Real-time motion detection in video surveillance using a level set-based energy functional

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ABSTRACT

This paper presents a real-time motion detection algorithm for surveillance application based on a new level set-based energy functional. The proposed algorithm for minimizing the energy functional combines automatically motion segmentation and denoising operation in real time, and it provides robust and efficient motion detection at various noise levels of image sequences. Experimental results using surveillance camera show that it is very efficient in segmenting moving objects regardless of environment conditions. It has a very low false alarm rate even at night, when relatively few motion occur.

INTRODUCTION

The surveillance system keep watch on the areas with hundreds of surveillance cameras. The video streams are transmitted to a central location, displayed on several video monitors. The security officers are in charge of observing hundreds of video channel displayed on the monitors. Intelligent video surveillance systems attempt to reduce the burden on the security officers by applying motion detection algorithm to determine where object moved in a given scene. The officers only need to focus on the monitors where movement of the object are detected.

The surveillance system also need to records observed whole video data, even if there is no motion. To store such excess video data on a limited capacity of storage, video compression algorithm has been used. However, in a dark environment, its compression efficiency is deteriorated due to noise in the image sensor [6]. To overcome this problems, motion detection algorithm have been demanded, especially at night.

In conventional surveillance system, most of motion detection is based on some variation of thresholding, such as Mixture of Gaussian [3], Pfinder [4], W^4 [5], and so on. In these method, segmentation of moving object is achieved by pixel based threshold of the difference image between background and current image and morphological filter as a postprocessor. These method work well in day time, while, at night, false positive and false negative alarms are induced by noise in the image sequences.

To deal with this problem, we propose *adaptive bimodal segmentation* which discriminate effectively between moving objects and noise, at night. Adaptive bimodal segmentation is based on solving a nonlinear partial differential equation that combines automatically segmenting of motion and denoising operation at the same time. As a consequence, the segmentation algorithm adopts to various noise level of the input image sequences. The real-time performance is

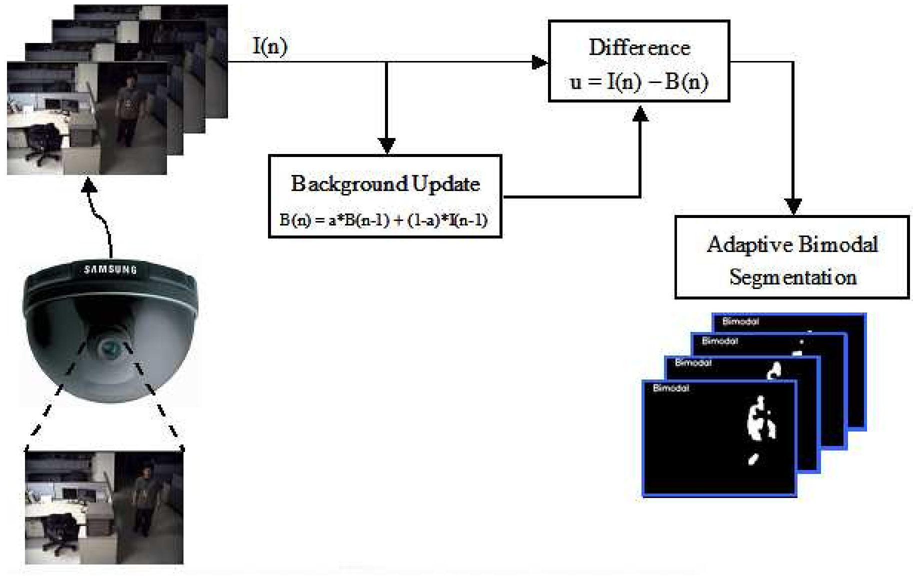

Figure 1. Main structure of the proposed motion detection system based on adaptive bimodal segmentation. Adaptive bimodal segmentation is applied to separate moving objects from background in a dark environment. Background is updated with simple adaptive filter.

achieved without any special hardware accelerator. Based on this segmentation algorithm, we could further develop intelligent surveillance algorithms, such as object tracking, object identification, object classification, etc.

The adaptive bimodal segmentation was motivated from Chan and Vese model [1], in which image u is segmented by a level set function ϕ which is a minimizer of the following energy functional:

$$E(\phi) = \int |\nabla H(\phi)| dx + \int [\lambda_1 (u(x) - c^+(\phi))^2 H(\phi) + \lambda_2 (u(x) - c^-(\phi))^2 H(-\phi)] dx \qquad (1)$$

where λ_1 and λ_2 are non-negative parameters, ϕ is the level set function and $c^+(\phi)$ and $c^-(\phi)$ are the average values of $u(x)$ in the regions $\{\phi \geq 0\}$ and $\{\phi < 0\}$, respectively. Here, $H(\phi)$ is the one-dimensional Heaviside function with $H(s) = 1$ if $s \geq 0$, and $H(s) = 0$ if $s < 0$. In [2], Lee and Seo developed a modified version of Chan-Vese energy functional with showing the stationary global minimum.

$$E(\phi) = \int [\lambda_1 (u(x) - c^+(\phi))^2 \phi H(\alpha + \phi) - \lambda_2 (u(x) - c^-(\phi))^2 \phi H(\alpha - \phi)] dx \qquad (2)$$

Here, ϕ is multiplied for stabilization of the *local minimum* problem and $H(\pm\phi)$ is shifted by $\mp\alpha$ $(\alpha > 0)$ to obtain fast segmentation. The above mentioned Chan-Vese type model could be applied to detect moving object in surveillance system using difference image $u(x)$. In particular, the bimodal segmentation works very well provided the noise level of the image sequence is quite low, while it fails to obtain successful segmentation in a dark environment without any regularization term. This model also cause lots of false alarm, if there is no motion in the image sequences.

For a robust and efficient motion detection system, we need background maintenance method, separation method between foreground and background, and morphological filter. Fig.1 shows main structure of the proposed system. We maintain background recursively using a simple adaptive filter [4],

$$B(x, t+1) = \gamma I(x, t) + (1-\gamma)B(x, t) \tag{3}$$

where γ is the update rate and should be kept small to prevent artificial $tails$ forming behind moving objects, and $I(x, t)$ is the input image and $B(x, t)$ is the background image at the time t. We develop the proposed energy functional to separate object from noisy background.

$$\begin{aligned} E_{ad}(\phi) &= \int_\Omega \Phi(|\nabla \phi|)dx \\ &+ \lambda_1 \int_\Omega \frac{F_+(\alpha, \phi, P^+(\phi, u))}{G(\phi, P^+(\phi, u), P^-(\phi, u))}dx \\ &- \lambda_2 \int_\Omega \frac{F_-(\alpha, \phi, P^-(\phi, u))}{G(\phi, P^+(\phi, u), P^-(\phi, u))}dx \end{aligned} \tag{4}$$

where α is small positive value, $P^{\pm}(\phi, u)$ are values depending on ϕ and the histogram of u, and $u = u(x, t)$ is the difference image at time t between the input image $I(x, t)$ and the updated background image $B(x, t)$. *The explicit description of $F_\pm$ and G will be explained in the talk due to the patent process.*

The role of the non-linear function $P^+(\phi, u)$ is to attract the image of moving object automatically, while $P^-(\phi, u)$ attracts the noisy background by taking account of the global structure of the difference image. Hence, the above energy functional for level set function ϕ do competition between the normalize metric related to the two attraction and its regularity.

EXPERIMENTAL RESULTS OF ADAPTIVE BIMODAL SEGMENTATION

In this section we present experimental results on image sequences. We use harmonic regularization in equation (4) , $\Phi(x) = \frac{1}{2}x^2$, as a trade off between speed and accuracy. On the other hand, [1] used curvature regularization. We choose $P^+(\phi, u) = c^+(\phi) + \epsilon_1(u)$, where $c^+(\phi) =$ average(u) in $\{\phi \geq 0\}$ and $\epsilon_1(u)$ is an empirical function depending on u. Also we choose $P^-(\phi, u) = c^-(\phi)$, where $c^-(\phi) =$ average(u) in $\{\phi < 0\}$. Finally, we choose initial level set function with the result of threshold on difference image u with predefined threshold level. The threshold level is determined as $c^-(\phi) + \epsilon_2(u)$, where ϵ_2 is an empirical function depending on u. In Fig. 4, we show that our model can detect moving object in a dark environment quite well.

Figure 2. Segmentation of the moving object lying in a relatively dark region. Top: the original image sequences. Bottom: results using the proposed model.

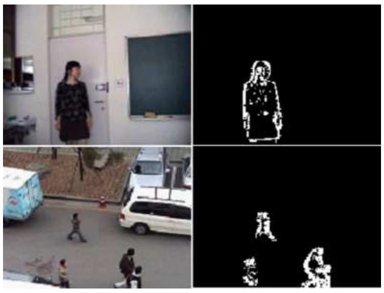

Figure 3. Segmentation of the moving object in a day time.

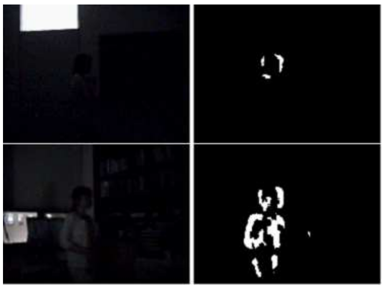

Figure 4. Segmentation of the moving object in a dark environment.

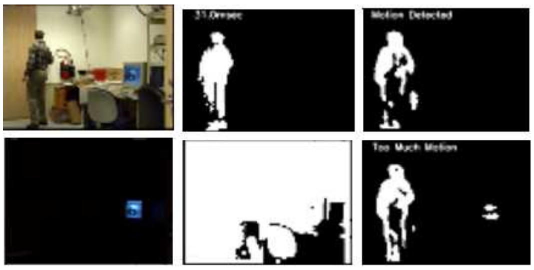

Figure 5. Detection of the fast illumination change using the proposed model. Left: Input Image sequence. Center: The result of the Mixture of Gaussians[3]. Right: The result of the proposed model.

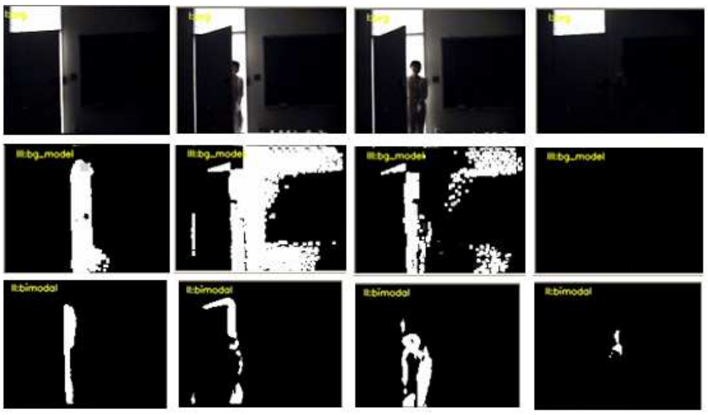

Figure 6. Segmentation performance comparison with Mixture of Gaussian model. Top: input image sequence. Middle: the result of the Mixture of Gaussian model. Bottom: the result of the proposed model.

DISCUSSION

The proposed motion detection method is a region based segmentation based on an energy functional of a level set function. The main advantage of the proposed algorithm is that threhsolding and the morphological filter is done at the same time. In addition, the algorithm is being implemented on hardware to reduce computing time. The applications of the adaptive bimodal segmentation are not limited to motion detection. Generally, it can be served for the detection of significant deviation in noisy environment.

ACKNOWLEDGEMENT

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