Improved locally adaptive least-squares detection of differences in images

Abdellatif Gherabi,[1] Henri H. Arsenault,[1,*] and Pascuala García-Martínez[2]

[1]*Department of Physics, Université Laval, Ste-Foy, QC, G1K 7P4, Canada*
[2]*Departamento d'Òptica, Universitat de València, 46100-Burjassot, València, Spain*
**Corresponding author: arseno@phy.ulaval.ca*

Received July 5, 2007; revised September 7, 2007; accepted October 9, 2007;
posted October 15, 2007 (Doc. ID 84903); published November 6, 2007

We introduce a method for change detection under nonuniform changes of intensity using an improved least-squares method. A locally adaptive normalizing window is correlated with the two images, and a morphological postprocessing is then applied to isolate objects that have been added or removed from the scene. We use a modification of the least-squares solution to get rid of clutter caused by intensity changes that do not satisfy the model assumed for the least-squares solution. © 2007 Optical Society of America

OCIS codes: 100.2000, 150.0150.

Change detection is a significant and difficult research problem in automated surveillance [1]. Most change detection algorithms assume that the illumination of a scene will remain constant between images. But this assumption is not always valid, for examples outdoors. Many methods have been proposed for change detection [1–4]. These techniques can be classified into two categories: pixel-based and region-based approaches. At the pixel level, change detection requires less computation since only one pixel is considered at a time. Change detection at the pixel level is simple differencing of gray levels of the images followed by a thresholding operation [5]. With this approach it is important to select the appropriate threshold. The more robust methods adaptively select the threshold based on the noise estimation at each pixel based on the gray level distribution of the background [6]. Pixel-based methods for change detection are faster, but the process is very sensitive to noise. Region-based approaches are more robust and are mostly adopted for applications in real environments. Using the difference image as the statistical test, the statistical approaches proposed by Toth *et al.* [7] and Aach and Kaup [8] were originally designed for achieving better detection results and increasing robustness against changing illumination conditions. Toth *et al.* assume that the image noise follows a Laplacian distribution, and hypothesis testing by thresholding the sum of the absolute difference within a sliding window is carried out [7]. Aach and Kaup [8] model the noise as a Gaussian distribution with different parameters. To obtain the probability density functions, some parameters like the variance need to be estimated. These methods indicate the areas where it is likely that changes have taken place, but in this Letter we are interested in methods that specifically indicate the changes that have taken place, that is if an object has been removed or added, the resulting image would indicate only that object [9]. Some methods require the image to be broken up into segments [10], but this usually results in artifacts appearing at the boundaries of the segments. Our method is global and processes the whole image at once, although the processing is locally adaptive.

In this Letter we assume that the change intensity is modeled by the simple realistic model of Eq. (1), where a and b are unknown parameters that vary slowly over the original scene $S_1(x,y)$:

$$S_2(x,y) = aS_1(x,y) + b. \tag{1}$$

Because the proposed method is locally adaptive and we use a small window, it is only required that the unknown parameters a and b be approximately constant over the window used, which is typically 5×5 pixels. Lefebvre *et al.* [11] defined a nonlinear filtering method known as the locally adaptive contrast invariant filter (LACIF) for pattern recognition, which is invariant under any linear intensity transformation. This LACIF uses three correlations involving local statistics and nonlinearities. It was applied directly to scenes containing unsegmented targets.

One of the advantages of the LACIF method is that no *a priori* information about the constants involved in the linear illumination model is assumed. Now for change detection with intensity changes of the type of Eq. (1), we use a method similar to that, which we used for the LACIF invariant pattern recognition under nonuniform changes of illumination [11]. We apply a moving window over the scene and calculate the local variance over the window. Then we divide the intensity of each pixel by the variance of the local window. So in locations where $S_2(x,y)=aS_1(x,y)$, the local variance for the scene is

$$\sigma_2 = \sigma_{a1} = a\sigma_1, \tag{2}$$

where the subscripts 1 and 2 refer to the images $S_1(x,y)$ and $S_2(x,y)$. Therefore

$$\frac{S_1(x,y)}{\sigma_1} - \frac{S_2(x,y)}{\sigma_2} = \frac{S_1(x,y)}{\sigma_1} - \frac{aS_1(x,y)}{a\sigma_1} = 0. \tag{3}$$

In locations where there is a change of object, the result will be a linear combination of $S_1(x,y)$ and $S_2(x,y)$, depending on the value of parameter a. It has been shown [1] that normalizing image windows in this manner is the solution to a least-squares minimization problem for linear intensity changes of the type of Eq. (1) because the least-squares method is an estimation of the variance. Although it is possible to calculate the local variance in the neighborhood of each point over the whole image, this can be a time-consuming calculation, but it can be carried out faster by means of correlations. The local variance for each point over the scene $S_2(x,y)$ is connected with correlations [11],

$$\sigma^2(x,y) = \frac{(S_2^2(x,y) * \diamondsuit(x,y))}{N} - \frac{(S_2(x,y) * \diamondsuit(x,y))^2}{N^2}, \tag{4}$$

where $\diamondsuit(x,y)$ is a square window of say, 5×5 pixels and N is the number of pixels in the window.

Consider a scene illuminated by different sources in different positions, as shown in Fig. 1(a) and 1(b). For a new approach, we used the reversed difference between the two scenes, $S_1(x,y)$ and $S_2(x,y)$, normalized by the local variance. We calculated their sum, as shown in

$$\begin{aligned} S(x,y) &= \left(S_1(x,y) - \frac{\sigma_{S1}}{\sigma_{S2}} S_2(x,y)\right) \\ &\quad + \left(S_2(x,y) - \frac{\sigma_{S2}}{\sigma_{S1}} S_1(x,y)\right) \\ &= \left(S_1(x,y) - \frac{\sigma_{S1}}{\sigma_{S2}} S_2(x,y)\right)\left(1 - \frac{\sigma_{S2}}{\sigma_{S1}}\right), \end{aligned} \tag{5}$$

where σ_{S1} and σ_{S2} are the local variances for $S_1(x,y)$ and $S_2(x,y)$, respectively.

At locations where something has changed, for instance, an object has been added or removed, the sum image, $S(x,y)$ can be positive or negative depending on whether an object has been added or removed.

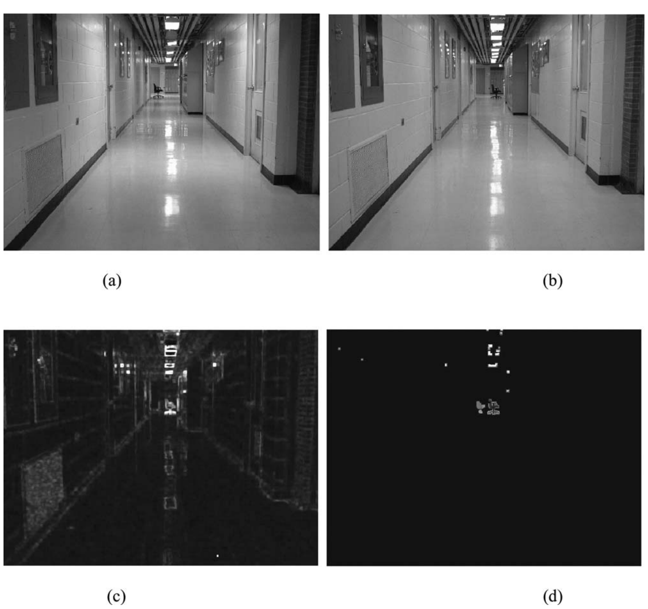

Fig. 1. Change detection results: (a) initial scene, (b) illuminated scene with a moving object (chair), (c) least-squares method result, and (d) our method after a morphological processing and a thresholding of 0.6.

Moreover, the sum image would be zero, where nothing has changed or where $S_1(x,y)$ and $S_2(x,y)$ are connected by an intensity transformation as shown in Eq. (1). So Eq. (5) is a good estimator for detection with intensity changes.

To eliminate the influence of illumination changes not satisfying Eq. (1), we used Eq. (5), which is based on the observation that in the two terms, the illumination changes that do not satisfy Eq. (1) and that cause clutter occur with different signs. Such nonlinear changes can be caused by light sources in different positions that cause a change of intensity that depends on the geometry of the scene and that do not satisfy Eq. (1). See for instance images from Figs. 1(a) and 1(b), where any point on the wall and on the ground is illuminated not only by the sources of light used but by the multiple reflections at various angles.

In addition, this method is useful for quadratic intensity transformations between the scenes, which are small changes of the form $cf^2(x,y)$. In this case the local variances have proportionality by means of the average of the original scene, $S_1(x,y)$. When we use a small window and the transformation varies slowly over the scene, the pixel values and the average calculated over this window are approximately equal. In this way the rate of local variances in the last expression compensate the changes due to illumination.

Figure 1(c) shows the result for the least-squares method. From Fig. 1(c), this method cannot handle the illumination changes well. After using Eq. (5) we dilate the image of the sum, $S(x,y)$, with a structural element that consists of a circle with a diameter of four pixels. All the areas due to the changes appear in a binary mask. The binary mask obtained is multiplied with Fig. 1(b) to show more clearly what was added or what was moved. The result of this procedure is shown in Fig. 1(d).

We propose an improved change detection approach based on local variance normalization. It detects changes when the images are affected by intensity transformations. Moreover, it proved to be much better than the pure least-squares method for change detection for varying nonuniform illumination conditions. The method involves local normalization that can be accomplished by means of correlations, and an additional morphological processing is required here to display the changes in the scene.

This work was supported by grants from the Natural Sciences Research and Engineering Council of Canada and the Spanish Ministerio de Educación y Ciencia under the project FIS2007-60626.

References

1. M. Xu, R. Niu, and P. K. Varshney, in *International Conference on Image Processing (ICIP '04)* (IEEE, 2004), Vol. 4, p. 2595.
2. C. C. Chang, T. L. Chia, and C. K. Yang, Opt. Eng. **44**, 027001 (2005).
3. E. Durucan and T. Ebrahimi, in *European Signal Processing Conference EUSIPCO, 2000* (EUSIPCO-2000), p. 1141.

4. E. Durucan and T. Ebrahimi, Proc. IEEE **89**, 1368 (2001).
5. P. Rosin, in *Sixth International Conference on Computer Vision* (IEEE, 1998), p. 274.
6. L. Li and M. K. H. Leung, IEEE Trans. Image Process. **11**, 105 (2002).
7. D. Toth, T. Aoch, and V. Melzter, in *European Signal Processing Conference EUSIPCO, 2000* (EUSIPCO-2000), p. 2081.
8. T. Aach, A. Kaup, and R. Mester, Signal Process. **31**, 165 (1993).
9. H. H. Arsenault, A. Gherabi, and Pascuala García-Martínez, Proc. SPIE **6312**, 1 (2006).
10. S. Satoh, Y. Idehara, H. Mo, and T. Hamada, in *Proceedings of the 2001 Internation Conference on Images Processing* (IEEE, 2001), Vol. 2, p. 725.
11. D. Lefebvre, H. H. Arsenault, P. García-Martínez, and C. Ferreira, Appl. Opt. **41**, 6135 (2002).