論文
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New edge detection algorithm and its application to a visual inspection
(새로운 에지 검출 알고리듬과 시각적 검사에서의 그 응용)

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ABSTRACT

We describe a characteristic behavior of edge signal intensity, the strictly monotonic variation of intensity across edges and propose a new algorithm for edge detection based on it. We define an extended directional derivatives, which is nonlocal and beyond scaling in the pixel space, to describe that the algorithm is adaptive to the various widths of edges and relevant as an optimal edge detection algorithm. As an industrial application of the algorithm, we discuss a simple computer vision procedure for an example of visual inspection

요 약

에지 시그널의 세기가 갖는 특징적인 성질로서, 에지를 가로질러 엄격하게 단조적인 세기 변화가 나타남을 설명하고 이를 바탕으로 하는 새로운 에지 검출 알고리듬을 제안한다. 스케일링에 무관하고 비국소적인 확장된 방향미분을 픽셀 공간에서 도입하여, 본 알고리듬이 에지 폭의 다양한 변화에 적응성을 가지며 최적의 에지 검출 알고리듬으로서 적절함을 설명한다. 본 알고리듬의 산업적 응용으로서, 시각적 검사에 대한 간단한 컴퓨터 비전 프로시저의 한 예를 살펴본다.

1. Introduction

An edge signal is detected as a significant local change in the image intensity and its ideal features should be associated with a discontinuity in either the image intensity or its first order derivatives. However, because of the low frequency mode effect introduced by the physical limit of sensing devices, the sharp discontinuity rarely appears in real signals and the step edge is blurred into the ramp edge. In the real image, the edge may have widely varying ramp width or acuity. Therefore, the task of detecting and locating edge features precisely in real images poses a challenging problem in usual and have inspired the development of various advanced algorithms for the optimal edge detector.[1-9] One

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of significant early contributions to this subject was made by Marr and Hildreth,[1] and further developed by Canny[2] employing different scales in the inspection of intensity changes. More operational refinements of their strategy have been accomplished by using the matched filter for detecting and locating edges.[3-6]

From the different physical origins, there can appear sharp lines along with blurred boundaries in the same image. Accordingly, the reliable detection of the significant intensity changes corresponding to the edges with various widths requires adjustments in filter length to construct several edge maps with respect to each of several pertinent length scale. In the edge detection algorithm by template matching, we assume a specific functional form for the intensity change associated with edge. In the Gaussian model of edge template, the profile of edge signal intensity is described by the integral of a Gaussian added to a fixed background, where we assume the *strictly monotonic* intensity profile of edge and two parameters for the edge detector. The one is the amplitude of Gaussian representing the magnitude of transition, i. e. the difference in the intensity between the regions bounded by the edge, and the other is the variance of Gaussian indicating the signal slope and hence the edge acuity. Therefore in order to handle different length scales implied by varying edge width, we may require to adjust the filter length, which is accomplished by the adjustment of the Gaussian variance as a parameter of the edge detector in practice.[3-6,9]

In this paper, we modify the directional derivative extensively to introduce an extended (nonlocal) directional derivative of *grey level* as the signal attribute characterizing an edge in the pixel space, which is to be referred to as *adaptive directional derivative of grey level.* In terms of this attribute, we can detect an edge by verifying the presence of a region with strictly monotonic change of intensity without bothering to adjust the edge width parameter such as the Gaussian variance. In order to locate a single edge pixel, we find the *local center of directional derivative* within the edge width

In the next section, we introduce the adaptive directional derivative of grey level to suggest a criterion for the verification of the presence of edges. In the section 3, we explain how to locate the edge pixel exactly and describe the edge detection algorithm. An example of applying the algorithm accompanied by the median filtering or Gaussian low pass filtering[7,8,9] as preprocessing is presented in the section 4. As another example of a industrial application, we suggest a simple computer vision procedure for visual inspection, where we can represent the (features of) image simply by resampling the edge pixels on a grid without extra descriptors such as chain codes.[10,11] In the final section, we discuss some other aspects of the algorithm.

2. New criterion for identifying ramp edges

The edge pixels correspond to the boundary points located between some different regions representing objects or background in the image. Therefore, the neighborhood of an edge point always includes some points belonging to each of the different regions. On the contrary, an interior pixel of a region in the 2-dimensional image should have all of its 8 neighboring pixels similar in the intensity (or color components) of image. Hence the pixel is an edge point only if it has at least one neighboring pixel whose intensity is different from the others in the neighborhood (or the pixel itself, equivalently) more than the value allowed by the similarity criterion, say T in practice. That is, the edge point has a significant intensity change larger than the threshold value T between one of its neighboring pixels at least and may be associated with some discontinuities in the image intensity. For the sake of the simplicity in discussion. we assume that the image is gray-scaled. With respect to the set of nonnegative integers Z_+, let (i, j) be the spatial rectangular coordinates of a digitized image in pixel units with $i, j \in Z_+$. Then, the image function is defined as a mapping

$$f:\ Z_+ \times Z_+ \rightarrow G$$

where $f(i, j) \in G$ is the grayscale intensity of a pixel whose coordinates are $(\boldsymbol{i}, \boldsymbol{j})$, with $0 \leq i \leq W$ and $0 \leq j \leq H$. The hight and width of the digitized image f are identified as H and W respectively with $H, W \in Z_+$. If the grayscale intensity is quantized by l levels, $G = \{0, 1, \cdots, l-1\}$ from the darkest level 0 to the brightest $l-1$. We introduce the pixel position vector $\boldsymbol{p} = (i, j)$ and define eight direction vectors as

$$\boldsymbol{u}_{\pm x} \equiv \pm(1, 0), \quad \boldsymbol{u}_{\pm y} \equiv \pm(0, 1),$$
$$\boldsymbol{u}_{\pm +} \equiv \pm(1, 1), \quad \boldsymbol{u}_{\pm -} \equiv \pm(1, -1), \qquad (1)$$

where $\boldsymbol{u}_{\pm +}$ and $\boldsymbol{u}_{\pm -}$ are not properly normalized. In terms of these vectors, we define the directional derivatives of a function F at $\boldsymbol{p}$ in the pixel space as

$$D_\theta F(\boldsymbol{p}) \equiv F(\boldsymbol{p} + \boldsymbol{u}_\theta) - F(\boldsymbol{p})$$
$$= -D_{-\theta} F(\boldsymbol{p} + \boldsymbol{u}_\theta), \qquad (2)$$

where θ parametrizes the eight directions to the neighboring pixels of $\boldsymbol{p}$ with $\boldsymbol{u}_{\pm\theta} = \pm\, \boldsymbol{u}_\theta$ in the above definition (1). D_θ is the natural equivalent to the directional derivative of the continuum space

$$\frac{dF}{dq_\theta} = \lim_{\Delta q_\theta \to 0} \frac{F(\boldsymbol{p} + \Delta q_\theta \boldsymbol{u}_\theta) - F(\boldsymbol{p})}{\Delta q_\theta}$$

if $\boldsymbol{u}_\theta$ is normalized. Applying D_θ to the image function f, we obtain the directional derivative of gray level (DDGL)

$$v_\theta(\boldsymbol{p}) \equiv D_\theta f(\boldsymbol{p}) = f(\boldsymbol{p} + \boldsymbol{u}_\theta) - f(\boldsymbol{p}), \quad (3)$$

which can be used to determine the boundary features of the image. Since the gray level difference between the edge pixel and at least one of its neighboring pixels is larger than some threshold value T, *we can identify the pixel* $\boldsymbol{p}$ *as an edge pixel only if the criterion* $|v_\theta(\boldsymbol{p})| \geq T$ *with respect to the absolute value of a directional derivative of gray level for one of* θ *directions at* $\boldsymbol{p}$ *is satisfied.* When $\boldsymbol{p}$ is an edge pixel with $|v_\theta(\boldsymbol{p})| \geq T$, we can find that $\boldsymbol{p} + \boldsymbol{u}_\theta$ is paired to be an edge pixel also since $v_\theta(\boldsymbol{p}) = -v_{-\theta}(\boldsymbol{p} + \boldsymbol{u}_\theta)$ doubly identifying the same edge feature of an object in the image. The edge pixels detected by the criterion is gathered and linked to construct an edge or the other edge features such as points and lines. Therefore, it can be easily seen that we can detect all of these edge features by using this criterion alone without employing any other special masks for each of them. For example, the usual point detection mask is applied to the pixel $\boldsymbol{p}$ producing the response $-\sum_\theta v_\theta(\boldsymbol{p})$ and $-\sum_{(\boldsymbol{k}=0,\ \boldsymbol{u}_{\pm y})} (v_x(\boldsymbol{p} + \boldsymbol{k}) + v_{-x}(\boldsymbol{p} + \boldsymbol{k}))$ is the response of the usual line detection mask in the y direction. With respect to the typical point and line, $v_\theta(\boldsymbol{p})$ and $v_{\theta'}(\boldsymbol{p} + \boldsymbol{u}_{\theta''})$ in the above reponses of detection mask have the same signs and some relevant threshold values for the absolute values of the above mask responses results in the equivalents to our simple criterion by $v_\theta(\boldsymbol{p})$. In order to detect discontinuities in general, we can use the gradient of the image f. Using the Sobel mask, the x component of the gradient is represented as

$$G_x(p) = 2(v_x(p + u_{-x}) + v_x(p)) + v_+(p + u_{-+}) + v_+(p) + v_-(p + u_{--}) + v_-(p) \quad (4)$$

With respect to the typical sharp edge normal to x direction for example, the y component of the gradient $G_y(p) \simeq 0$, and the DDGL's $v_\theta(p)$ and $v_{\theta'}(p + u_{\theta''})$ in $G_x(p)$ of (4) have the same signs. Therefore the result from detection criterion using a certain relevant threshold value for the magnitude of the gradient $\sqrt{G_x^2 + G_y^2}$ is equivalent to our simple criterion by $v_\theta(p)$.

In practice, edges are blurred to yield ramp-like profile due to optical condition, sampling rate and other image acquisition imperfection, with degree of blurring being a measure of the performance of image generating system. However, the previous criterion may not detect a ramp edge with gradually changing gray level. In order to include ramp edges, we modify the DDGL to define the adaptive directional derivative of gray level (ADDGL)

$$\triangle_\theta(p) \equiv [1 - \delta_{s_\theta(p), s_\theta(p - u_\theta)}] \sum_{k=0}^{\infty} \delta_{k+1, N_\theta(p,k)} v_\theta(p + k\, u_\theta) \quad (5)$$

where

$$N_\theta(p,k) \equiv \sum_{n=0}^{k} |s_\theta(p + n\, u_\theta)| \delta_{s_\theta(p), s_\theta(p + n\, u_\theta)}, \quad (6)$$

$$s_\theta(p) \equiv \begin{cases} +1, & v_\theta(p) > 0 \\ 0, & v_\theta(p) = 0 \\ -1, & v_\theta(p) < 0 \end{cases} \quad (7)$$

and $\delta_{(\ ,\ )}$ is the Kronecker delta. According to this definition, $\triangle_\theta(p)$ has a nonvanishing value only when p is the starting pixel of a strictly monotonic interval of the profile of f in the θ direction. That is, if f starts to increase or decrease strictly at p and ends at $p + w\, u_\theta$ from $f(p)$ to $f(p + w\, u_\theta)$ along the θ direction then

$$\triangle_\theta(p) = \sum_{n=0}^{w-1} v_\theta(p + n\, u_\theta) = f(p + w\, u_\theta) - f(p). \quad (8)$$

Since the ADDGL is defined extensively over some consecutive pixels in general, the normalization irregularity of u_θ is not significant in contrast to the case of DDGL. Using the *pairing* property $v_\theta(p + n\, u_\theta) = -v_{-\theta}(p + (n+1)\, u_\theta)$, this equation can be rewritten as

$$\begin{aligned} \triangle_\theta(p) &= -\sum_{n=0}^{w-1} v_{-\theta}(p + w\, u_\theta + (w-1-n)\, u_{-\theta}) \\ &= -\sum_{n=0}^{w-1} v_{-\theta}(p + w\, u_\theta + n\, u_{-\theta}) \\ &= -(f(p + w\, u_\theta + w\, u_{-\theta}) - f(p + w\, u_\theta)) \\ &= -\triangle_{-\theta}(p + w\, u_\theta). \end{aligned} \quad (9)$$

According to the definition, $\triangle_{\pm\theta}(p + h\, u_\theta) = 0$ for $0 < h < w$. Hence we can notice that the ADDGL $\triangle_\theta(p)$ specifies the strictly monotonic change of intensity and the corresponding interval $[p,\ p + w\, u_\theta]$ along some fixed θ direction.

In the Gaussian model of a ramp edge, the edge signal is described by the integral of a Gaussian added to a background object signal. For the directional derivative in the direction normal to an edge, whose absolute value is equal to the magnitude of gradient, this implies a functional form of template

$$\partial_n f \equiv v_n(q_n) = \frac{A}{\sqrt{2\pi}\sigma} \exp\left(-\frac{q_n^2}{2\sigma^2}\right) \quad (10)$$

in terms of the length parameter q_n along the edge normal direction. Here, the amplitude A

indicates the sign and magnitude of the transition in the image intensity between the two edged regions and the standard deviation σ describes the slope of edge signal i. e. the edge acuity or edge width. Then the directional derivative of the direction with angle ϕ from the edge normal direction has the template function

$$\partial_\phi f \equiv v_\phi(q_\phi) = (\cos\phi)\,\partial_n f \\ \equiv \frac{A}{\sqrt{2\pi}\sigma_\phi}\exp\left(-\frac{q_\phi^2}{2\sigma_\phi^2}\right), \qquad (11)$$

where $\sigma_\phi \equiv \frac{\sigma}{\cos\phi}$ and $q_\phi \equiv \frac{q_n}{\cos\phi}$. Since $|v_\phi(q_\phi)| = |(\cos\phi)v_n(q_n)| \le |v_n(q_n)|$ and $v_\phi(q_\phi)$ is equivalent to $v_\theta(p)$ for some ϕ, the previous criterion $|v_\theta(p)| \ge T$ reduces to

$$|v_n(q_n)| = \sqrt{G_x^2 + G_y^2} \ge T, \qquad (12)$$

where $|v_n(q_n)|$ is the absolute value of the directional derivative in the edge normal direction and equal to the magnitude of gradient $\sqrt{G_x^2+G_y^2}$ of the image intensity. Therefore the criterion $|v_\theta(p)| \ge T$ is equivalent to that of the usual edge detection algorithm employing the magnitude of gradient as the signal attribute characterizing an edge. With respect to an ramp edge described by the template function (11), the condition (12) is represented as

$$|v_n(0)| = \frac{|A|}{\sqrt{2\pi}\sigma} \ge T(\sigma), \qquad (13)$$

where we note that the threshold value T should be parametrized according to the edge width or the length scale of edge detection filter described by σ in such a way as $T(\sigma) = T_0/(\sqrt{2\pi}\sigma)$ in order to detect the edge signals with varying widths. That is, the significant change of image intensity by $|A| \ge T_0$ across the ramp edge, say, can be detected as an edge by adjusting the edge detector parameter $T(\sigma)$ according to the edge width parameter σ under the condition (13). In the actual application, we have no idea of fixing the exact edge pixel with $q_n = 0$ in advance. Therefore instead of the criterion (13), we should employ the criterion $|v_n(p)| \ge T(\sigma)$ or

$$|v_\theta(p)| \ge T(\sigma), \qquad (13)'$$

which can cause multiple identification of edge pixels at a single crossing of a ramp edge and demand an extra thinning to locate an exact edge pixel.

We can employ our ADDGL as the signal attribute characterizing an edge instead of the magnitude of gradient i. e. the absolute value of DDGL in the edge normal direction. With respect to the template of ramp edge satisfying the equation (11), for example, the ADDGL in the direction with angle ϕ from the edge normal direction is estimated as

$$\triangle_\phi(p) = \begin{cases} A, & \phi \ne \pi/2 \\ 0, & \phi = \pi/2 \end{cases} \qquad (14)$$

at the starting point p of the strictly monotonic change of intensity for a ramp edge along the fixed direction, which is independent of σ. That is, $\triangle_\phi(p)$ detect the significant change A in the gray level associated with an edge unless the direction is tangential to the edge, regardless of the edge width. Therefore, we can find that $\triangle_\theta(p)$ can detect the ramp edges which are strictly monotonic in gray level along the θ direction except the edge parallel to the θ direction, which can be detected by another $\triangle_{\theta'}(p)$ with a different direction θ'. In order to identify ramp edges, we thus implement a new criterion by $\triangle_\theta$:

(CRE) *The absolute value of an adaptive directional derivative of gray level at* p *is larger than* T, *i. e.* $|\triangle_\theta(p)| \geq T$ *for one of* θ *directions.*

Employing this criterion, the local maximal length interval $[p, p+w\, u_\theta]$ of strictly monotonic gray level along the $\pm\theta$ directions satisfying $|f(p+w\, u_\theta)-f(p)| \geq T$ is identified to belong to the width of a ramp edge, and one of $w+1$ pixels in the interval is determined as the edge pixel. Since the ADDGL $\triangle_{\theta_1}(p)$ or $\triangle_{\theta_2}(p)$ of two non-parallel directions θ_1 and θ_2 can detect the edges of all directions, we can use the two fixed directions $\theta_1 = x$ and $\theta_2 = y$ in practice. Hence we can describe our edge detection strategy as the following procedure:

P1. We scan the image along the x direction to find the strictly monotonic intervals such as $[p, p+w_x\, u_x]$ over which the variation of intensity $|f(p+w_x\, u_x)-f(p)|$ i. e. $|\triangle_x(p)|$ satisfies the criterion (CRE).

P2. Locate an edge pixel within the interval $[p, p+w_x\, u_x]$.

P3. Repeat the procedures with respect to the y direction to find the strictly monotonic interval such as $[q, q+w_y\, u_y]$ and locate an edge pixel in between.

Here, we note that this procedure can detect an edge regardless of spatial blurring or scaling which are concerned with the edge width parameter σ, and extract the exact edge only if a relevant method of locating edge pixels within the strictly monotonic intensity variation of ramp edges is presented.

3. Location of edge pixels and edge detection algorithm

In the previous section, we described the method how to verify the presence of an edge in detail. However, in order to complete the edge detection algorithm, we have to be provided with a way how to locate an edge pixel exactly as stated in the above procedure. In the scan of image along a fixed θ direction, the range of location of an edge is restricted to the strictly monotonic interval $[p, p+w\, u_\theta]$ of intensity change with the ADDGL $\triangle_\theta(p)$ satisfying the criterion (CRE). In order to locate an edge pixel within that interval, we define the local center of directional derivative(LCDD) as

$$p+k_C\, u_\theta \equiv \frac{\sum_{k=0}^{w-1}[p+k\, u_\theta]\, v_\theta(p+k\, u_\theta)}{\sum_{k=0}^{w-1} v_\theta(p+k\, u_\theta)}$$

$$= p+\frac{\sum_{k=0}^{w-1} k\, v_\theta(p+k\, u_\theta)}{\triangle_\theta(p)}\, u_\theta. \quad (15)$$

In the pixel space, k_C should be rounded off to obtain the integer value

$$(k_C) \equiv \mathrm{round}\left[\frac{\sum_{k=0}^{w-1} k\, v_\theta(p+k\, u_\theta)}{\triangle_\theta(p)}\right] \quad (16)$$

and the edge pixel is determined as $p+(k_C)\, u_\theta$, which is represented as

$$p+(k_C)\, u_\theta = p + k_C\, u_\theta - [k_C - (k_C)]\, u_\theta$$
$$= \frac{\sum_{k=0}^{w-1}[p+k\, u_\theta]v_\theta(p+k\, u_\theta)}{\triangle_\theta(p)}$$
$$- \left[\frac{\sum_{k=0}^{w-1} k\, v_\theta(p+k\, u_\theta)}{\triangle_\theta(p)} - (k_C) \right] u_\theta. \quad (17)$$

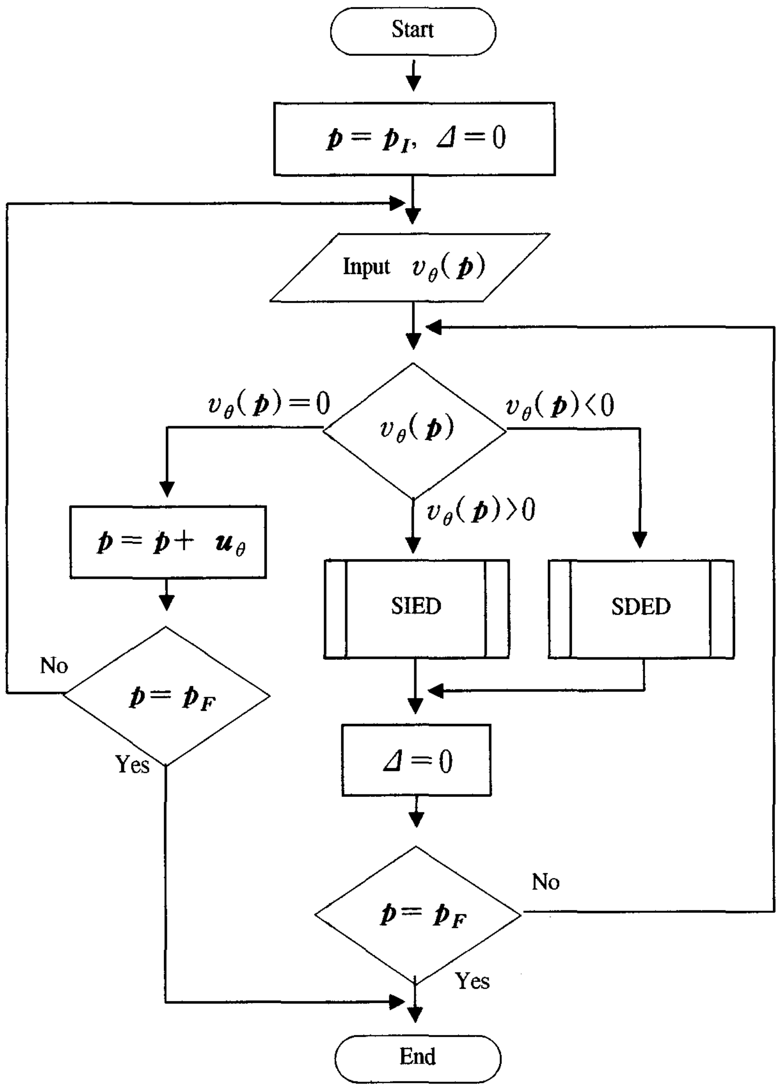
We can expect that this pixel determined by the LCDD can locate the edge of single pixel width out of the ramp edge without employing an extra thinning mechanism.

With respect to strictly increasing intervals, we apply the strictly increasing edge detection (SIED) procedure to detect and locate an edge pixel, which is suspended at the end pixel p_F of the line and specified in the following pseudo code:

Procedure SIED:

1. While $v_\theta(p)>0$ and $p \neq p_F$ with respect to the value $v_\theta(p)$ of DDGL from successive scan pixel by pixel along the θ direction, do
   1-1. Put $\sum \mathbf{VP}=0$ and $\sum \mathbf{kV}=0$ initially.
   1-2. Calculate $\Delta = \sum_p v_\theta(p)$.
   1-3. Count the scanned pixels to get the value of k.
   1-4. Add $v_\theta(p)p$ and $kv_\theta(p)$ to $\sum \mathbf{VP}$ and $\sum \mathbf{kV}$ respectively to obtain their new values.
2. When $v_\theta(p)\leq 0$ or $p = p_F$ (i. e. at the end of the strictly increasing interval), if $\Delta \geq T$,
   2-1. Calculate $(k_C) \equiv$ **round**$[\sum \mathbf{kV}/\Delta]$
   2-2. Write $\frac{\sum \mathbf{VP}}{\Delta} - \left[\frac{\sum \mathbf{kV}}{\Delta} - (k_M)\right] u_\theta$ as an edge pixel.

With respect to strictly decreasing intervals, we apply the strictly decreasing edge detection (SDED) procedure, which is obtained simply by replacing $v_\theta(p)$ with $-v_\theta(p)$ in the SIED procedure. In order to construct the algorithm for detecting edge pixels from scanning the whole of a single line in the θ direction, we combine the SIED and SDED procedures as the sub-procedures for the pixels with $v_\theta(p)>0$ and $v_\theta(p)<0$ respectively, together with the bypassing procedure which produces no output for the pixels with $v_\theta(p)=0$. We then obtain the edge pixels identified with the LCDD from the SIED or SDED procedures as the output of this algorithm for edge detection from single line scan (EDSLS). This EDSLS algorithm with respect to the line starting at $p=p_I$ and ending at $p=p_F$ in the two dimensional image is simply illustrated in the flow chart of [Fig. 1] We apply the EDSLS algorithm to every linear sequence of pixels in x or y direction to accomplish the complete edge detection from the image. That is, a complete edge detection algorithm of an image is constructed by the integration of the EDSLS algorithm over all the complete lines of both the principal directions $\theta=x$ and y.



[Fig. 1] The EDSLS algorithm. The algorithm for detecting edge pixels along the single line starting at $p=p_I$ and ending at $p=p_F$.

[그림 1] $p=p_I$에서 시작하여 $p=p_F$에서 끝나는 한 직선을 따라 에지 픽셀을 검출하는 EDSLS 알고리즘.

4. Applications

Our edge detection algorithm is absolutely dependent on the strictly monotonic behavior of intensity change, which is very sensitive to the speckle noise or isolated pixel noise. That is, the isolated pixel noise deteriorates badly the strictly monotonic behavior of substantial edge signals and should be eliminated for the EDSLS algorithm not to result in the false edge detection. In order to reduce this speckle noise in practice, we can employ the median filter which is nonlinear but preserve edge characteristics.

(a)

(b)

(c)

(d)

[Fig. 2] (a) Original image and (b) its edge detection with $T=30$. The results of edge detection from (c) median filtering by 3×3 neighborhood ($T=30$) and (d) additional Gaussian smoothing with 7 pixel filter size ($T=15$).

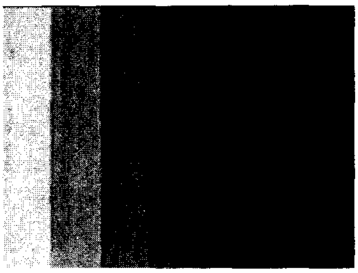
[그림 2] (a) 원 영상과 (b) $T=30$ 을 사용한 그 에지 검출. (c) 3×3 이웃으로 중간값 필터를 적용한 후에 에지를 검출한 결과와 (d) 추가로 7 픽셀 크기의 가우시안 필터를 적용하고 $T=15$ 를 사용한 에지 검출.

We first illustrate the application of our algorithm and the role of noise reduction techniques such as median filtering or Gaussian smoothing via the 2-D image in [Fig. 2] In the result [Fig. 2](b) for the original image without preprocessing, we can notice that there appear many speckle objects complicating the detected edges or delineated by false edges with $T=30$ in the criterion (CRE). The result [Fig. 2](c) represents the edges from the median filtering with filter size of 3 pixels using $T=30$ again. With respect to the 2-D image in general, the median filter with filter size $\lambda=2\rho+1$ is applied to the $\lambda\times\lambda$ neighborhood of each pixel to remove the noise objects wide up to ρ pixel size. Therefore, we have the single pixel (noise) objects eliminated and obtain the pertinent detection of edges for principal objects in [Fig. 2](c). When we apply the Gaussian low pass filter to a sequence of stepwise adjacent edges, the corresponding sequence of strictly monotonic intensity intervals can be smeared into a single interval of strictly monotonic intensity if the filter size exceeds the distance between edges far. Therefore, the Gaussian smoothing may suppress some edges and should be used restrictively in applying our edge detection algorithm. In the result [Fig. 2](d) from Gaussian smoothing with the filter size of 7 pixels, we can find that some elaborate edges of [Fig. 2](c) disappear even with $T=15$.

The other example of applying our edge detection algorithm is presented for a industrial automation of visual inspection. At the final stage of testing the performance of image display appliances like television or their parts like crystal oscillator, the manufacturer usually carry out the visual inspection to compare the display states of a standard test image relying on the tester's bare eyes. A typical standard test image is displayed at a good state in [Fig. 3](a) and a bad state in [Fig. 3](c). This visual inspection procedure can be done by the computer vision technique, whose core operation is the representation of the model of test image and displayed test images. In order to represent the images, we can employ a pertinent grid to resample the edge pixels on. A relevant representation of the model image can be described by the collection of resmapled edge pixels on the grid. Since the test image has the simple texture, we do not have to perform the edge linking to obtain the complete boundaries of the image or image segmentation and thereby chain codes neither. Therefore, we suggest a simple procedure of visual inspection comprised of following steps:

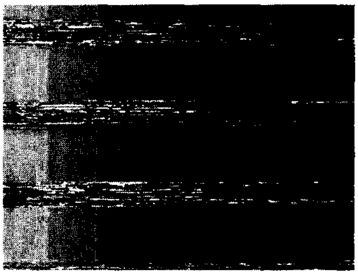
Step 1) Acquisition and preprocessing of images.
Step 2) Edge detection.
Step 3) Resampling edge pixels on a grid into a collection to represent the image.
Step 4) Comparison of the collections to estimate the state of displayed image.

Since the texture of test image is coarse and regular, we can employ the Gaussian low pass filter as well as the median filter extensively, in applying our edge detection algorithm. The results of edge detection are presented in [Fig. 3](b) and [Fig. 3](d) under the same filtering conditions.

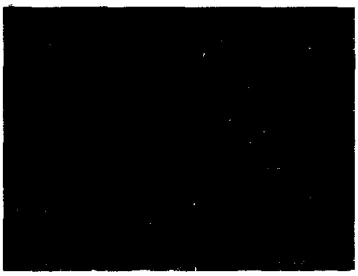


(a)

(b)



(c)



(d)

[Fig. 3] (a) A good and (c) a bad displayed test image, and their edge detections (b) and (d) respectively by the Gaussian smoothing of 7 pixel size and the median filtering of 15 pixel size with $T=15$.

[그림 3] (a) 시험 영상의 좋은 표시 상태와 (b) 7 픽셀 크기의 가우시안 필터와 15 픽셀 크기의 중간값 필터를 적용하고 $T=15$를 사용한 에지 검출. (c) 시험 영상의 나쁜 표시 상태와 (d) 동일한 조건에서의 에지 검출.

5. Discussions

In order to verify the presence of edges, we only have to investigate the ADDGL's $\triangle_x(p)$ and $\triangle_y(p)$ independently. Therefore, this algorithm seems to have relative simplicity of calculation compared to the usual ones employing the magnitude of gradient $\sqrt{G_x^2+G_y^2}$, which include the floating point operation for the calculation of square root. However, the operators $\triangle_x(p)$ and $\triangle_y(p)$ are badly nonlocal, and cause another kind of calculational expense to be estimated. Although the use of median filter to reduce the false positive or negative effect of isolated pixel noises can cause some complexity compared to the linear filter such as the uniform or Gaussian filter, the expensiveness is not so bad at all for calculation if the filter length is restricted to 3 pixels discarding the single pixel noises only. The median filter is especially effective in eliminating isolated pixel noises. However, if we want to smooth the texture, we may well use the Gaussian filter, or equivalently replace $v_x(p)$ and $v_y(p)$ into the corresponding Sobel gradient components in the definition of $\triangle_x(p)$ and $\triangle_y(p)$. The use of linear smoothing filter can improve the connectivity in edge linkage.

In using the ADDGL as the characteristic attribute of edge signal, the gradual change of intensity over large area of a single surface, which can be caused by the nonuniformity in scene illumination, may be recognized as a false edge. In order to prevent this false positive effect in particular, we need the unsharp masking or flat-fielding procedure before applying the edge detector.

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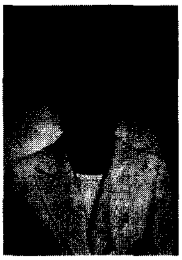

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