A Three-step Technique of Robust Line Detection with Modified Hough Transform

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ABSTRACT

Line detection is one of the most long-lasting problems in image processing. In this paper, we address the problem of detecting strong/weak lines and long/short lines in gray level images simultaneously. Our technique consists of three steps: image gradient enhancement, modified Hough Transform (HT) and line fitting. The gradient direction is fully exploited in our technique, which provides additional cues for weak line detection. Experiments on various images are presented to verify our approach. The results show that our technique has a superior detection rate than conventional HT algorithm, especially for short and weak lines.

Keywords: line detection, Hough Transform, Canny edge detector, gradient enhancement

1. INTRODUCTION

Line detection is one of the most long-lasting problems in image processing. A number of existing techniques utilize the Hough Transform to solve this problem. Recent surveys[3, 4, 5] reviewed the development and extension of the HT concerning computational complexity and storage requirement. However, for those conventional HT-based algorithms, short lines are difficult to detect due to their poor voting weights; and in order to detect lines in gray level images, the conventional HT should be adapted by employing the gradient information of images. Cucchiara and Filicori[1] compared the widely used Gradient Weighted HT (GWHT) and their Vector-Gradient HT (VGHT). Both transforms consider the shape detection in gray level images. Based on the connectivity of lines, Yang et al.[2] proposed a connectivity weighted HT (CWHT) to detect short lines.

In this paper, we address the problem of detecting strong/weak lines and long/short lines in gray level images simultaneously. Our technique consists of three steps: image gradient enhancement, modified Hough Transform and line fitting. The gradient direction is fully exploited in our technique, which provides additional cues for short/weak line detection. In the first step, the Canny edge detector with a very low threshold (e.g., 0.01) is employed to emphasize the weak lines. A continuity criterion of gradient directions is then applied to enhance the gradient intensities along the lines. Subsequently, the enhanced gradient intensities are mapped to the thin edge detected by Canny. This step results in a gradient map in which weak lines are well enhanced. Second, a modified Hough Transform which is slightly different from GWHT and VGHT is used to detect the lines. Since the gradient direction at a pixel is highly related to the line direction, the voting weight is determined by the gradient direction together with the gradient map which represents the intensity of the possible line. In the final step, the direction of each line is considered respectively in order to protect the weak lines from being flooded by the voting of strong lines. A coarse direction grouping is applied to the initial lines. The lines are then extracted from each group separately. At different gray levels, a finite state machine model is utilized to verify and refine the lines obtained in previous steps.

This paper is organized as follows: The three steps are described in Section 2, 3, and 4 respectively, together with corresponding experimental results. And in Section 5, we provide the conclusion.

2. GRADIENT ENHANCEMENT

In a gray level image, since the lines are the straight edges of objects, the gradient intensities and the continuity of gradient directions are more significant along the lines than in the other image areas. This fact is shown in figure 1(a), (b), (c), and (d). For the first step of our algorithm, Canny edge detector with a very low threshold (e.g. 0.01) is selected to protect weak lines (see figure 1(b)). From figure 1(c), we can see that mild blocks appear near the edges of the buildings. So, high continuity implies the present of lines. To employ this information, two problems must be solved: 1) how to define the continuity of gradient direction along the lines; 2) how to use it for the gradient enhancement. In our application, the gradient direction's continuity θ^c at point $A(x_0, y_0)$ in an image is defined as

$$\theta^c[x_0, y_0] = \sum_{x \in Dx_0} \sum_{y \in Dy_0} \big(w(x, y)\big) \tag{1}$$

where Dx_0 and Dy_0 define a neighbor region of $A(x_0, y_0)$, and $w(x, y)$ is point $B(x, y)$'s contribution to the continuity with respect to point A. Obviously, the continuity is a regional property. The contribution of point $B(x, y)$ for point A is defined as

$$w(x, y)_{(x_0, y_0)} = f(d_{(x,y,x_0,y_0)}) \times g_1(\alpha_{(x,y,x_0,y_0)}) \times g_2(\beta_{(x,y,x_0,y_0)})$$

$$f(d_{(x,y,x_0,y_0)}) = 1/d_{(x,y,x_0,y_0)}, \quad \left.\begin{array}{l} g_1(\alpha_{(x,y,x_0,y_0)}) = Gauss_{\delta 1}(\alpha_{(x,y,x_0,y_0)}) \\ g_2(\beta_{(x,y,x_0,y_0)}) = Gauss_{\delta 2}(\beta_{(x,y,x_0,y_0)}) \end{array}\right\rangle \delta 1 < \delta 2 \tag{2}$$

where $d(x, y, x_0, y_0)$ is the distance between A and B, $\alpha(x, y, x_0, y_0)$ is the difference between the gradient direction at A and the gradient direction at B, $\beta(x, y, x_0, y_0)$ is the difference between the direction of line AB and the gradient direction at A, δ_1 and δ_2 are the standard deviations of zero mean Gaussian functions. The smaller of d affects more on the continuity; so do α and β. Thus we use the function f, g1 and g2 to weight d, α and β respectively, and the condition $\delta_1<\delta_2$ is considered to stress the change of the main factor α. Figure 1(f) shows the result of the gradient direction's continuity along the lines under our definition. It can be seen that the white regions in figure 1(f) are corresponding to the mild blocks in figure 1(c).

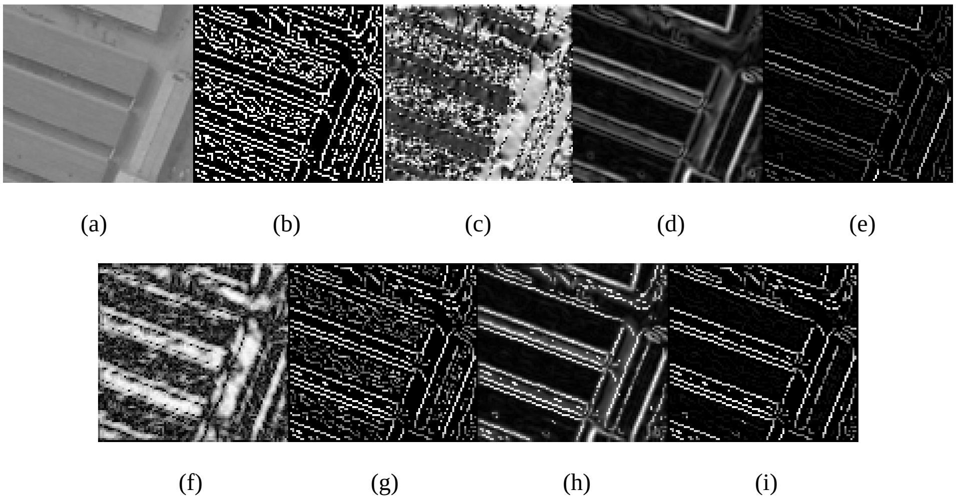


Fig.1 Image gradient enhancement: (a) Original image 95 * 89. (b) Thin edge of (a) by Canny edge detector with threshold 0.01. (c) Gradient direction of (a) by Canny filter (mapping -90º~90º to 0~255). (d) Gradient intensity of (a) by canny filter. (e) Mapping the intensity of (d) to (b). (f) Continuity of (c) by our method with a 5 * 5 neighboring range. (g) Thinning of (f) according to (b). (h) Enhanced gradient intensity of (a) by (g). (i) Mapping the intensity of (h) to (b)

As a regional property, the continuity should be refined to enhance the gradient intensity along the lines. A natural way is to exploit the thin edges (see figure 1(b)). The result is given in figure 1(g). To illustrate the performance of our algorithm, we map the gradient intensity to the thin edge, called GM (see figure 1(e)). Comparing figure 1(e) with 1(g), we can see that some edges in figure 1(g) are highlighted, which correspond to dim edges in figure 1(e). Subsequently, we combine the gradient intensity and the continuity of gradient direction, and generate the well enhanced gradient intensity (see figure 1(h)). Also, the enhanced gradient intensity is mapped to the thin edge, called GEM (see figure 1(i)). Comparing figure 1(i) and figure 1(e), contours in figure 1(i) are clearer, in which the weak lines are better emphasized.

3. MODIFIED HOUGH TRANSFORM

Almost all the HTs use the polar equation $\rho=y\sin\theta+x\cos\theta$, where ρ and θ are the two polar parameters of the line. However we should be cautious of the gradient direction. Let us consider a line with slope k and intercept b, as following

$$
\left.\begin{array}{l} y = k\cdot x + b \\ k = ctg(\theta) \end{array}\right\rangle \Rightarrow y = \frac{\cos(\theta)}{\sin(\theta)} x + b \ \ (\theta \in [-\pi/2, \pi/2])
$$
$$
\Rightarrow y\sin(\theta) - x\cos(\theta) = b\sin(\theta) = \rho \tag{3}
$$
$$
\Rightarrow \rho = y\sin(\theta) - x\cos(\theta)
$$

Now we can safely use the real θ which denotes the gradient direction of the line. Our modified HT, called Directional Gradient Hough Transform (DGHT), is then defined as

$$
DGHT(\rho,\theta) = \iint \left| g_3\left(\left|\varphi(x,y) - \theta\right|\right) \right| PG(x,y) \cdot \delta\left(\rho - y\sin(\theta) + x\cos(\theta)\right) dxdy \tag{4}
$$

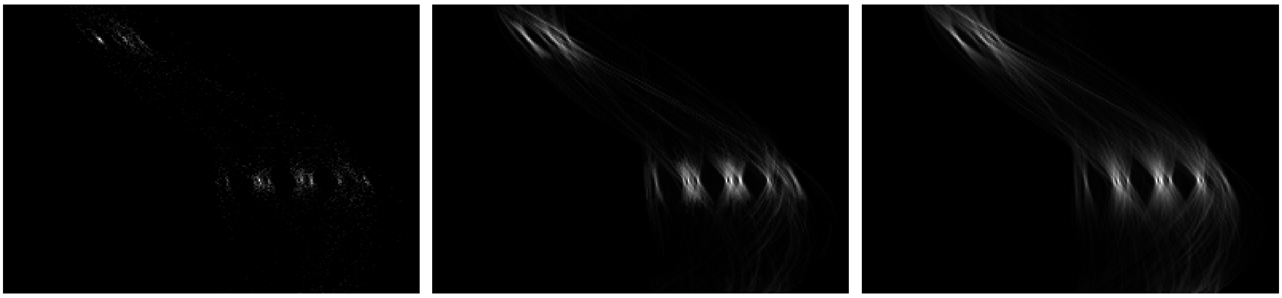
where ρ and θ are the polar coordinates of the line as mentioned above, g_3 is a directional weighting function, $\varphi(x,y)$ is the gradient direction at point (x,y), $PG(x,y)$ is the gradient intensity to be processed, and $\delta(.)$ is the Dirac impulse function. We can use a Gaussian function or other functions such as cosine function[1] to estimate the g_3. And the PG can be GM, GEM, or other formulation of the gradient intensity. For comparison, the formulations of GWHT and VGHT[1] with slightly changes are present here

$$
GWHT(\rho,\theta) = \iint PG(x,y) \cdot \delta\left(\rho - y\sin(\theta) + x\cos(\theta)\right) \delta\left(\varphi(x,y) - \theta\right) dxdy \tag{5}
$$

$$
VGHT(\rho,\theta) = \iint \cos\left(\varphi(x,y) - \theta\right) PG(x,y) \cdot \delta\left(\rho - y\sin(\theta) + x\cos(\theta)\right) D\left(1 - \left|\cos\left(\varphi(x,y) - \theta\right)\right|\right) dxdy \tag{6}
$$

where $D(x)$ is a finite window function equal to $1/\tau$ (if $x \in [-\tau/2, \tau/2]$) or 0 (otherwise). The differences of the three HTs are the directional weighting function and the directional selecting function. GWHT uses an identity function as directional weight, while VGHT uses a cosine function, and a Gaussian function is used in our approach. GWHT selects direction only for the angle $\varphi(x,y)=\theta$ in a restrictive way, and VGHT uses a window to select the voting points, while our implement uses a Gaussian function to handle the both in a successive way.

Figure 2 illustrates the images representing the parameter space of the HTs. Although VGHT has positive or negative sign corresponding to the application[1], here we just implement it with normal, i.e., use $|cos(\varphi(x,y)-\theta)|$ instead of the original one. Due to the restrictiveness of GWHT, we can see from figure 2(a) that poor lines are detected. And the difference of window and non-window selection can be seen in figure 2(b) and 2(c).



(a) (b) (c)

Fig.2 The parameter space of HT (ρ in horizontal direction and θ in vertical direction): (a) GWHT. (b) VGHT with the angle range of D: 10º and splitting positive/negative sign corresponds. (c) DGHT using a Gaussian function.

4. LINE FITTING

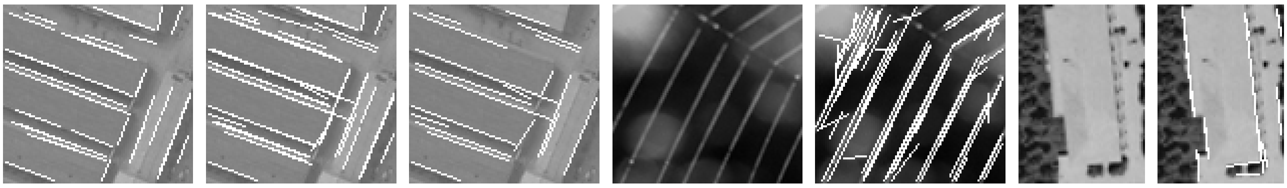
The general postprocessing of HT is the peak detection[4] in the parameter space, while we deal with it simply. A coarse direction grouping is applied by dividing the maximum voting weight of each direction into several intervals. The lines are then extracted from each group separately.

We perform the line fitting on the GEM by a finite state machine (FSM) model. The first step is to obtain the input string for the FSM. We scan the GEM along the direction of a line $\rho=ysin\theta-xcos\theta$, the output result is

$$\begin{cases} 1 & \textit{if } \mathrm{GEM}(x,y) > T, \text{ otherwise} \\ -1 & \textit{if } |\theta| \geq 45^\circ \textit{ and } (\mathrm{GEM}(x,y-1) > T \text{ or } \mathrm{GEM}(x,y+1) > T), \text{ otherwise} \\ -1 & \textit{if } |\theta| < 45^\circ \textit{ and } (\mathrm{GEM}(x-1,y) > T \text{ or } \mathrm{GEM}(x+1,y) > T), \text{ otherwise} \\ 0 & \textit{others} \end{cases}$$

where *T* is a threshold used to fit lines at different gray levels. Then we verify and refine the lines from the output string of the scan. By defining several rulers for the FSM at different gray level *T* and with different considerations on present of 1, -1, and 0, we can find the lines meeting our demands, e.g. a long strong line or a weak line, etc.

The results of line detection are showed in figure 3. Figure 3(a) and 3(b) show the effect of the gradient enhancement, it can be seen that in figure 3(b) more detailed and weak lines are detected, especially the disconnected line segments in figure 3(a). Figure 3(c) presents the result of strong line detection using a higher *T*. Figure 3(d) and 3(e) is an example of cobweb, and results for another building are showed in figure 3(f) and 3(g).



(a) (b) (c) (d) (e) (f) (g)

Fig. 3 Results of line detection: (a) All lines (strong/weak, multiple rules at different T) detection of figure 1(a) using GM. (b) All lines detection of figure 1(a) using GEM. (c) Strong lines detection of figure 1(a) using GEM with a single rule and a higher T (192). (d) Image of cobweb 95 * 89. (e) All lines detection of (d) using GEM. (f) Another image of building 63 * 89. (g) All lines detection of (f) using GEM.

5. CONCLUSION

A modified Hough Transform, called Directional Gradient Hough Transform (DGHT), is presented. By a preprocessing of the gradient enhancement along the lines, we emphasize the weak lines and generate a well enhanced gradient map which is then used for voting in DGHT. We simplify the peak detection in parameter space under the guarantee of line fitting by the FSM. Then robust results are given.

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