CHANGE DETECTION WITH AUTOMATIC REFERENCE FRAME UPDATE AND KEY FRAME DETECTOR

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ABSTRACT

In this paper a new reference image approach for real world surveillance applications is presented. The presented algorithm is composed of two steps. In the first step, A statistical test is performed between a reference and a current image, and a decision is made whether there is a change at a given pixel position. In the second decision step, the possibility to update a reference frame is provided. The second step allows to use the the proposed overall algorithm as a surveillance key frame extractor. These key frames are indicating significant changes with respect to a previously stored reference frame as well as to dynamically updated reference frames chosen from the ongoing sequence.

1. INTRODUCTION

Video based surveillance systems assumed a large interest for applications in public environments such as monitoring of railway stations and airports, road traffic analysis, corridors in important buildings such as banks, museums, etc. for detecting objects. Change detection is a good basis for surveillance systems because it reduces the amount of raw image data to be processed before any further processing [1].

As a result the great variety of applications mentioned above, there is a significant amount of algorithmic surveillance solutions in the literature. These solutions differ in the assumptions and constraints made on the application, in the mathematical approach, in complexity, and in time consumption. As a rule of thumb it can be assumed that the algorithms meant for surveillance circumstances should [2]:

- have as few number of assumptions as possible,
- be as simple as possible, and
- be implementable in real time.

The overall surveillance system should also be robust in real world applications with its broad variety of events, such as:

- Illumination changes like car headlights, torches, different kind of daylight and artificial light;
- Shadows created by artificial light and daylight, moving and still-standing shadows, various sorts of reflections;
- Moving objects like persons, animals, vehicles;
- Randomly Moving objects like plants, curtains, fire, objects on the wall (papers, clothes), etc.;

Triggering an alarm or not depends on the requirements and expectations of the end user.

Keeping the mentioned rules in mind, it is clear that having an assumption like "*target objects are moving at a constant speed in a constant direction* [3]" could bring conflicts for real world applications where the movement is, in general, neither constant in speed nor in direction.

The aim of this work is to provide a fast surveillance algorithm which is as general as possible and which provides information on events that could be important for further processing.

Following this introduction, an example surveillance application will be discussed in the next section. The method for detecting scene changes along with the key-frame extractor will be presented. After illustrating our method on the test sequences, an analysis of the results will be provided. Finally, some concluding remarks will be given.

2. A SURVEILLANCE APPLICATION EXAMPLE

There are several change detection algorithms in the literature which do provide an information about changes between an incoming frame and a stored reference frame. Consider the following Shading Model example [4]. The Shading Model is based on the physical decomposition of the intensity of light into a product of illumination and reflectance.

This model depends only on the physical structure of an object.

$$F = I \times R, \tag{1}$$

where F is the intensity at a given pixel position, I is the illumination at the same position, and R is the reflectance or shading coefficient of the object at that pixel location.

By computing the ratio of pixels contained in a defined area a,

$$\frac{F_{a,1}}{F_{a,2}} = \frac{I_{a,1}}{I_{a,2}} \times \frac{R_{a,1}}{R_{a,2}} \tag{2}$$

of two frames, and calculating their variances, it is possible to verify if a physical change had occurred between these two frames. Fig. 1 is a binary image resulting from the shading model method applied to the sequence shown in Fig. 3(a) and (b). We can see that the person in a corridor is detected regardless of the illumination change.

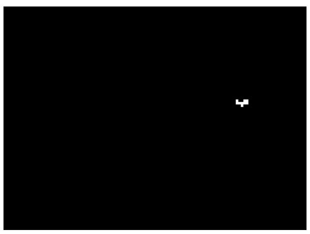


Figure 1: *Physical change detection result. The reference frame is Fig. 3(a) and the current frame is Fig. 3(b).*

This application is useful when we do not want to take illumination changes into account, and we are only interested in the physical changes. On the other hand, it is not so useful if the illumination change information is needed for further processing. For the given example in Fig 1, if we expect the change of light to trigger an alarm, that would not be possible since the illumination information is lost. A method is needed which keeps this kind of information that is always sensitive to significant changes, meanwhile ignoring constant changes, such as the constant flux of people moving in a train station. Hence, significant changes may correspond to the detection of

- the detection of rush hours in metro and train stations,
- rush hours in road and sidewalk traffic,
- congestion of traffic, and
- abrupt lighting condition changes in closed areas,

as examples. All these items constitute the key frames of a sequence, which should be detected by scene change detection algorithms for surveillance applications.

3. CHANGE DETECTION ALGORITHM

The proposed change detection algorithm begins with a grey level difference image $d_x = b_r(x) - b_c(x)$ between a reference image and a current image respectively at pixel locations. The change detection could be treated as a statistical hypothesis testing with:

- The *Null hypothesis* H_0, i.e. there is no change at pixel i
- The H_1 test, i.e. a significant change occurs at pixel i

When we assume Laplacian noise in the grey-tone difference image, the hypothesis testing can be done for the case that the absolute difference is used as a test statistics:

$$\Delta_i = \sum_{x \in w_i} \gamma |d_x| \tag{3}$$

where γ is a normalization parameter which depends on the noise, and w_i is a sliding window on the image with "i" denoting the center pixel of the window. For the purpose of most powerful test statistic estimation [6], the likelihood ratio

$$l(d_x) = \frac{p(d_x \mid H_0)}{p(d_x \mid H_1)} \tag{4}$$

should only depend on Δ_i Hence we require that the probability density function for H_0 and H_1 depends on Δ_i. The joint *pdf*s of H_0 and H_1 leads to a Laplacian distribution which is used, for example, for the characterization of prediction error images [5]. As a result, d_x obeys

$$P(d_x \mid H_0) = \frac{\gamma}{2} e^{-\gamma |d_x|} \tag{5}$$

and the normalized variable $\delta_x = 2\gamma d_x$ has the property

$$P_\delta(\delta_x \mid H_0) = \frac{1}{4} e^{-\frac{\delta x}{2}} \tag{6}$$

3.1. Decision step 1

The decision whether a pixel has changed or not can now be performed on the basis of $P((\tilde{\Delta} = 2 \times \Delta_i) \mid H_0)$. For this purpose we specify a significance level "a" and calculate a corresponding threshold "t_a" according to

$$a = P(\tilde{\Delta} > t_a \mid H_0) \tag{7}$$

When the test statistic is chosen, the test does not require a calculation for H_1 anymore because it is the complementary statistics of H_1[5]. The statistics $\tilde{\Delta}$ is then calculated at each center pixel "i" of the sliding window w_i, and at locations where it goes beyond "t_a", the pixel is marked as changed, otherwise as unchanged. The result is a binary image with white color for changed and black color for unchanged pixels (see Fig's 2 and 3).

The outlined method of subtraction between a current image and a stored reference image followed by a decision statistics works well when the changes of environmental conditions such as changes of illumination and background movements are small. However it fails in real world surveillance applications where illumination conditions may change drastically or objects in the reference image may move. An illustration of different illumination conditions can be seen in Fig. 2(a),(b) and Fig. 3(a),(b). The algorithm proposed in [5] and outlined above is no more sensitive to moving objects after the illumination conditions change. The figures 2(c), 3(c) illustrates this phenomenon. This property conflicts with the essence of surveillance systems where detection of moving objects is the main goal [1], [3].

3.2. Decision step 2

To cope with the problem of sudden illumination changes in surveillance applications, a second decision step is necessary to update the reference image. The subtraction from a fixed reference frame and making the decision using this difference image is, in fact, a linear operation. However, we introduce a reference update algorithm which changes the statistics assumptions and makes the overall system nonlinear.

We calculate the number of changed pixels and define a threshold whose value depends on the change of illumination and on the moving objects. Comparing the sum of changed pixels with the second threshold, the algorithm either keeps the former reference image or updates the reference image, and recalculates the statistics with the new selected reference frame.

The second decision threshold can either be a pre-determined fixed threshold or can be calculated adaptively based on the information obtained from several previous frames. In this work, the mean of the total number of changed pixels in the change detected frames are taken and when the changes in the latest incoming frame are a certain percentage higher than the mean, a new reference frame is taken. These reference frames are, then, stored in a database, and they can be used as key frames for further processing.

4. SIMULATIONS

The surveillance sequences have been provided by an industrial partner covering several entrance hall, corridor, cellar, room and outdoor scenes. The sequence and the results can be viewed at “http://ltsswww.efl.ch/∼surveillance”. In this section, we will concentrate on the results of the following two sequences:

- Keller 2 : This is a color sequence of an underground corridor which is bright at the beginning but totally dark at the end.
- Flur 3: Once again a color sequence of a very long dark corridor, a person is entering trough a door and turns the light on, than the illumination changes successively.

In both of the simulation examples, there are illumination changes that occur during the scene. Furthermore, in sequence ”Flur”, there is a moving object (human) that interferes with the changing illumination conditions, which makes object tracking very difficult.

5. TEST RESULTS

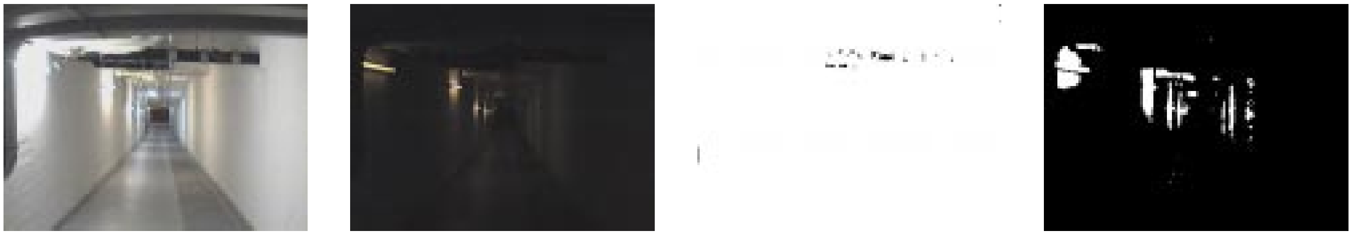
The early results show that our algorithm is a promising method that performs well under fairly difficult conditions. In the cellar sequence (Fig. 2), the proposed system remains sensitive to high illumination changes and even the moving person at the end of the corridor is continued to be detected Fig. 3(d) after the change in the lighting condition.

On the other hand, the Shading Model does not detect any changes in the sequence ”Keller”, although the change of the illumination condition due to turning on the lights, may be essential for alarm generating. Our proposed algorithm solves this critical problem. It detects the illumination changes (Fig. 2(c)), and by the reference frame update, it remains sensitive to moving objects and other changes (Fig. 2(d)).

This method could also be used as a key frame detector [7] for arbitrary video sequences because it is sensitive to high illumination and scenery changes. The changed reference frames which are used for alarm generation can be readily used as key frame candidates which supply a summary of the whole video data. In essence, the key frames are mostly composed of scene cut changes and other framewise major changes. The proposed algorithm assigns these changes as updates of the reference frames, therefore the reference frame database already contains most of the desired key frames to summarize the video.

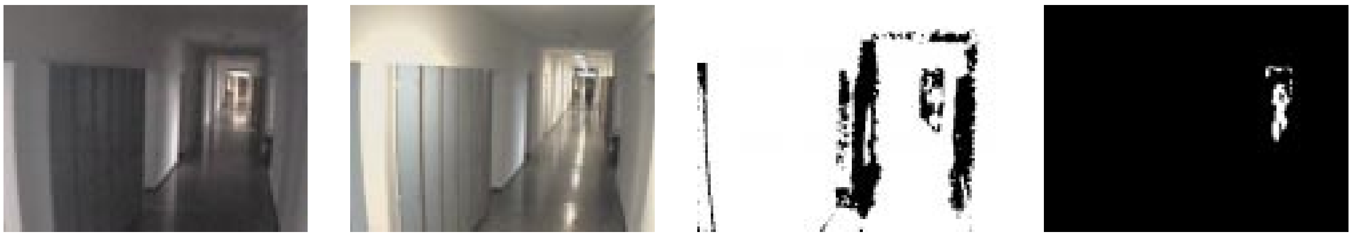
6. CONCLUSIONS

In this paper we presented a robust change detection algorithm with automatic reference frame update. The proposed algorithm successfully detected all the major changes in the test sequences provided by the industrial partner. The significant improvements over the Shading Model method is illustrated with the two examples in the Section 5. In fact, our algorithm satisfied the requirements for alarm generating conditions for all the considered test sequences. Furthermore, the algorithm also satisfies the rules of thumb



(a) (b) (c) (d)

Figure 2: *(a) Reference image (b) Current image (c) Sum of absolute differences as test statistics (d) With second decision threshold*



(a) (b) (c) (d)

Figure 3: *(a) Reference image with twilight (b) Current image with moderate light change (c) Sum of absolute differences as test statistics (d) With second decision threshold*

provided in the introduction section. Its implementation is simple, execution time is small, and it has very few assumptions on the nature of the video sequence. The simplicity of the implementation is also suitable for hardware implementation which is quite critical for real time applications. The software, as is, can process three frames per second under SGI O2 workstations. This speed is sufficient for most of the surveillance applications to generate an alarm, when necessary.

The frames with significant changes are simultaneously stored for a possible further processing. Since these frames correspond to significant changes in consecutive frames, they also correspond to key frames of the overall video. As another application, our algorithm may become a key frame detector by simple fine tuning of the present software.

7. REFERENCES

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