Morphological Change Detection Algorithms for Surveillance Applications

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Abstract

Vision-based systems for remote surveillance usually involve change detection algorithms for intruders, obstacles or irregularities detection. In particular, there is a potentially very cost-effective approach to perform inspection with autonomous robot navigation, computer vision, and change detection based on automatic image registration and subtraction. In these cases, a model of the working environment is compared with data acquired during the system functioning in order to extract region of interests. Real time applications require simple, fast and reliable algorithms and methodologies presented in the literature show that morphological change detection satisfies these requirements. In this paper novel morphological algorithms for scene change detection are introduced; the proposed methods allow to obtain a system whose performances are relatively stationary also with varying environmental condition.

1 Introduction

Computer vision systems with detection tasks usually include a module aiming at detecting relevant changes in the guarded environments [1][2][3][4]. If the output of such modules is further processed by a classifier, as in [2], change detection operation must be as accurate as possible, in order to minimize classification errors.
Change detection (CD) techniques presented in the literature can be divided in two classes: pixel-based and region-based algorithms [5]. Pixel-based algorithms compute the output by analyzing the values assumed by correspondent pixels in the two analyzed images; region-based algorithms compare features extracted from correspondent regions in the two images. Pixel based methods, (e.g. CD based on binary difference) present the advantage of the simplicity that makes possible real-time applications, whereas region-based techniques (e.g. CD based on the illumination model [6]) provide results more robust to false alarms introduced by noise. A further class of CD algorithms detects changed regions by means of edge comparisons [5]. These methods are quite expensive from the computational point of view and therefore they are not indicated for applications having strict temporal requirements.

Each CD technique is characterized by the metric introduced in order to quantify the difference between pixels or regions, and by a threshold value allowing to decide if the analyzed pixel or region is changed with respect to the reference image. The threshold setting is a crucial step because different threshold values provide extremely different results.
It would be desirable that CD algorithms presented the advantages of both pixel and region based techniques. This goal has been reached by considering binary morphological filters applied to the output of binary difference of CD systems [7][8]. In this paper new CD algorithms based on statistical soft morphology (SSM) are presented. Two implementations are proposed: the first one in which binary SSM is applied instead of binary filters usually applied; the second one in which SSM filtering is applied before the binarization step; applying the thresholding after the filtering, makes the system more stable with respect to the threshold settings, i.e. easier to be initialized.
This paper is organized as follows: the next section presents the main characteristics of morphological CD algorithms used in the literature; section 3 shows the proposed CD algorithms and section 4 presents preliminary results obtained by measuring CD performances versus threshold value for different CD system architectures. Preliminary results are very promising; they show that usually performances reached by the proposed method are better than ones reached by conventional morphological CD systems; moreover, the proposed algorithms provide results that present a lower sensitivity to the threshold setting.
Further results show the improvement in performances of higher level image processing modules (i.e. image segmentation module) introduced by using the proposed CD algorithms.

2 Scene Change Detection Algorithms Based on Morphological Filters

This section shows briefly the main characteristics of conventional CD algorithms based on mathematical morphology (MM), whose architecture is shown in Fig.1.
CD is usually performed by comparing a reference image, representing the guarded environment, to the image of the current situation [1][2]. This comparison makes possible the detection of changes in the guarded environment, and it is based on the pixel-to-pixel binarized difference between the two images. Let $\mathbf{B} = \{B(i) \mid i = 1 \dots N\}$ the background image, composed by N pixels, and $\mathbf{I}_{t_k} = \{I_{t_k}(i) \mid i = 1 \dots N\}$ the current analyzed frame (t_k is the instant in which the current image has been acquired), for each pixel i the result of the binarized difference is obtained by setting to the value '1' the output if the difference is greater than a value *th*. The threshold *th* indicates the minimal illumination difference to consider two pixels different; in the ideal case, this distance is equal to one gray level, but due to the noise introduced by the acquisition device, the operation is more robust by setting a higher threshold.
When the processed images assumes vectorial values, for instance they presents R, G, and B color components, then the operation is applied to each image channel, and the binary result is obtained by performing a *logical OR* among the results obtained from each channel.
The choice of the threshold *th* is a critical step: if *th* is too low, an excess of pixels is detected as changes (false alarms), but if *th* is too high, pixels belonging to intruded object could be lost. Fig.2 shows an example of change detection obtained with different

threshold levels. It is possible to notice the result variety dependent upon different threshold settings.

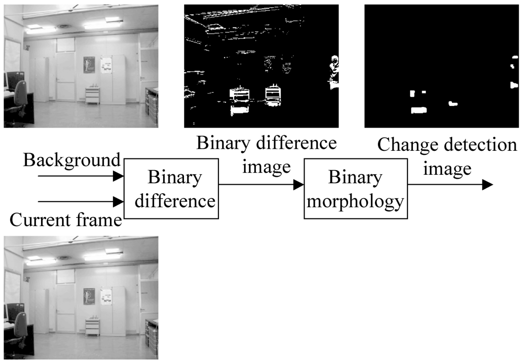


Figure 1. Change detection based on binary morphology

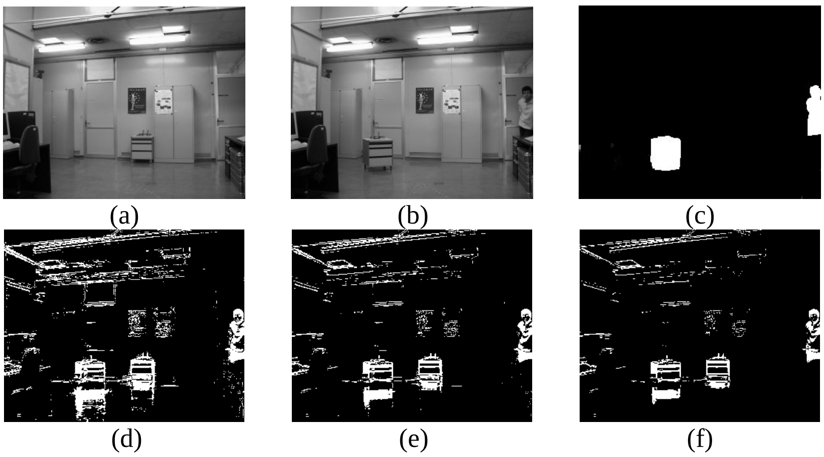


Figure 2. Example of change detection based on binary difference; a) Background image, b) current frame, c) ideal change detection output, d) binary difference with *th*=10, e) binary difference with *th*=15, (f) binary difference with *th*=20.

In order to make change detection more stable with respect to the threshold choice, morphological post-processing steps are introduced [1][2][3][4].
Usually, in video surveillance systems, binary openings [7] or binary statistical openings [8] are applied. Opening is an operator obtained by combining the two basic morphological operations: erosion, applied for eliminating isolated noisy pixels, followed by a dilation, applied for recovering interesting data filtered out by the erosion and recompose split regions.
The output of binary dilation (erosion) is obtained as follows [7][10]:

$$H_i = \begin{cases} 1 & \text{if } M^1_{B_i} \geq 1 \ (M^1_{B_i} \geq card(B)) \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

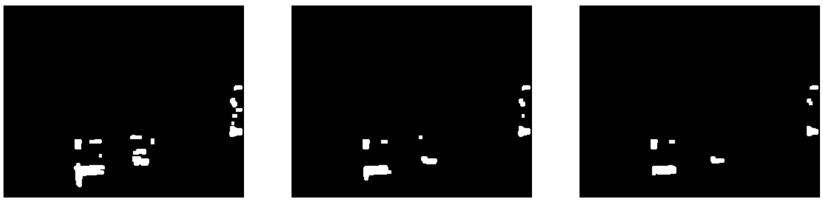
where $M^1_{B_i}$ represents the number of elements equal to '1' inside the filtering mask B_i and *card(B)* represents the number of elements of the filtering mask.

As shown in Fig.3, morphological filtering compacts regions of changes and eliminates isolated noisy pixels.

Statistical morphology (SM) [11] is an extension of mathematical morphology that introduces an improvement to CD performances because the filtering is less drastic. Regazzoni *et al.* in [10] presented how to implement fast binary statistical morphological filters. The binary output for statistical dilation is:

$$H_i(\beta) = \begin{cases} 1 & \text{if } M^1_{B_i} \geq \dfrac{card(B_i)}{\exp(\beta)+1} \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

where β>0 is a parameter of the statistical distribution introduced in [11] for deriving statistical morphological operators. The output of the erosion is obtained by considering negative β values.



(a) (b) (c)

Figure 3. Binary openings applied to: a) Fig.2d, b) Fig.2e, and c) Fig.2f.

3 The proposed Change Detection Algorithms

The proposed CD algorithm aims at reducing the influence of threshold setting on system performances. It is based on statistical soft morphology (SSM) introduced in [9]. The main differences between SSM and SM lies in the definition of a structuring element *B* composed by two sets: the hard one *A* to which more importance is associated by introducing a positive parameter *r*, and the soft one *B\A*. Output for statistical soft dilation is given by:

$$F_i(\beta) = \sum_k \frac{r N^h_{i,k} \exp\left(\beta N^h_{i,k} I_k\right) + N^s_{i,k} \exp\left(\beta N^s_{i,k} I_k\right)}{\sum_j r \cdot N^h_{i,j} \exp\left(\beta N^h_{i,j} I_j\right) + N^s_{i,j} \exp\left(\beta N^s_{i,j} I_j\right)} I_k \qquad (5)$$

where the neighborhood sets N_i^h and N_i^s are related to pixels falling inside the filtering mask A_i and $(B \setminus A)_i$ respectively. As in statistical morphology, β>0 is a parameter of the probability distribution introduced for statistically extending soft morphology morphological operators. Details on the method can be found in [9]. It is possible to notice that a greater weight is associated to pixels belonging to neighborhood set N_i^h. The output of SSM erosion is obtained by considering negative β values.

For binary data, the output of binary SSM dilation can be easily derived and it assumes the following form:

$$H_i(\beta) = \begin{cases} 1 & \text{if } M^1_{B_i} \geq \dfrac{r \cdot card(A) + card(B \setminus A)}{\exp(\beta)+1} \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

As shown in the next section, binary SSM applied instead of mathematical or statistical morphology allows to obtain better results.
A further improvement SSM can be obtained by considering the architecture shown in Fig.4. We propose to perform the thresholding operation after the morphological filtering; this allows to maintain a greater amount of information, resulting in a more reliable and stable system.
Examples of results obtained by applying the proposed architecture with different threshold values are shown in Figs.5, in which it is possible to notice that results are more invariant with respect of the threshold value.

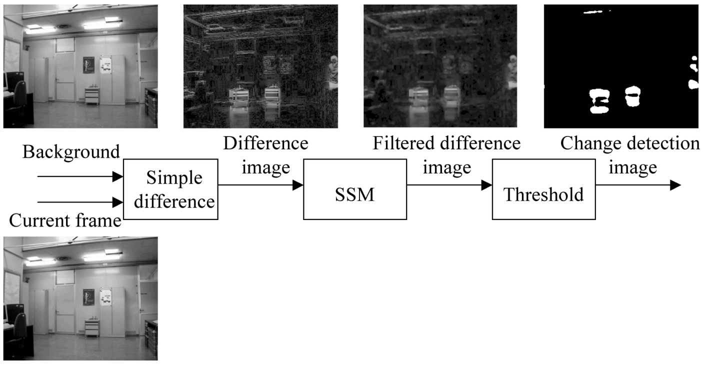


Figure 4. Change detection based on SSM

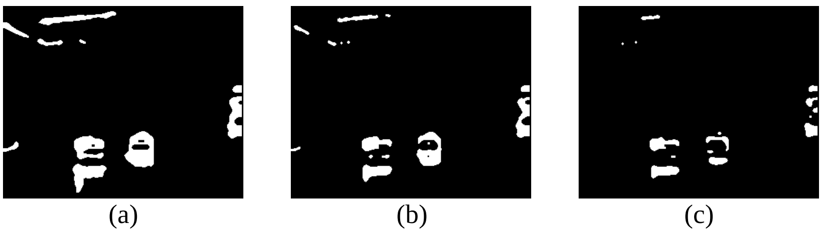


Figure 5. Change detection based on SSM: a) *th*=10, b) *th*=15, and c) *th*=20.

4 Results

4.1 Low-level performance evaluation

In this section we present preliminary results by comparing performances of morphological CD algorithms existing in the state of the art with the ones proposed in this paper. The considered error measure to be minimized is defined as follows:

$$Error = \frac{1}{2}(Pfa + Pma) * 100$$

where:

- *Pma* represents the probability that a pixel belonging to a changed area is not recognized;
- *Pfa* represents the probability that a pixel is erroneously detected as belonging to a changed area.

The following experiments have been carried out considering Fig.2a and Fig.2b as input of CD operations:

Exp1. Binary differences followed by morphological opening with square 5x5 structuring element;

Exp2. Binary differences followed by 2 statistical openings (5x5 square SE, beta scheduling such that $\beta^{n+1} = 4\beta^{n}$ and $\beta^{0} = 0.002$);

Exp3. Proposed method 1: binary difference followed by 2 binary SSM openings (5x5 square SE, 3x3 square hard SE, *r*=8, beta scheduling such that $\beta^{n+1} = 4\beta^{n}$ and $\beta^{0} = 0.002$)

Exp4. Proposed method 2 (architecture shown in Fig.4): simple difference followed by 2 SSM openings (5x5 square SE, 3x3 square hard SE, *r*=8, beta scheduling such that $\beta^{n+1} = 4\beta^{n}$ and $\beta^{0} = 0.002$) and binarization as last operation.

For all the experiments, threshold values ranging from 10 to 35 have been considered. Experience suggest that threshold values out of the considered range are not convenient for real applications because too much high false alarm or misdetection rates would be obtained.

Fig.6 shows the obtained error curves and Table I shows the mean value of errors reported in Fig.6.

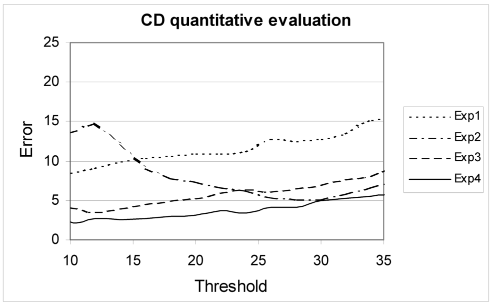


Figure 6. Change detection evaluation: curves are related to errors measured with the four considered CD algorithms.

Table I
Error comparisons

Exp.1	Exp.2	Exp.3	Exp.4
11.423	8.122	5.703	3.646

Table I. Change detection mean errors obtained in the four experiments. The proposed methods (Exp.3 and 4) provide the best results.

It is noteworthy that proposed methods provide considerable performance improvements in the considered threshold range. Moreover, they present errors with smaller variations for different threshold values. In particular, it is interesting that in the range $th \in [10,20]$ the performance curve of SSM-based CD algorithm is approximately flat. This means that small variations of environmental conditions (e.g. illumination variations) do not affect CD performances meaningfully.

Another important consequence of the stability of results lies in the portability of the proposed methods. Having a CD system whose performances do not strongly depend on threshold values means to have the possibility of installing a vision system in different environments without spending a lot of time for the parameter tuning operation. To prove that, we tried to apply morphological CD algorithms also to other environments, reported in Fig.7. Performed experiments are the same described in Exp1-Exp4, with *th*=15; quantitative results are shown in Table II, in which it is possible to notice that performances are more stable with the proposed methods by considering the environments Env1 (Fig.2), Env2 (Fig.7a), and Env3 (Fig.7b).


(a)


(b)

Figure 7. Environments in which proposed methods have been tested.

Table II
Performances in different environments

	Exp.1	Exp.2	Exp.3	Exp.4
Env1	11.933	6.200	3.702	2.211
Env2	7.394	5.165	2.971	2.516
Env3	8.095	3.977	2.895	2.348

Table II. CD performances in different environments. Errors are lower and more stable by considering the proposed methods.

4.2 High-level performance evaluation

Further results are related to the influence of the low level change detection algorithm in object detection. Experiments have been carried out by considering different change detection algorithms in a simple system for object detection, whose architecture is shown in Fig. 8. The blob detection algorithm is the one introduced in the system presented in [4] and it is based on the following operation:

- "split and merge" algorithm, in order to detect and label different regions;
- region filtering: regions with area lower that a threshold (100 pixels, for the considered experiments) are deleted;
- blob definition by tracing the minimum bounding box surrounding regions;

- blob merging: blobs presenting border with distance lower that a threshold are merged in a unique blob (in the experiments, bobs have been merged if their distance was lower than two pixels).

Average results have been measured by processing 5 images for each of the three sequences acquired in laboratory. These small sequences are interesting because they present variations of the global luminance and high reflections in the floor, which may cause easily false alarms; the illumination variations are due to adjustments of the automatic gain of the sensor used during acquisitions.

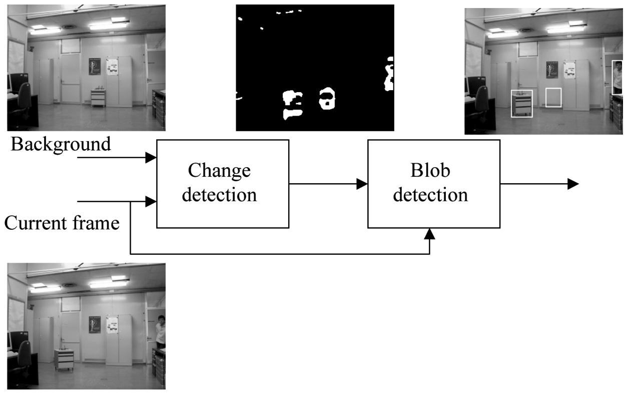


Figure 8. Architecture of the considered object detection system.

In these experiments, performances are based on the blob detection probability. The definition of detection probability is important: it has been computed by counting the object correctly detected in each frame of the sequence. Two or more separate objects detected and merged into one blob, or objects split in more blobs, are not counted because in this case the detection is not good.

Table III shows the detection probability obtained by considering the four change detection algorithms used in experiments Exp1-4, applied with binarization threshold equal to 15. Values reported in Table III confirm the conclusions obtained by performing algorithm evaluation at a lower level: the proposed methodologies are able to provide more stable results.

Table VI reports the misdetection probability of the considered algorithms. It is noteworthy that the proposed methods provide a very low misdetection probability.

In the computation of misdetection probability, we consider only object not detected at all. Objects erroneously detected as merged into one blob or split in several blobs, even not counted in the correct detection probability, do not increase misdetection probability.

Table III
Blob Detection Probability

Exp.1	Exp.2	Exp.3	Exp.4
0.30	0.58	0.75	0.92

Table III. Blob detection probability obtained with different CD algorithms. Only cases related to good detection are considered: cases of objects detected but split in more blobs or merged with others are considered as erroneous detection.

Table IV *Blob Misdetection Probability*			
Exp.1	Exp.2	Exp.3	Exp.4
0.41	0.25	0.08	0.08

Table IV. Blob detection probability obtained with different CD algorithms.

5 Conclusions

This paper presents novel scene change detection algorithms for remote monitoring and surveillance applications. The proposed change detection algorithms can be implemented for low-level processing in computer vision systems whose aim is to detect objects or relevant changes in the working environment.
The proposed methods are based on innovative morphological image processing. Compared to usual morphological CD algorithms, the proposed methods provide better performances that are less sensible to the system parameter setting. This is a desirable property because in real applications computer vision systems (e.g. video surveillance systems, autonomous vehicles, etc) must function in environments in which working conditions can vary with time and adaptive parameter regulation is often prohibitive for computational time requirements.
The simplicity of the methods makes them suitable for different applications, in particular for remote video surveillance systems. For instance, a mobile inspection system acquiring data to be transmitted to a central control station could easily reject uninteresting information by using the proposed methods, making possible the reduction of the amount of data to be transmitted in real-time and eventually used for further processing.

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