A BACKGROUND MODELLING ALGORITHM BASED ON ENERGY EVALUATION

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Abstract: Detecting moving objects is very important in many application contexts such as people detection, visual surveillance, automatic generation of video effects, and so on. The first and fundamental step of all motion detection algorithms is the background modeling. The goal of the methodology here proposed is to create a background model substantially independent from each hypothesis about the training phase, as the presence of moving persons, moving background objects, and changing (sudden or gradual) light conditions. We propose an unsupervised approach that combines the results of temporal analysis of pixel intensity with a sliding window procedure to preserve the model from the presence of foreground moving objects during the building phase. Moreover, a multilayered approach has been implemented to handle small movements in background objects. The algorithm has been tested in many different contexts, in both indoor and outdoor environments. Finally, it has been tested even on the CAVIAR 2005 dataset.

1 INTRODUCTION

Many computer vision tasks require robust segmentation of foreground objects from dynamic scenes; this general assertion is particularly true for video surveillance applications. The most used algorithms for moving objects detection are based on background subtraction: the foreground objects are extracted by subtracting the current image from a reference background model. Therefore, the first and crucial step of these kind of algorithms is the background creation.

Many algorithms proposed in literature in the last years present some common characteristics. Usually, independently from the applicative context, the main features that each background modeling algorithm has to handle are:

- Presence of foreground and/or moving background objects during the model building phase;
- Gradual and/or sudden variations in illumination conditions.

Many authors have dealt with the problem of background modeling, as both a stand-alone task or a module in a complete motion detection system.

A first group of algorithms uses statistical approaches to model background pixels. In (Wren,1997 and Kanade,1998) a pixel-wise gaussian distribution was assumed to model the background. In (Wren,1997) the algorithm was used for an indoor motion detection system, whereas in (Kanade,1998) the authors tested the algorithm in outdoor contexts. However, the presence of foreground objects during the building phase could cause the creation of an unreliable model, such as in presence of light movements in the background objects, or sudden light changes. These observations suggest that probably the proposed algorithms work well in presence of a supervised training, during which ideal conditions are granted by the human interaction.

The natural evolution of these approaches was proposed in (Stauffer,1999). In this work a generalized mixture of gaussians was used to model complex non-static background. In this way the great drawback of the moving background objects was solved by using many gaussians to model crucial pixels in that regions. However, the presence of foreground objects during this phase could heavily alter the reliability of the model immediately after the creation phase, like happened under sudden light changes.

The approach proposed in (Haritaoglu,1998) was conceptually similar to that proposed in (Wren,1997). But in this work the authors did not construct a real gaussian distribution, while they

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preferred to maintain general statistics for each point (minimum and maximum values registered, max difference between two consecutive values). In this way they cope with the movements in background objects, even if they waive a correct segmentation of foreground objects in those regions. However, like previous works, they could encounter misdetection in presence of foreground objects during the modeling phase. The natural improvement of this approach was proposed in (Kim,2004): the basic idea of (Haritaoglu,1998) was iterated in order to build a codebook for each point, providing a set of different possible values for each point. This algorithm was conceptually similar to the mixture of gaussians proposed in (Stauffer,1999), and the experimental results proposed by the authors appeared interesting.

All previous approaches use statistical information, at different complexity level, for the background modeling.

A different category is composed by the approaches that use filters for temporal analysis. In (Koller,2004) authors used a Kalman-filter approach for modeling the state dynamics for a given pixel. In (Elgammal,2000) a non-parametric technique was developed for estimating background probabilities at each pixel from many recent samples over time using Kernel density estimation. In (Doretto,2003) an autoregressive model was proposed to capture the properties of dynamic scenes. A modified version of this algorithm was implemented in (Monnet,2003, and Zhong,2003) to address the modelling of dynamic backgrounds and perform foreground detection. In (Toyama,1999) a modified version of the Kalman filter, the Weiner filter, was used directly on the data. The common assumption of these techniques was that the observation time series were independent at each pixel.

All the approaches above presented were tested on real sequences, producing interesting results, even if each of them suffered in almost one of the critical situations listed above. The approaches that apparently were able to work well in every conditions implicitly require a supervised background model construction, in order to prevent, critical situations.

In this work we present a background modeling algorithm able to face all the crucial situations typical of a motion detection system with an unsupervised approach; no assumptions about the presence/absence of foreground objects and changes in light conditions was required. The main idea is to exploit the pixels energy information in order to distinguish static points from moving ones. To make the system more reliable and robust, this procedure has been integrated in a sliding windows approach, that is incrementally maintained during the training phase; in this way the presence of sudden light changes and foreground objects is correctly handled, and it does not alter the final background model. In order to cope with the presence of moving background objects, a multilayered modeling approach has been implemented, combining temporal and energetic information.

In the rest of the paper the details of the whole procedure will be explained, and then the experimental results obtained on real image sequences will be reported.

2 BACKGROUND MODEL

The main goal of a modeling algorithm is to create a reliable model limiting the memory requirements. In an ideal case the best background model could be created by observing a-posteriori all the frames of the training phase; however this solution is not reasonable then one of the constraint of our approach is to work in an incrementally mode, to reduce hardware requirements, without losing the reliability.The implemented background modeling algorithm is based on two distinct phases; each of them tries to solve a particular modeling problem (see par. 1).

Firstly, the energy information of each image point, evaluated in a small sliding temporal window, is used to distinguish static points from moving ones. In this way we are able to obtain a statistical background model with only the contribution of background points, without the effects of foreground objects. However, with this proposed technique, the small movements of the background objects are not included in the model.

3 ENERGY INFORMATION

One of the main problems of background modeling algorithm is their sensitiveness to the presence of moving foreground objects in the scene.

The proposed algorithm exploits the temporal analysis of the energy of each point, evaluated by means of sliding temporal windows. The basic idea is to analyze in a small temporal window the energy information for each point: the statistical values relative to slow energy points are used for the background model, while they are discarded for high

energy points. In the current temporal window, a point with a small amount of energy is considered as a static point, that is a point whose intensity value is substantially unchanged in the entire window; otherwise it corresponds to a non static point, in particular it could be:

- a foreground point belonging to a foreground object present in the scene;
- a background point corresponding to a moving background object.

At this level, these two different cases will be treated similarly, while in the next section a more complex multilayer approach will be introduced in order to correctly distinguish between them.

A coarse-to-fine approach for the background modeling, is applied in a sliding window of size W (number of frames). The first image of each window is the coarse background model. In order to have an algorithm able to create at runtime the required model, instead of building the model at the end of a training period, as proposed in (Lipton,2002), the mean (1) and standard deviation (2) is evaluated at each frame; then, the energy content of each point is evaluated over the whole sliding window, to distinguish real background points from the other ones. Formally, for each frame the algorithm evaluates mean and standard deviation, as proposed in (Kanade,1998):

$$\overline{\mu^t(x,y)} = \alpha\mu^t(x,y) + (1-\alpha)\overline{\mu^{t-1}} \quad (1)$$

$$\overline{\sigma^t(x,y)} = \alpha \mid \mu^t(x,y) - \overline{\mu^t(x,y)} \mid +(1-\alpha)\overline{\sigma^{t-1}} \quad (2)$$

only if the intensity value of that point is substantially unchanged with respect to the coarse background model, that is:

$$\left| I^t(x,y) - B_C(x,y) \right| < th \quad (3)$$

where *th* is a threshold experimentally selected and $I^t(x,y)$ is the intensity value of point (x,y) at time t..

In this way, at the end of the analysis if the first W frames, for each point the algorithm evaluates the energy content as follows:

$$E(x,y) = \int_{t \in W} \left| I^t(x,y) - B_C(x,y) \right|^2 \quad (4)$$

The first fine model of the background BF is generated, as

$$B_F(x,y) = \begin{cases} (\mu(x,y),\sigma(x,y)) & if\ E(x,y) < th(W) \\ \phi & if\ E(x,y) > th(W) \end{cases} \quad (5)$$

A low energy content means that the considered point is a static one and the corresponding statistics are included in the background model, whereas high energy points, corresponding to foreground or moving background objects cannot contribute to the model. The whole procedure is iterated on another sequence of W frames, starting from the frame W+1. The coarse model of the background is now the frame W+1, and the new statistical values (1) and (2) are evaluated for each point, like as the new energy content (4). The relevant difference with (5) is that now the new statistical parameters are averaged with the previous values, if they are present; otherwise, they become the new statistical background model values. Formally, the new formulation of (5) become:

$$B_F(x,y) = \begin{cases} (\mu(x,y),\sigma(x,y)) \ if\ E(x,y) < th(W) \\ \wedge\, B_F(x,y) = \phi \\ \beta * B_F(x,y) + (1-\beta) * (\mu(x,y),\sigma(x,y)) \\ if\ E(x,y) < th(W) \wedge B_F(x,y) \neq \phi \\ \phi \qquad if\ E(x,y) > th(W) \end{cases} \quad (6)$$

The parameter β is the classic updating parameter introduced in several works on background subtraction ((Wren,1997), (Kanade,1998), (Haritaoglu,1998)). It allows to update the existent background model values to the new light conditions in the scene.

The whole procedure is iterated N times, where N could be a predefined value experimentally selected to ensure the complete coverage of all pixels. Otherwise, to make the system less dependent from any a-priori assumption, a dynamic termination criteria is introduced and easily verified; the modeling procedure stops when a great number of background points have meaningful values:

$$\#(B_F(x,y) = \phi) \cong 0 \quad (7)$$

4 MULTILAYER ANALYSIS

The approach described above allows the creation of a reliable statistical model for each point of the image, even if temporarily covered by moving objects. However, it is not able to distinguish movements of the background objects (for example, a tree blowing in the wind) from foreground objects. So, the resulting model is very sensitive to the presence of small movements in the background objects, and this is a crucial problem, especially in outdoor contexts.

The solution we propose uses a temporal analysis of the training phase in order to automatically learn if the detected movement is due to the presence of a foreground or a moving background object. The starting point is the observation that, if a foreground object appears in the scene, the variation in the pixel intensity levels is unpredictable, without any logic

and/or temporal meaning. Otherwise, in presence of a moving background object, there will be many variations of approximately the same magnitude, even if these variations will not have a fixed period (this automatically excludes the possibility to use frequency-based approaches, i.e. Fourier analysis).

In order to motivate this assumption, we have analysed the mean values registered in some points belonging to the different image regions over a long observation period (in fig. 1 some images of this sequence are reported).

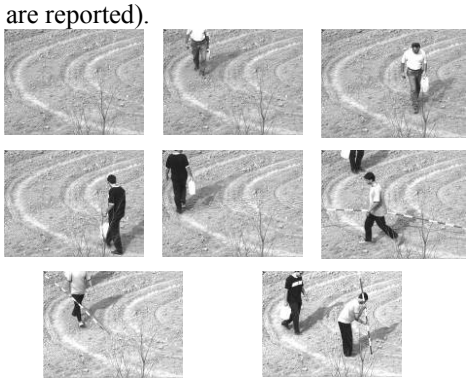


Figure 1: some images of the examined sequence.

The first group is composed by static background points (zone A in the first image of fig. 1), while the second (B) is composed by moving background points (background points that are temporarily covered by a moving tree). The third group (C) corresponds to some static adjacent background points that are covered by both moving people and a moving tree. Finally, the last region (D) corresponds to a region covered by only foreground objects. We have chosen to select a group of points for each class instead of a single point to reduce the effects of noise; on the other hand, for each group, the selected points are very spatially closed, because of their intensity values need to be similar for a correct analysis of their variations comprehension. Indeed, the values assumed by each point in the same group have been averaged, and in figure 2 the temporal trend of each group of that zones is plotted.

The static points (first graph) assume values that can be considered constant over the entire observation period (apart from the natural light changes). Points corresponding to static background (last graph), but covered by a foreground object (in this case, a person moving in the scene) assume, for a certain period, values that differs from the standard background value, but in an unpredictable way. On the other hand, static points that sometimes are covered by moving background objects (second graph), assume values that return many times in the whole observation period, even if they have not a fixed frequency. In the third graph the trend of a background point covered by both moving background objects and foreground ones is represented. Some values are admissible since they return several times, while some others are occasional, so they need to be discarded.

Starting from this assumption, the goal of this step is to use a multilayer approach for the modelling, with the aim of discarding layers that correspond to variation exhibited only a few times for a given point. Differently, layers that in the observation period return more times will be taken (they probably correspond to static points covered by background moving objects).

Formally, the main idea proposed in the previous section remains unchanged, but it is now applied to all the background layers. The concept of mean and standard deviation proposed in (1) and (2) become:

$$\overline{\mu_i^t(x,y)} = \alpha\mu_i^t(x,y) + (1-\alpha)\overline{\mu_i^{t-1}} \tag{8}$$

$$\overline{\sigma_i^t(x,y)} = \alpha \mid \mu_i^t(x,y) - \overline{\mu_i^t(x,y)} \mid +(1-\alpha)\overline{\sigma_i^{t-1}} \tag{9}$$

where i changes in the range (1…K), and K is the total number of layers. Similarly, for each frame of the examined sequence, the decision rule proposed in (3) for the updating of the parameters becomes

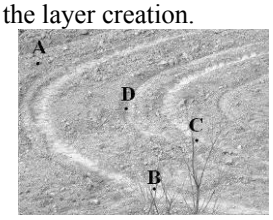
$$\left| I^t(x,y) - B_C^i(x,y) \right| < th \tag{10}$$

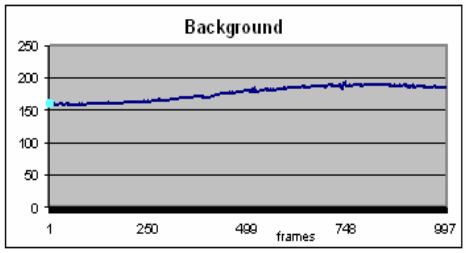
where the notation i indicates the examined layer. It should be noted that, initially, there is only one layer for each point, the coarse background model (that correspond to the first frame).

Starting from frame #2, if the condition (10) is not verified, a new layer is created. In this way, at the end of the observation period, for each point the algorithm builds a statistical model given by a serious of couple (μ,σ) for each layer. The criteria for selecting or discarding these values is based again on the evaluation of the energy content, but now the equation (4) is evaluated for each layer i:

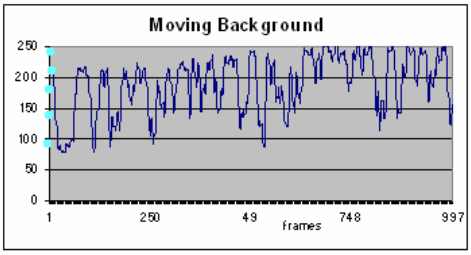
$$E^i(x,y) = \int_{t\in W} \left| I^t(x,y) - B_C^i(x,y) \right|^2 \tag{11}$$

Different layers are created only for those values that occur a certain number of times in the observation period. However, in this way both foreground objects and moving background ones contribute to the layer creation.

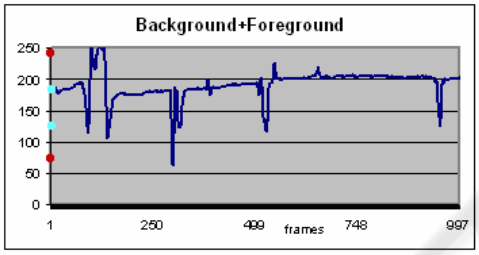




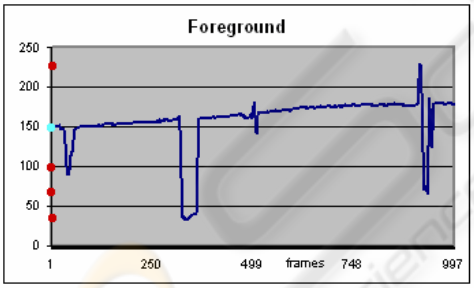
Region A



Region B



Region C



Region D

Figure 2: the position of the examined regions in the whole image (first line) and the trend observed in these regions. Red points correspond to layers that do not belong to the correct model, while blue points correspond to correct background layers.

In order to distinguish these two different cases, and maintain only information about moving background objects, the *overall occurrence* is evaluated for each layer:

$$O^i(x,y) = \#W \big| (x,y) \ \textit{that contributes to the statistics of the layer } i \quad (12)$$

$O^i(x,y)$ counts the number of sliding windows that contributes to the creation of the statistic values for the layer *i*. At this point, the first K layers with the highest overall occurrences belong to the background model, while the others are discarded.

After the examination of all the points with (12), the background model contains only information about the static background and moving background objects, while layers corresponding to spot noise or foreground objects are discarded since they occur only in a small number of sliding windows.

The use of sliding windows allows to greatly reduce the memory requirements; the trade-off between goodness and hardware requirements seems to be very interesting with respect to the others proposed in (Monnet,2003) and (Lipton,2002).

5 EXPERIMENTAL RESULTS

We have tested the proposed algorithm on different sequences, in different conditions, in both indoor and outdoor environments. In table 1 the characteristics of each test sequence are reported. Some sequences from the CAVIAR dataset (http://groups.inf.ed.ac.uk/vision/CAVIAR/CAVIARDATA1/) have also been considered.

Each sequence represents a different real situation, and different frame rates demonstrate the relative independency from the size of the sliding window (in our experiments, we have chosen to use a sliding window containing 100 frames, independently from the considered context and the camera frame rate).

The first test was carried out to evaluate the number of layers necessary for a given situation. In table 2 the mean number of layers for each context is reported. This value is smaller for more structured contexts (laboratory, soccer stadium), while it is higher in generic outdoor contexts (archeological site, CAVIAR seq. 1). The maximum number of layers in our experiments has been fixed to 5.

Table 1: Characteristics of the test sequences.

Test Sequence	Context	Frame rate	Size
Archeological site	Outdoor	30	768X576
Laboratory	Indoor	30	532X512
Museum	Indoor	15	640X480
Soccer stadium	Outdoor	200	1600X900
Beach	Outdoor	20	720X576
CAVIAR seq. 1	Outdoor	25	384X288
CAVIAR seq. 2	Indoor	40	384X288

The presence of moving background objects in the beach and archeological site contexts increases the number of layers. In more controlled environments, like the laboratory, probably the multilayer approach can be avoided.

Table 2: the mean number of layers for each of the examined different contexts.

Test Sequence	Mean number of layers
Archeological site	3.12
Laboratory	1.23
Museum	2.05
Soccer Stadium	1.92
Beach	4.33
CAVIAR seq. 1	2.28
CAVIAR seq. 2	1.54

In order to have a quantitative representation of the reliability of the background models, we have chosen to test them by using a standard, consolidated motion detection algorithm, proposed in (Kanade,1998). A point will be considered as a foreground point if it differs from the mean value more than two times the standard deviation:

$$\left|I(x,y) - B^i(x,y)\right| > 2 * V^i(x,y) \qquad (13)$$

A quantitative estimation of the error, characterized by the Detection Rate (DR) and the False Alarm Rate (FAR), has been used as suggested in (Jaraba,2003):

$$DR = \frac{TP}{TP + FN} \qquad FAR = \frac{FP}{TP + FP} \qquad (14)$$

where TP (true positive) are the detected regions that correspond to moving objects; FP (false positive) are the detected regions that do not correspond to a moving object; and FN (false negative) are moving objects not detected. In table 3 we can see the results obtained on the seven test sequences after a manual segmentation of the ground truth. The FAR parameter is always under the 6%, and it is higher for more complex environments (i.e. beach, museum), while it assumes small values in more controlled contexts (i.e. soccer stadium).

We have preferred to propose our experimental results instead of compare them with the same obtained by others because of we consider that implementation of algorithms of other authors can be not perfect, so the obtained results could be corrupted by this incorrect implementation.

As a future work, we are including the background modelling algorithm in a complete motion detection system, able to take advantage of the main characteristics of the proposed algorithm.

Table 3: Rates to measure the confidence.

Test sequence	DR (%)	FAR (%)
Archeological site	87.46	3.72
Laboratory	93.81	4.16
Museum	89.12	4.83
Soccer stadium	94.31	2.26
Beach	88.56	5.26
CAVIAR seq. 1	89.18	3.24
CAVIAR seq. 2	91.15	3.85

REFERENCES

Wren, C.R., Azarbayejani, A., Darrell, T., Pentland, A.P. (1997). Pfinder: real-time tracking of human body, *IEEE Trans. PAMI.*, 19(7), pp. 780 – 785, July.

Kanade, T., Collins, T., Lipton, A. (1998). Advances in Cooperative Multi-Sensor Video Surveillance*, Darpa Image Und. Work.*, Morgan Kaufmann,pp.3-24, Nov.

Stauffer, C. and Grimson, W. (1999). Adaptive background mixture models for real-time tracking, *Proc. of CVPR*, pages II 246-252

Haritaoglu, I., Harwood, D., Davis, L.S. (1998). Ghost: A human body part labeling system using silhouettes, *Fourteenth Int. Conf. on Patt. Rec.*, Brisbane, Aug.

Kim, K., Chalidabhongse, T.H., Harwood, D., Davis, L. (2004). Background modeling and subtraction by codebook construction, *ICIP*, Vol.5, pp3061–3064

Koller, D., Weber, J. and Malik, J. (2004). Robust multiple car tracking with occlusion reasoning, *ECCV 1994*, pages 189-196, Stockholm, Sweden, May

Elgammal, A., Harwood, D., Davis, L.S. (2000). Non-parametric model for background subtraction, *ECCV*, Vol. 2, pp. 751-767

Doretto, G., Chiuso, A., Wu, Y.N. and Soatto, S. (2003). Dynamic textures, *IJCV*, 51 (2), pp 91-109, Febr.

Monnet, A., Mittal, A., Paragios, N. and Ramesh, V. (2003). Background modelling and subtraction of dynamic scenes, *ICCV*,pp.1305-12, Nice(Fr), October

Zhong, J. and Sclaroff, S. (2003). Segmenting foreground objects from a dynamic, textured background via a robust kalman filter in *ICCV*, pp.44-50, Nice(Fr), Oct.

Toyama,K., Krumm,J., Brumitt, B. and Meyers, B. (1999). Wallflower: Principles and practice of background maintenance, *ICCV*,pp.255-61, Kerkyra(Gr), Sept.

Lipton, A.J. and Haering, N., (2002). ComMode: an algorithm for video background modeling and object segmentation, *Proc. of ICARCV*, pages 1603-08, vol.3

Jaraba, E.H., Urunuela, C. and Senar, J. (2003). Detected motion classification with a double-background and a Neighborhood-based difference, *Pat. Recogn. Letter*,pp.2079-82 (24).