

# Change detection using comparagram of images under varying illumination

S.Q. Wu, Z.G. Li, S.L. Xie and S. Rahardja

A method using a comparagram of images for change detection under varying illumination is presented. For each greyscale level an adaptive thresholding, using weighting variances, is proposed. The experimental result demonstrates that the proposed method outperforms traditional methods.

**Introduction:** Change detection refers to identifying image difference at different times, which is widely applied to surveillance, event detection, medical diagnosis and so on. The popular method is based on image difference  $\Delta I = I_2(x, y) - I_1(x, y)$ , and the difference map is then binarised by thresholding  $\zeta$ . One of the main challenges in using this method is the determination of this threshold. Another issue is that this method cannot work if scene illumination is not under control. To cope with this problem, some typical methods such as intensity normalisation [1], polynomial fitting [2], the shading model [3], etc., have been proposed to find some features which are invariant to illumination changes. However, these methods suffer in accuracy owing to the nonlinear property of imaging systems. In this Letter, we consider the image difference as  $\Delta I = I_2(x, y) - f(I_1(x, y))$ , where  $f$  is the pixel mapping between two images  $I_1$  and  $I_2$ , which is derived from the comparagram of images.

**Comparagram:** The comparagram  $C(z_1, z_2)$  is first proposed in [4] and is defined as a two-dimensional joint histogram between two images  $I_1$  and  $I_2$ . Let  $N$  be the total number of greyscales within images  $I_1$  and  $I_2$ , the comparagram  $C(z_1, z_2)$  has dimensions of  $N$  by  $N$ , and each element  $C(z_1, z_2)$  represents the number of pixels which satisfies  $I_1(x, y) = z_1$  and  $I_2(x, y) = z_2$  simultaneously. A comparagram captures all information about the pixel relationship between the two images while discarding spatial information in the images. Fig. 1 gives an example of a comparagram, in which the histogram counts are low in dark and high in bright areas.

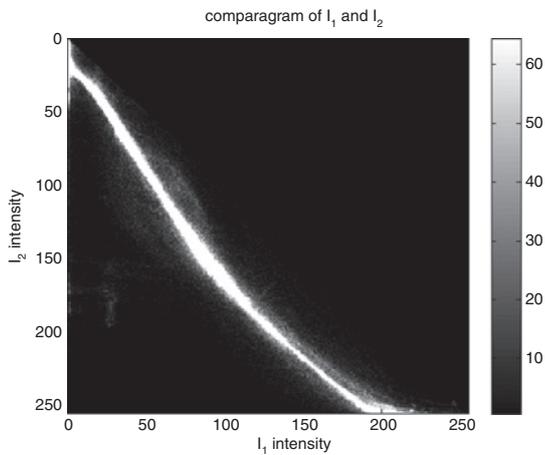


Fig. 1 Comparagram of two images

**Adaptive thresholding for change detection:** It is observed from Fig. 1 that a comparagram is distributed as an image instead of a curve. The projection of  $C(z_1, z_2)$  onto  $I_1$  is actually the histogram  $H_2$  of  $I_2$ . If we set  $z_1 = a$ , the resulting vector  $H_2(a, z_j)$  indicates the distribution of intensities in  $I_2$  corresponding to  $I_1 = a$ . Our large experiments reveal two features of  $C(z_1, z_2)$ : (i) the intensities in  $I_2$  corresponding to  $I_1 = a$  mainly centralise in a specific region, but the pixels beyond the region do not mean that the pixels are noise; (ii) the distributions of the intensities in  $I_2$  corresponding to different intensities in  $I_1$  are different owing to image noise, quantisation, mosaicing and the nonlinear property of the imaging system. This leads us to provide an adaptive thresholding method for each pixel level using weighting variances.

Suppose  $I_1$  is the reference image, for each greyscale level  $z_i, i = 1, 2, \dots, N$ , we find

$$Z_j^i = \arg \max_{j=1, 2, \dots, N} (C(z_i, z_j)) \quad (1)$$

i.e.  $Z_j^i$  is the majority of pixel level in  $I_2$  mapping from  $z_i$  in  $I_1$  and the histogram  $H_2(a, z_j)$  indicates the correctness of mapping. Accordingly,

the mapping function  $f$  is defined as

$$f(z_i) = z_j^i \quad (2)$$

and the weighting variance in  $I_2$  corresponding to  $z_i$  in  $I_1$  is computed as follows:

$$\sigma_i = \sqrt{\frac{\sum_{j=1}^N W_j^i H_2(z_i, z_j) * (z_j - f(z_i))^2}{\sum_{j=1}^N W_j^i H_2(z_i, z_j)}} \quad (3)$$

where the weighting function is defined as:

$$W_j^i = 1 - \frac{\|z_j - f(z_i)\|}{N} \quad (4)$$

For the pixel  $z_j$  in  $I_2$ , if

$$\|z_j - f(z_i)\| > k\sigma_i \quad (5)$$

where  $k$  is a specific constant,  $z_j$  is then classified as a change pixel.



Fig. 2 Two images captured in different gains

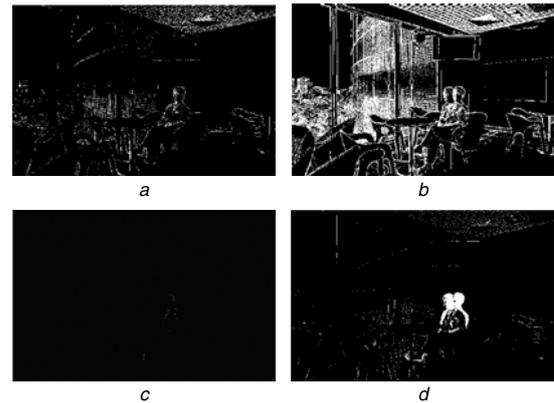


Fig. 3 Change masks

- a Intensity normalisation
- b MDL method
- c Shading model
- d Our method

**Results:** Fig. 2 shows two images captured in different camera gains. The scene is relatively simple: the human subject moved his body and head back and forth. It is noted that the scene has wide dynamic range: the outdoor region is so bright that some pixels are an over-exposed, while the indoor part is very dark and some pixels are under-exposed. Before obtaining the comparagram, we notice that although the camera gain is generally nonlinear over the incident radiance, the camera response curve is always monotonically increasing [4], i.e. if the radiances  $E_i$  satisfies  $E_1 < E_2$ , then the pixel intensities have  $z_1 < z_2$ . Therefore, the pixels which do not follow the monotonous property are excluded for comparagram computation. The comparagram of the two images in Fig. 2 are shown in Fig. 1. Selecting Fig. 2a as a reference, the best results of change masks detected by intensity normalisation [1], MDL [2], the shading model [3] and the proposed method are shown in Fig. 3. It is seen that the methods of intensity normalisation and the shading model cannot detect the change of the moving person. While the MDL method detects the outline of the moving person, it also detects too many pixels that are false alarm. The proposed method detects the whole region of the moving person while maintaining a low false alarm rate. Table 1 shows the operation times of different algorithms, which indicates that our method is much faster than the others.

**Table 1:** Operation times of different methods

Method	Normalisation	MDL	Shading model	Our method
Time (s)	11.83	62.84	37.31	0.54

*Conclusion:* Information is extracted from a comparagram of images for change detection and an adaptive thresholding technique is proposed. Experiment results demonstrate that this method is accurate and efficient.

© The Institution of Engineering and Technology 2010

6 May 2010

doi: 10.1049/el.2010.1223

One or more of the Figures in this Letter are available in colour online.

S.Q. Wu, Z.G. Li, S.L. Xie and S. Rahardja (*Signal Processing Department, Institute for Inforcomm Research, 1 Fusionopolis Way, 21-01 Connexis, 138632, Singapore*)

E-mail: shiqian@i2r.a-star.edu.sg

## References

- 1 Lillestrand, R.: 'Techniques for change detection', *IEEE Trans. Comput.*, 1972, **21**, (7), pp. 654–659
- 2 Durucan, E., and Ebrahimi, T.: 'Change detection and background extraction by linear algebra', *Proc. IEEE*, 2001, **89**, (10), pp. 1368–1381
- 3 Leclerc, Y.G., Luong, Q.-T., and Fua, P.V.: 'Self-consistency and MDL: a paradigm for evaluating point-correspondence algorithms, and its application to detecting changes in surface elevation', *Int. J. Comput. Vis.*, 2003, **51**, (1), pp. 63–83
- 4 Mann, S.: 'Comparametric equations with practical applications in quantigraphic image processing', *IEEE Trans. Image Process.*, 2000, **9**, (8), pp. 1389–1406