Object-wise multilayer background ordering for public area surveillance

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Abstract — Public area is one of the most significant places which need video surveillance. However, pixel-wise adaptive background subtraction methods are disturbed by incessantly passing or temporally staying foreground due to its adaptability. In such an environment, even the initialization of background is not free from the influence of foregrounds. If the adaptability is modified carelessly for selective learning, the stability of the background model will be damaged. Adjusting or fusing the learning rate slows down the false learning rate but cannot solve the problems. In this paper, we present a multilayer background modeling algorithm for public area surveillance. We efficiently cluster regions in object-wise using spatiotemporal cohesion together with spectral similarity by comparing inputs with background layer. And we classify the clustered regions and update the multi-layer model according to the results. Using the PETS data, we show that the proposed method not only maintain the background robustly but also initialize background with stationary object detection in crowded public area.

Keywords - video surveillance; multilayer background modeling

I. INTRODUCTION

Public area is one of the most significant places which need video surveillance. In that region, however, pixel-wise adaptive background subtraction methods cannot model the background accurately because many people are incessantly passing or unmoving for a while. To overcome this problem, we propose a new background modeling method using object-wise multi-layer background ordering.

Crowded background modeling differs from the modeling dynamic backgrounds such as waving trees. It may be disturbed more easily by incessant foreground because it tries to models the meaningless changes of input sequence.

Figure 1 shows general framework of pixel-wise background modeling methods. Extracted features which effectively reflect characteristics of each backgrounds are learned by one or multiple learning methods which use different learning algorithm.[1,2] Many kinds of probabilistic distribution models are used such as single Gaussian, mixtures of Gaussian and non-parametric distribution with appropriate learning rate.[3,4] And the estimated results are checked with several conditions and compared with each other for ensemble. The detection result can be reused to adjust some learning parameters. At the beginning of learning, background initialization algorithms improve the accuracy of background model. [5]

Most pixel-wise learning algorithms are based on following equation, a form of recursive filter.

\[
\theta(t) = (1 - \eta(t)) \cdot \theta(t - 1) + \eta(t) \cdot \nabla(x(t); \theta(t - 1))
\]  

\(\theta(t)\) is a model parameter at time \(t\), and \(\eta(t)\) is a learning rate. \(\nabla\) is an estimating function and \(x(t)\) is a current input. It is an effective and stable method when the interval between the appearances of foregrounds is sufficiently long. However, if the input sequences from foregrounds last or are inputted again more frequently than the sequences from backgrounds, the background model loses its valid values. The learning rate can be adjusted or fused with some rules [6, 7], but it only can slow down the false learning rate. After all, the model cannot help following the input of foreground. It is serious problem in public area. One of the simple methods is using a mask which prevents the learning for the foreground regions. But careless use of the mask damages the adaptability of background model permanently. Many kinds of post-processing methods are used to improve the detection accuracy. Motion check[8] and foreground region model[9] are used a mask to prevent background model learning foreground. MRF[7] is used as
spatiotemporal check to enhance the detection accuracy in a small space with computational complexity.

In this paper, we propose region based background learning methods which combine region clustering in multi-layer with ordering the clusters among the layers. We do not adjust learning rate or use multi-modal distribution. Instead, we learn the multilayer background model which are updated pixel-wise and reordered object-wise. In Section 2, efficient pixel-wise learning algorithm is presented for each layer. Based on the spatiotemporal cohesion, object-wise region clustering method is addressed in Section 3. And then clustered regions are examined and reordered in Section 4. In the next section, experimental results are shown using various public and conclusion is drawn in the last section.

II. EFFICIENT PIXEL-WISE BACKGROUND LEARNING

To cluster the input pixels as a region, we do not cluster similarity like [10] but use multi-layer background model as spectral and spatiotemporal clustering method. Therefore effective background learning is demanded as a basic operation. In this section, pixel-wise simple and noble learning method is presented. Based on this, the clustering method is presented in next section.

We simplify the popular method presented in [3]. The mean and variance of each Gaussian are updated by following equation.

\[
\mu(t) = (1 - \rho)\mu(t-1) + \rho x(t)
\]
\[
\Sigma(t) = (1 - \rho)\Sigma(t-1) + \rho(x(t) - \mu(t-1)) (x(t) - \mu(t-1))
\]
\[
\rho = a\eta(x(t); \mu(t-1), \Sigma(t-1))
\]

These equations are rearranged to compute difference values of the parameters at each frame.

\[
\Delta \mu(t) = a\eta(x(t); \mu(t-1), \Sigma(t-1))\Delta s
\]
\[
\Delta \sigma = -\sigma(t) \pm \sqrt{\sigma(t)^2 + \rho(\Delta s^2 - \sigma(t)^2)}
\]
\[
\Delta s = x(t) - \mu(t-1)
\]

The change of parameters at each frame is determined by \(\Delta s\). Figure 3 and 4 shows the changes of parameters according to \(\Delta s\).

![Figure 3: The values of \(\Delta \mu(t)/\rho\) over \(\Delta s\) (a solid line) and its approximated step function (a dotted line) when \(\sigma\) is 5.](image)

![Figure 4: The values of \(\Delta \sigma\) over \(\Delta s\) (a solid line) and its approximated step function (a dotted line) when \(\sigma\) is 5 and \(a\) is 0.005](image)

We approximate the sinusoidal-like function as step function like the dotted line whose width of step function \(3\sigma\) in figure 3 and \(2\sigma\) in figure 4, respectively. To compute the height of the step function, we integrate sinusoidal-like function as following equation.

\[
h = \frac{1}{3\sigma} \int_0^1 \frac{\Delta \mu(t)}{\alpha} d(\Delta s) \equiv H
\]
\[
h' = \frac{1}{2\sigma} \int_{-\sigma}^\sigma \Delta \sigma d(\Delta s) \equiv H'
\]
\[
h'' = \frac{1}{2\sigma} \int_{-\sigma}^{2\sigma} \Delta \sigma d(\Delta s) \equiv H''
\]
The result of the Gaussian integral is a constant independently with \( \sigma \). As a result, the updating equations are simplified as following.

\[
\mu(t + 1) = \begin{cases} 
0 < \Delta \sigma < 3 \sigma & : \mu(t) + H \\
-3 \sigma < \Delta \sigma < 0 & : \mu(t) - H \\
\text{otherwise} & : \mu(t)
\end{cases} \quad (11)
\]

\[
\sigma(t + 1) = \begin{cases} 
0 < \Delta \sigma < \sigma & : \sigma(t) - H' \\
\sigma < \Delta \sigma < 3 \sigma & : \sigma(t) + H'' \\
\text{otherwise} & : \sigma(t)
\end{cases} \quad (12)
\]

The exact value of \( H \) or another value can be used to adjust the learning rate. However, we fixed the values as one for simplicity. As a result, the learning rate is increased because the exact value is less than one. Each layer is learned separately in a pixel-wise by the simplified method.

### III. OBJECT BASED REGION CLUSTERING METHODS

Using the induced equations, \( K \) background layers are learned competitively. The winner is determined and only the winner can update its parameters as follows with (11), (12) in a pixel-wise.

\[
\text{winner} = \arg \min_k (\Delta s_k), \text{ if } |\Delta s_k| < 3 \sigma_k \quad (13)
\]

\[
\omega_k = \begin{cases} 
\text{if } k \text{ is winner} & : \omega_k = \omega_k + 1 \\
\text{otherwise} & : \omega_k = \omega_k - 1
\end{cases} \quad (14)
\]

The weights are simply updated and normalized. If there is no winner, a pixel of the stationary object layer which has the smallest weight is initialized by a new one. At the beginning of the learning, only the background layer (see figure 2) is allowed to learn the input sequences. After the initial training, however, the third and fourth stationary object layer starts to compete with the background layer for learning the input values. Because the background layer stably learns the background changes within its own range, the object layers win only when the input is changed suddenly over the range of the background layer. The regions that the stationary object layers win over the background layer are clustered and maintained separately with background layer. And then the clustered regions are classified as stationary object, uncovered background or sudden illumination changes. These regions have spectral and spatiotemporal cohesion because it comes from object-based changes. We cluster the regions using two stationary object layers.

According to the weights of the stationary object layers, each pixel of layers has the one among three different states that are a sure background, a normal background and a stationary region. In the initialization, we cannot know which region is real background or stationary foreground in which the foreground may move after sometimes. Therefore we temporally assume that all pixel which initially learned by background layer are the sure background at the beginning. After the initialization, the learning of stationary object layers is allowed. In the region where exist stationary object layer, the state of the pixels is changes from the sure background to the normal background. The stationary region is determined by the weights of the stationary object layer, which become high where a new stationary object is added, or where the background is uncovered by a leaving object, or where illumination is suddenly changed. The three cases are classified in next section. The three states are used as stationary object detection or confidence measure to compute the boundary similarity. Whenever the background layer win over the stationary object layers, the stationary object layers are discarded. Therefore the short changes from the passing foreground cannot increase the weights of the stationary object layers and the inputs are discharged from the layered model.

Each clustered region grows or shrinks continually. Though object based changes are occurred with spatiotemporal cohesion, it take some time to cluster its entire region. A cluster of stationary object layer grows until meets the sure background at its boundary. Premature clusters are insufficient to compute the boundary similarity. Only matured clusters are tested whether it is uncovered background or stationary foreground.

![Figure 5. the state machine for the pixel of background layer](image)

### IV. BACKGROUND ORDERING USING REGION-BASED PROPERTIES

Thanks to spatiotemporal cohesion, clusters are obtained
in an object-wise by separated multi-layered model. They are not interfered by other passing objects using spectral similarity. In this section, we reinitialize and maintain the background layer by reordering matured clusters among the multiple layers. Figure 6 shows how to classify the uncovered background with the newly added stationary object. Column (a) is current input images and (b) is current background images. First row shows that a person comes into the view and stops. Therefore (1b) has right background. But, in second row, (2b) has the background covered by objects which was falsely initialized at the beginning of learning. In both cases, the same region is clustered but there boundary similarity with the background layer is quite different. To use this difference, we extract boundary region through morphological operation and measure the similarity. At that time, only the pixels whose state is the sure background are used to compute the similarity. The similarity is simply computed by absolute difference in the local region.

The region of the sudden illumination change is brightened or darkened due to the light through windows or the shadow of a stationary object. It is also clustered as the stationary object clustering. Among the pixels of stationary object layer, candidate pixels are selected according to an illumination model. And then the candidate pixels are clustered and the accordance is checked with the background layer using local binary patterns. If the regions meet the condition of the illumination model and the texture similarity, the illumination layer (the first layer) is initialized by the region. As a result, the background layer is initialized and maintained like the row (d).

Figure 7 shows the entire process. The proposed algorithm maintains the background layer and recursively initializes the uncovered background continuously. It is not just an initializing method but a region-based automatic recovering process because false learning of background layer is reinitialized in the same way with the uncovered background. Add to this, the stationary objects are detected and updated separately.

V. EXPERIMENTAL RESULTS

We tested various sequences acquired in public areas. The proposed algorithm shows promising results in crowded area. Figure 8 shows the result of PETS 2002 data at the frame 1091.[11] The three persons are standing for a while in front of show window. The pixel-wise learning algorithm have a difficulty to detect the foreground. But proposed algorithm initializes and maintains the background, and detects the region of stationary objects. The white regions in (c) has classified as stationary object after the boundary test with the sure background which are filled as black. The gray regions are the normal background state. And the detection result is shown in (d). Figure 9, 10 shows the results of PETS 2007 at the frame 970 and 1610.[12] In figure 9, three men and a woman are detected as stationary object and not learned by background layer though they stay for a long time and many people are passed. In figure 10, part of the region of standing people where was learned as background is reinitialized as the occluded background which come into view according to their moving. In the PETS 2007 data, severe illumination changes appear because of the light through the windows. But the region is classified as the sudden illumination region and learned as the background layer. Tested image is 320x240 and gray scale. It works as 21 FPS in intel quad CPU 2.6G with 1G RAM. To improve the detection performance, we combined the detection algorithm based on the frame difference, like [13].
VI. SUMMARY AND CONCLUSION

Public area is one of the most significant places which need video surveillance. Because there are many foreground staying or passing, the pixel-wise recursive filter based learning algorithm has limitations. To overcome the problem we proposed an algorithm that learns the input sequences by multi-layered background model. The background layer and the stationary layers are updated competitively according to their accordance. The stationary layers only learn the continuously discordant region with background layer. The region is clustered in object-wise and classified as the stationary object, the uncovered background or the sudden illumination changes. And each case is learned by different manners using multi-layer model and each region is ordered among the layers. For the classification that determines which layer learns the inputs, we use spatial feature testing such as color, texture and boundary similarity add to the spectral competitive learning and its spatiotemporal clustering. For the boundary test, the weights of stationary object layer are used as a boundary confidence measure. Using this algorithm we learned the background changes which are caused by objects or sudden illumination changes separately.

We experimentally showed that the background is maintained and reinitialized robustly in crowed region. The proposed method not only maintains and reinitializes background, but also detects stationary object. It maintains background using not only spectra-temporal consistency which is computed by the recursive filter but region based spatial similarity condition through the verifying which is sure background. There are some limitations. The confidence of boundary similarity may be weakened in the case that the objects are at the corner of the view, in spite of the fact that our interest is generally mostly on the central region.

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REFERENCES


Figure 8. The result of PETS 2002 sequence.
Figure 9. The result of PETS 2007 sequence.

Figure 10. The result of PETS 2007 sequence.