-1}^{1}\sum_{j=-1}^{1} f(i,j)] / f(i,j) \\ & - [\sum_{i=-1}^{1}\sum_{j=-1}^{1} f(i,j)] / f_{max}(i,j) \end{aligned} \quad (7)$$

Dependence on the local intensities of the DIP operator enables excellent valley extraction in dark regions. Computation using the DIP operator is relatively simple even though another threshold value is needed to take account of the visual increment threshold in dark regions.

Ⅲ. DBAH/DBAG Operator and its Implements

As reviewed in the preceeding section, the presently existing operators possess their shortcomings for extracting sketch features since they either do not consider local intensities or have problems in dark regions. In the present study, new operators, DBAH and DBAG are proposed which are well appropriate for the effective extraction of sketch features similar to the human psychovisual phenomena. The DBAH operator calculates the difference between the arithmetic mean and the harmonic mean of the maximum intensity $f_{\max}(i,j)$ and the center-pixel intensity $f(i,j)$ in a window, which is defined as follows:

$$DBAH[f(i,j)] = \frac{f_{\max}(i,j)+f(i,j)}{2} - \frac{2f_{\max}(i,j)f(i,j)}{f_{\max}(i,j)+f(i,j)} \quad (8)$$

Meanwhile another operator DBAG calculates the difference between the arithmetic mean and the geometric mean of the maximum intensity $f_{\max}(i,j)$ and the center-pixel intensity $f(i,j)$ in a window, which is defined as follows:

$$DBAG[f(i,j)] = \frac{f_{\max}(i,j)+f(i,j)}{2} - \sqrt{f_{\max}(i,j)\times f(i,j)} \quad (9)$$

The interpretation of the feature extraction using the above DBAH and DBAG operator are explained as in Figure 1. Figures 1(a) and 1(b) show that the DBAH and DBAG tend to become larger for the greater intensity change. This tendency is the result that the arithmetic mean increases linearly and the harmonic mean(or the geometric mean) approaches the center pixel intensity with higher rate as the difference between the maximum and center pixel intensities increases. Figures 1(c) and 1(d) reveal that the DBAH and DBAG are apt to be larger in the dark region for the same intensity change rate. This tendency is the result that the arithmetic mean(or the geometric mean) decreases linearly but the harmonic mean(or the geometric mean) approaches more rapidly and close to the center pixel intensity for the lower sum of the maximum intensity and the center pixel intensity. As a result, the DBAH and DBAG tend to become larger for the greater difference between these two intensities and are apt to be higher in the dark region where the sum of these two intensities is lower. Moreover, it is noted that the DBAH and DBAG are extremely small in the very dark region because both of the intensities are quite small. The advantages of the DBAH and DBAG discussed so far are that the DBAH and DBAG can take into account the intensity change rate, the local intensity and the very dark regions as well in images, which make it possible to develope an efficient feature extraction technique akin to the human visual system.

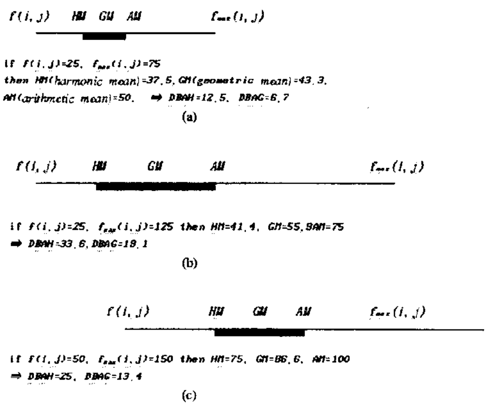


Figure 1. Example for the interpretation of DBAH/DBAG operation subject to local intensities and intensity changes.

However as shown in Equation (8) and (9), the DBAH is much easier than the DBAG for its implementation. The Device implementation for the DBAH presents in Figure 2 and its characteristics over the global image configuration describes in Figure 3.

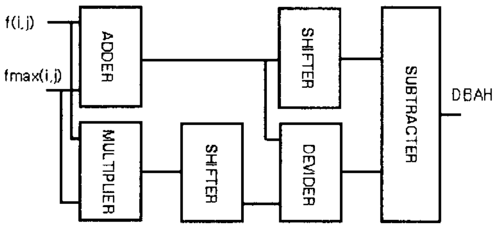
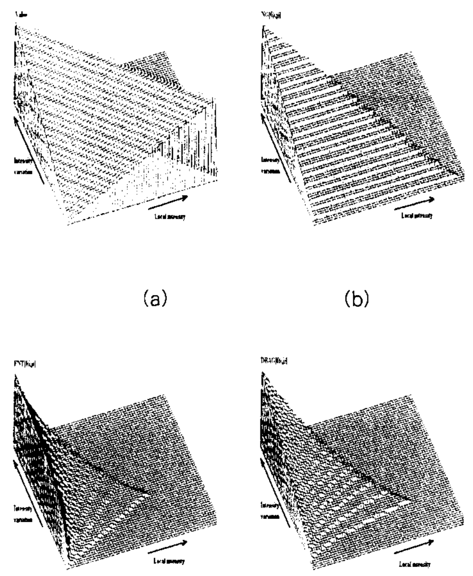


Figure 2. The DBAH implementation.

Figures 3 (b)-(d) show the outputs employing operators to a test image (Figure 3(a)): independent of the local intensity (Figure 3(b)), dependent on the local intensity (Figure 3(c), for example entropy or DIP operators) and considered with DBAH (Figure 3(d)). As it is seen in Figure 3(c), the outputs applying the entropy or DIP operator could not reveal the reality of images due to extremely high responding value for the small intensity change rates in the very low intensity regions. While the output of the DBAH as shown in Figure 3(d) agrees quite closely with the perception of human being especially in very dark regions. Therefore, the DBAH operator possesses unique advantages over the other operator for extracting sketch features.



(a) (b)

(c) (d)

Figure 3. (a) Test image, and the impulse responses. (b) Independent of the local intensity. (c) Dependent on the local intensity (for example entropy or DIP operators). (d) Applied with DBAH.

Ⅳ. Performance Results

Figure 4 shows the thresholded results taken from the edge strength image which was obtained with applying operators on a 3×3 neighborhood for a GIRL image, composed of 256 ×256 pixels with 8bits. The thresholds used for the operators were selected to get the best performance according to the visual quality of the resulting edge map. Cubic nonlinear functions were utilized for the logical Laplacian operator.

The results applying the nonlinear gradient and entropy operators, (a) and (d), revealed the extraction of edges with thick lines and the nonlinear Laplacian and logical Laplacian operators, (b) and (c), with lots of isolated spots. It is also seen that the nonlinear gradient, nonlinear Laplacian and logical Laplacian operators, (a)-(c), can not extract edges of dark regions properly. When the DIP and DBAG operators, (e) and (f), were applied on the other hand, the accurate extraction of edges was yielded in dark regions particularly. The DIP operator, however, possesses a disadvantage of relatively poor response in fairly bright regions and needs another threshold value to compensate the poor response in very dark regions. As mentioned in the previous section, the newly proposed DBAG operator depends on the spatial variations of intensities in a manner akin to human psychovisual phenomena. These capability of the DBAG operator can be found in the result of Figure 4(f) and has been checked with other types of images successfully as well.

(a) th=20 (b) th=15

(c) th=17500, weighting=x3 (d) th=0.9917

(e) th1=2.4, th2=15 (f) th = 0.7

Fig. 4. Detected edge locations for GIRL: (a) Nonlinear gradient, (b) Nonlinear Laplace, (c) Logical Laplace, (d) Entropy, (e) DIP and (f) DBAH.

V. Conclusion

In this paper, a new operator named the DBAH and the DBAG for extracting edges are proposed. However, the DBAH is much easier than the DBAG for its implementation. The impulse response of the DBAH agrees quite closely with the perception of the human being especially in dark regions. In addition, the computation process applying the DBAH is also very simple. Therefore, the DBAH operator possesses unique advantages over the other operator for extracting edges. The excellence in performance and the simplicity in computation make the DBAH operator attractive for wide range of applications such as robot vision, motion video transmission, etc.

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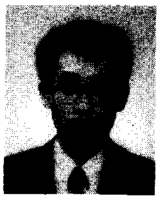
저 자 소 개



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