# A parallel algorithm for detection of linear structures in satellite images

# S.K. Parui, B. Uma Shankar\*, A. Mukherjee and D. Dutta Majumder

Electronics and Communication Sciences Unit, Indian Statistical Institute, Calcutta-700035, India

Received 24 April 1991

### Abstract

Parui, S.K., B. Uma Shankar, A. Mukherjee and D. Dutta Majumder, A parallel algorithm for detection of linear structures in satellite images, Pattern Recognition Letters 12 (1991) 765-770.

To enhance linear structures in a gray level image, local operations with an additive score are normally used. Here a multiplicative score is used instead which gives better results than the additive one. The problem of segmenting the image of the multiplicative score is then dealt with where the threshold value can be automatically selected. The experimental results on some satellite images are reported.

Keywords. Image processing, linear structures, enhancement, automatic thresholding, satellite images.

# 1. Introduction

An attempt is made in this paper to first enhance and then isolate curvilinear or line-like structures or patterns (like roads, small streams etc.) which may be present in satellite images. A set of masks of length of 5 pixels is considered here representing digital straight lines in all directions. Normally, for enhancing line structures, the score of such masks is a second derivative which is additive but has certain drawbacks (Rosenfeld and Kak, 1982). In order to overcome some of these drawbacks, a multiplicative score is proposed here. Results on some satellite images show that the multiplicative score is better than the additive score.

In Section 2, 52 masks are defined to enhance the line structures present in a gray level image. The output here is differential gray level images. In Section 3, an algorithm is proposed to isolate the enhanced line structures from the background. Results and conclusions are given in Section 4.

# 2. Enhancement of line structures

Here a set of masks is considered to enhance linear structures in a gray level image. It is seen that there are in all 52 possible 5-pixel long digital line segments in 2 dimensions. Thirteen such line segments making angles between 0 and 45 degrees (including 0 degree, but excluding 45 degrees) with the x-axis are shown in Figure 1. Others can be obtained by symmetry. A mask is defined for each of these 52 line segments. For example, the masks corresponding to the first two line segments of Figure 1 are shown in Figure 2. The output g of these 52 masks is

<sup>\*</sup> National Centre for Knowledge Based Computing Systems.

Volume 12, Number 12



Figure 1. Thirteen possible digital line segments of 5-pixel length making angles between 0 and 45 degrees with the x-axis.

# $+\sqrt{(A-B)(A-C)}$

if  $(A-B)(A-C) \ge 0$  and

$$-\sqrt{-(A-B)(A-C)}$$

otherwise, where  $A = (a_1 + \dots + a_5)/5$ ,  $B = (b_1 + \dots + b_5)/5$  and  $c = (c_1 + \dots + c_5)/5$ . For each mask, g gives directional differential image in which dark line structures against a bright background or bright line structures against a dark

b <sub>1</sub>	<sup>b</sup> 2	ь <sub>3</sub>	b <sub>4</sub>	b <sub>5</sub>		b <sub>2</sub>	b3	b <sub>4</sub>	<sup>b</sup> 5
0	0	0	0	0	$b_1$	0	0	0	0
$a_1$	a2	a <sub>3</sub>	a4	a <sub>5</sub>	0	a2	a <sub>3</sub>	a4	a <sub>5</sub>
0	0	0	0	0	<sup>a</sup> 1	0	0	0	0
°ı	°2	c <sub>3</sub>	с <sub>4</sub>	с <sub>5</sub>	0	°2	c3	c4	°5
					c1				

Figure 2. Masks corresponding to first two line segments in Figure 1.

background will show positive g values with high magnitude if the thickness of the line structures is less than or equal to three pixels. For pixels in areas of near uniform gray values or around the boundary of thicker (with thickness of more than three pixels) objects, g values will be close to zero. Lastly, for pixels in areas of monotonically increasing or monotonically decreasing gray values (in the direction perpendicular to the direction of the mask), g will have negative values.



Figure 3. Horizontal line structures with thickness 3 and 5 pixels are present in (a) and (b) respectively. The f images of (a) and (b) are shown in (c) and (d) respectively and the g images of (a) and (b) are shown in (e) and (f) respectively, where c = abs(a-b)/2 and d = abs(a-b).



Figure 4. Two satellite image windows of size  $128 \times 128$ .

The output g described above is a multiplicative score. The additive score which is normally used is

# f = abs(2.4 - B - C)/2

(Gonzalez and Wintz, 1987). Two horizontal line structures with different thickness, and their f and g values in the horizontal direction are shown in Figure 3. If the thickness is less than or equal to 3 pixels, then both f and g output a single line structure though f tends to output a thicker and more flattened pattern than g. But if the thickness is more than 4 pixels, f produces two thick parallel lines while g produces zero gray values, that is, no lines. Thus, g shows crisp lines for thin line structures but suppresses thick lines. On the other hand, f does not perform so well in that it shows flattened lines for thin line structures and splits thick line structures into two parallel lines. In Section 4, these observations are demonstrated on some satellite images.

### 3. Segmentation of line structures

The task now is to segment the highlighted linear patterns from the background in the g image. For this purpose, it is assumed that the g values for each mask follow a normal distribution with mean  $\mu$  and standard deviation  $\sigma$  ( $\mu$  and  $\sigma$  are not necessarily the same for all the masks) when there are no thin line structures in the original image. Thus, if there are such line structures in an image, the g values for pixels falling on these structures will be significantly greater than  $\mu$  and will lie in the right tail of the distribution. So, these values are expected to be more than the upper  $\alpha$ -cut-off point, that is,  $\mu + t_{\alpha}\sigma$  where  $t_{\alpha}$  is such that the probability that the standard normal variate is more than  $t_{\alpha}$  is (1- $\alpha$ ). (Normally  $\alpha$  is taken to be between 0.01 and 0.05.) Thus, segmentation can be made automatic if  $\mu$  and  $\sigma$  are known for each mask or direction. It is seen that  $\mu$  and  $\sigma$  can be



Figure 5. The g images from images in Figure 4 using mask 1 in Figure 1.



Figure 6. Images obtained by thresholding the images in Figure 5.

estimated from the g values in a differential image as the mean and standard deviation of g itself, as long as the number of pixels falling on the line structures is not very high as compared to the total number of pixels in the image. The pixels with g values greater than the cut-off point are made bright and others dark. In the process, some isolated bright pixels may appear even where there are no line structures. These noise pixels are removed by filtering this thresholded image. A median filter of 5-pixel length is considered for this purpose for each of the 52 masks (Figure 1). For example, for the horizontal direction, the filter mask is the  $1 \times 5$  pixel window.

Thus, each of the 52 masks produces one filtered binary image (call it  $A_i$  for the *i*-th mask) which contains line segments in the corresponding direction. Superimposition of these 52 binary images (that is, by exclusive OR) gives an image A which shows all the thin line structures in the original gray level image.

The lines in the segmented image A are not necessarily 1-pixel thick. A 1-pixel thick version of these lines can be obtained by a thinning algorithm in the following way. For each bright or object pixel P in A, the vertical and horizontal runs of object pixels containing P are considered. P is an output pixel of the thinning algorithm if P is in the middle of the shorter of these two runs. The output image B after thinning is always 1-pixel thick, and the thinning process involves only local operations and can be parallelized (Parui and Datta, 1991).

# 4. Results and conclusions

It is seen that all 52 masks are not necessary in practice. A subset (equispaced in terms of the angle



Figure 7. Images obtained after median filtering the images in Figure 6 using the  $1 \times 5$  pixel mask.



Figure 8. Images A obtained after superimposing 12 filtered images corresponding to 12 masks (using g).



Figure 9. Images obtained after thinning the images in Figure 8.



Figure 10. Images obtained after superimposing 12 filtered images using f.



Figure 11. Images obtained after thinning the images in Figure 10.

of orientation) of these masks normally serves the purpose of dealing with line structures of all orientations. The subset used here contains 12 masks which include masks 1, 4, 7 of Figure 1 (representing angles between 0 and 45 degrees) and 9 others (representing angles between 45 and 180 degrees) obtained from them by symmetry. Two image windows (spectral band 4) of size  $128 \times 128$ from Indian Remote Sensing Satellite are shown in Figure 4. The differential images g using the mask 1 (in Figure 1) obtained from the images in Figure 4 are shown in Figure 5 where the negative values of g are set to zero. The estimated values of  $\mu$  and  $\sigma$  from the images in (a) and (b) in Figure 5 are 1.13, 17.77 and 2.27, 12.96 respectively. The corresponding threshold values ( $\mu$ +1.96 $\sigma$ ) are 35 and 27 respectively (2.5% upper cut-off point) and the thresholded images are shown in Figure 6. The filtered images are given in Figure 7 which show that there are some significantly long horizontal line structures in (a) but none in (b). 12 such filtered images  $(A_i)$  are obtained using the 12 masks. By superimposing them, the image A is obtained which is shown in Figure 8. The thinned version of the images in Figure 8 is shown in Figure 9. The output images in Figures 8 and 9 are obtained using the multiplicative score g. Application of the additive score f on the input images tends to produce thicker and split linear structures as can be seen in Figures 10 and 11. The images in Figure 10 are obtained from images in Figure 4 using f in the same way as above (using g). The thinned images of the images in Figure 10 are shown in Figure 11. It can be seen that the thickness of the linear structures varies only a little in Figure 8 while in Figure 10 it varies so much that in some areas it vanishes altogether and in some other areas its large value blunts the linearity of the structures. Another drawback of f is demonstrated in Figure 10(b) where a phantom line (though broken) appears between the two parallel vertical lines. This line does not appear in Figure 8(b) which is obtained using g.

It is easy to see that the algorithms proposed above are implementable on a parallel machine. The algorithm to compute g is parallel both in terms of pixels and in terms of masks. So is the filtering algorithm. The thinning algorithm also is parallel.

Though g outputs more faithful and crisp linear features than f, the computational cost of g is higher than that of f because of the square root operation involved in computing g. Our future aim is to modify g so that the algorithm becomes faster without sacrificing the performance of g in a significant way.

### References

- Rosenfeld, A. and A.C. Kak (1982). Digital Picture Processing, Vol. 2. Academic Press, New York, 2nd edition.
- Gonzalez, R.C. and P. Wintz (1987). *Digital Image Processing*. Addison-Wesley, Reading, MA, 2nd edition.
- Parui, S.K. and A. Datta (1991). A parallel algorithm for decomposition of binary objects through skeletonization, *Pattern Recognition Letters* 12, 235-240.