Investigation Of Multiscale Product For Change Detection In Difference Images

M. Beauchemin and Ko B. Fung,
Canada Centre for Remote Sensing,
Natural Resources Canada, 588 Booth St., Ottawa, Canada, K1A 0Y7,
{mario.beauchemin, ko.fung}@ccrs.nrcan.gc.ca

***Abstract* - We investigate the potential of multiscale product as a measure for change detection in difference images. The rationale relies on exploiting the cross-scale correlation characteristics of signal and noise. We use Monte Carlo simulations to assess the detection and localization performances of the multiscale product for the detection of linear features of different widths. Comparisons are made with change detection based on single scale as well as other multiscale combination rules. Preliminary simulation results show that, overall, a good performance balance is obtained for change detection over the range of SNRs and line widths investigated.**

Keywords-Change detection; multiscale analysis

I. Introduction

Despite the existence of more complex algorithms, per-pixel univariate image differencing remains the most widely used change detection method (see [1] for a recent review). Generally, the technique employed to identify change pixels in a difference image consists in applying a threshold to the absolute value of each pixel. Pixels above the given threshold are then labeled as changes. Good image registration (accuracy < 0.5 pixel) and adequate radiometric rectification are prerequisite processing steps for these change detection algorithms. Obviously, pixels in the difference image having large absolute values relatively to assumed no-change areas will be easily identified (high signal-to-noise ratio, SNR). As the SNR of change pixels decrease, however, performance of per-pixel change detection analysis will be reduced. The detection rate of true changes decreases, the detection rate of false changes increases, and the spatial localization of true changes is less accurate.

Among others, the analysis of the difference image can be approached from the point of view of a feature detection problem. As such, the spatial scale at which the detection is performed plays an important role in the detection performance: better results are expected for those scales matching the spatial size of the area of changes. For earth observation remote sensing images, however, the selection of an appropriate scale is complicated by the facts that the spatial shape and extent of changes are not known a priori. Furthermore, the signal-to-noise ratio (SNR) of changes covers a wide range of values and changes of low SNR are frequent, requiring good spatial match to maximize detection performance. Consequently, a change detection strategy based on a combination of scales has a sound foundation.

In this paper, we investigate the potential of multiscale product as a measure for change detection in difference images. The strategy consists in exploiting the cross-scale correlation characteristics of changes. Monte Carlo simulations were used to assess the detection and localization performances of the multiscale product for the detection of linear features of different widths. Comparisons were made with change detection based on single scale and other multiscale combination rules.

II. Multiscale analysis for change analysis

The present study finds its roots from ideas put forward in [2], [3]-[4], where point-wise multiscale product of gradient operators were used for (nonlinear) edge detection. The multiscale product exploits the cross-scale correlation of signal and noise, and result in enhancement of true edges (signal) and reduction/suppression of false edges (noise). Reference [5] has applied edge detection by scale multiplication in the wavelet domain on a difference image. Here, the focus is not on edges but rather on the areas of change themselves. We therefore concentrate on lowpass versions of the difference image. For change detection, we propose the following measure:

$$p\ (i,j) = \prod_{k=1,3,5} \frac{y_k(i,j)}{\sigma_{yk}}, \tag{1}$$

where i,j are the row and column pixel coordinates, and y_k is given by:

$$y_k(i,j) = \sum_m \sum_n \phi(m,n)\, h_k(i-m, j-n), \tag{2}$$

where ϕ is the difference image, h_k is a lowpass spatial filter of support size k (in pixels), and m and n are dummy integer variables. σ_{yk} is the standard deviation of y_k for a given value of k. For the present experiment, we use a normalized box filter for h_k such that the resulting output y_k is the local average of pixel values within a window size of k x k pixels. The multiscale product involves thus the multiplication of a number of lowpass versions of the difference image. The cross-scale correlation coefficients, r, between pairs of y_k outputs for ϕ(i,j) provided by real-valued independent and identical distributions input signal is easily computed as $r_{1,3}$= 0.33, $r_{1,5}$= 0.2 and $r_{3,5}$=

0.6, where the indices refer to the windows pixel size (see (5) in [4]).

In a way similar to [3]-[4], two important statistical properties of p are examined for $\phi(x)$ Gaussian. To avoid rather lengthy algebra, they are derived from Monte Carlo experiments in which the image difference pixel values were generated randomly from a normal distribution with zero-mean and unit variance. All estimations are based on the average of 100 runs of 10^5 samples and the errors provided on estimations represent the standard deviation over the 100 runs. First, simulations indicate that the pdf of p is leptokurtic (Fig. 1). The variance of p is 0.102±0.002, the skewness is 0.0±0.4 and the kurtosis is 51±9. In other words, the pdf of p is highly peaked, non-Gaussian, symmetric and heavy-tailed. If only two scales were selected in (1), the resulting pdf would not have been symmetric. The use of an odd number of scales also preserves the sign of the changes. Second, the empirically derived autocorrelation function for p indicates that the multiscale product cannot be assumed a whitening process (i.e. produce an uncorrelated random variable). Although this is an expected result because of the smoothing process involved, the amount of correlation between neighboring pixels for p is much less important than for the single scale case k=5 where the normalized autocorrelation at a lag of 1 pixel is ~0.8 (and about 0.65 for k=3). The autocorrelation function of p at pixel lag d = [0, ±1, ±2, ±3, …, ±6] is $\rho(d)$ = [1.0000 0.2360 0.0976 0.0305 0.0094 0.0004]. The amount of correlation at $\rho(\pm 1)$, although not excessive, is nevertheless non-negligible.

III. SIMULATION EXPERIMENT AND RESULTS

The performance of (1) is evaluated through the analysis of a pair of synthetic images. Fig. 2 shows one realization of the image pattern used for the change detection experiment. Fig. 2a is generated with all pixels equal to a constant value over which white Gaussian noise was added. Fig. 2b is generated similarly to Fig.2a, except that a line with a higher constant pixel value is introduced to simulate changed pixels (before the addition of noise). The line is 10^4 pixels long, that is half the width of the entire image. The example shown in Fig. 2b has a line width of 3 pixels. Fig. 2c is the difference image. Fig. 2d and 2e are respectively the multiscale average and product results. The multiscale average combination rule is given by $p\ (i,j)=(1/k)\sum_{k} y_k(i,j)$. The right half side of images 2c to 2e, where no change exists between the noise-free images, is used to determine the rate of false detection.

Fig. 3 shows the detection results in a graphical form. Each small graph provides the detection results for a given SNR and a line width value. Graphs aligned horizontally have the same line width (changed pixels) while graphs aligned vertically have the same change SNR. Values used for the line widths are 1, 3 and 5 pixels. Values utilized for the change's SNR are 2, 3, 5 and 17. The SNR is defined as the difference of signal (line to no-line) in the noise-free images divided by the expected noise standard deviation in the difference image. Simulation results are shown for change detection based on single scales (k =1, 3, and 5) as well as the two multiscale combination rules (average and product). Each curves within a graph is the cumulative sum, along the rows of the simulated image that include the region comprising the true change line (i.e. half-left side of the image), of pixels detected above a threshold adjusted to obtain a rate of false detection of 0.01. Hence, each graph provides the rate of detection as a function of spatial position in a direction perpendicular to the line (expressed in percent of total number of pixel in a line). The pixel position of the centre of the line in the image is equal to 11 for all graphs.

The analysis of Fig. 3 reveals that, at low SNR (≤ 3), detection based on the multiscale average rule performs slightly better than the product rule, as the rate of false detection is lower at the edges the lines. Both multiscale measures outperform single scales detection that may have either a poorer true detection rate or a higher rate of false detection at the edges of the lines (blurring). As the SNR increase, the product rule gradually outperforms the average rule (again at the edges of the lines). The average rule at high SNRs produces a high rate of false detection at the edges of the lines, an effect much less severe with the product rule. As expected, per-pixel detection (k=1) outperforms all other measures for high SNRs. For k=3, 5, the rate of true detection are as good as for k=1 but significant blurring occurs at the edge of the line. Although the average rule is the best at low SNRs, its performance is tainted at high SNRs (blurring). Overall, the multiscale product rule provides a good performance balance for change detection over the range of SNRs and line widths investigated.

Other combination rules, such as point-wise maximum of y_k values have been examined. Normalized measures, such as standardization, have also been tested for the measure just mentioned and the average combination rule. None of these rules provided better results that the multiscale average and product rules.

IV. CONCLUSION

A preliminary investigation of multiscale product of lowpass versions of difference images has been conducted. For Gaussian white noise, we derived empirically that the pdf of the multiscale product is leptokurtic. We also shown that the amount of spatial correlation for p is much less important, at a lag of 1 pixel, than for the individual scales that are involved in the product (excepted for k=1 which is white noise). In situation for which the a priori spatial scale for best detection is unknown, the multiscale product rule provides, overall, a good performance balance for change detection over a range of SNRs and line widths. The present experiment is restricted to a rather simple case and more complex synthetic images as well as real images should also be tested for a thoughtful assessment of the method. Moreover, the choice of the spatial filter and its support size has not been investigated.

REFERENCES

[1] P.R. Coppin, I.G. Jonckheere, K. Nackaerts, B. Muys, E.F. Lambin, "Digital change detection in ecosystem monitoring: A review, " International Journal of Remote Sensing, vol. 25, pp. 1565-1596, May 2004.

[2] A. Rosenfeld, "A nonlinear edge detection technique," IEEE Proc., pp. 814–816, May 1970.

[3] B. M. Sadler and A. Swami, "Analysis of multiscale products for step detection and estimation," IEEE Trans. Information Theory, vol. 45, pp. 1043–1051, April 1999.

[4] B. M. Sadler and A. Swami, ''On multiscale wavelet analysis for step estimation'', in Int. Conf. On Acoustics, Speech, and Signal Processing (ICASSP'98), Seatle, WA, vol. 3, pp. 1517-1520, April 1998.

[5] L.M.T., Carvalho, L.M.G., Fonseca, F. Murtagh, and J.G.P.W. , Clevers, ''Digital Change detection with the aid of mlutiresolution wavelet analysis,'' International Journal of Remote Sensing, vol. 22, pp. 3871-3876, 2001.

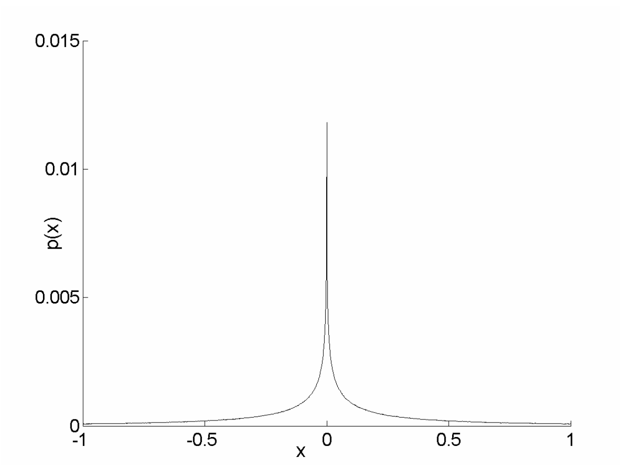

Figure 1. Estimated pdf of p(x).

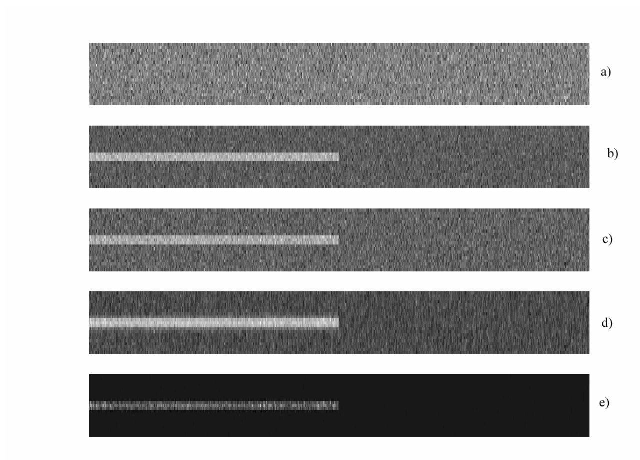

Figure 2. Synthetic images a), b). Difference image c) [from b)-a)]. Multiscale average, d). Multiscale product, e). Line width is 3 pixels. SNR is 3.

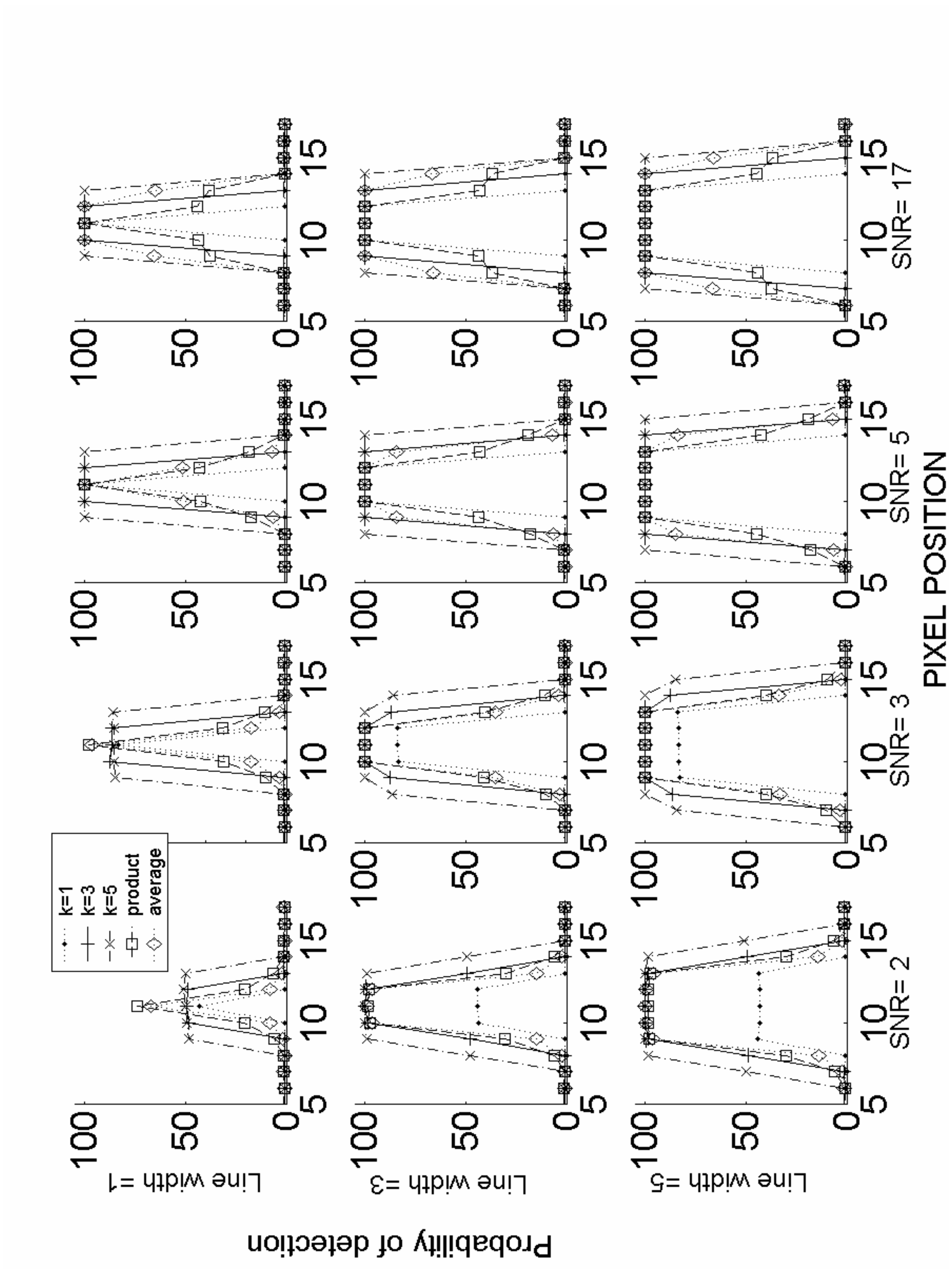

Figure 3. Probability of detection of changes as a function position for different signal-to-noise ratios (SNR) and line widths (in pixels).