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A Novel Approach for Moving Object Detection from Dynamic Background

Ms. Pinky R. Rathod, Mrs. Avani H. Patel
Assistant Professor, Veerayatan Institute of business administration and computer applications, Jakhaniya, Mandvi, Kachchh – 370460
Assistant Professor, Veerayatan Institute of business administration and computer applications, Mandvi, Jakhaniya, Kachchh - 370460

Abstract
In computer vision application, moving object detection is the key technology for intelligent video monitoring system. Performance of an automated visual surveillance system considerably depends on its ability to detect moving objects in thermodynamic environment. A subsequent action, such as tracking, analyzing the motion or identifying objects, requires an accurate extraction of the foreground objects, making moving object detection a crucial part of the system. The aim of this paper is to detect real moving objects from un-stationary background regions (such as branches and leafs of a tree or a flag waving in the wind), limiting false negatives (objects pixels that are not detected) as much as possible. In addition, it is assumed that the models of the target objects and their motion are unknown, so as to achieve maximum application independence (i.e. algorithm works under the non-prior training).
Keywords- Object detection, dynamic background, false negative

I. INTRODUCTION

Video surveillance is a process of analyzing video sequences. It is an active area in computer vision. It gives huge amount of data storage and display. There are three types of Video surveillance activities. Video surveillance activities can be manual, semi-autonomous or fully-autonomous [1]. Intelligent visual surveillance (IVS) refers to an automated visual monitoring process that involves analysis and interpretation of object behaviors, as well as object detection and tracking, to understand the visual events of the scene [4]. Main tasks of IVS include scene interpretation and wide area surveillance control. Scene interpretation detects and track moving objects in an image sequence. It is used to understand their behaviors. Moving object detection is fundamental and most important step of information extraction in many computer vision applications, including video surveillance, people tracking, traffic monitoring and semantic annotation of videos. There are typically a number of challenges associated with the chosen scenario in a realistic surveillance application environment, such as dynamic background, illumination changes, and occlusions.

II. OVERVIEW OF THE PROPOSED SYSTEM

Automatic tracking of moving objects can be the foundation for many interesting applications. An accurate and efficient tracking capability at the heart of such a system is essential for building higher level vision-based intelligence. And the performance of the tracking object depends on how accurately the object has been segmented. The goal of the work documented in this dissertation is three-fold: (a) to segment the moving object efficiently from un-stationary background (b) to set up an appropriate algorithm for the optical flow based motion segmentation. (c) to make the approach accurate by removing noise and false alarm. To achieve the first goal, we reduce the resolution of the image to be a low resolution image. A low resolution image is done by reducing spatial resolution of the image with keeping the image size. For the second goal we proposed a method based on gamma distribution of velocity vector's magnitude which is more suitable than other methods for the optical flow based motion segmentation. And for third goal, we use energy minimization method based on a Markov Random Field (MRF).Which is a robust technique for removing noise from the image as well as give sufficient result in case of false alarm. Figure 1 shows the framework of presented robust approach for moving object detection.

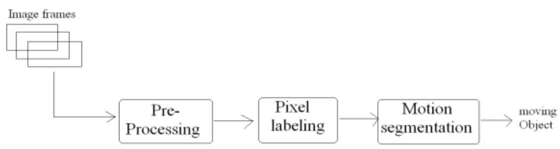

Fig.1 Framework of the method

III. PRE- PROCESSING

The first process in the motion detection is capturing the image information using a video camera. The motion detection stage includes some image preprocessing step such as; gray-scaling and smoothing, reducing image resolution using low resolution image technique, morphological operation and labeling. The preprocessing steps are applied to reduce the image noise in order to achieve a higher accuracy of the tracking. Here we will use the low resolution concept. The low resolution image is performed in three successive frames to remove the small or fake motion in the background. In order to reduce the processing time, gray-scale image is used on entire process instead of color image.

IV. PIXEL LABELING

Optical flow is defined by the velocity field in image plane due to motion of objects in image sequences. Let I be the intensity of a pixel (x, y) of an image in time t. In traditional optical flow analysis techniques, the optical flow constraint equation is expressed as [2].

$$I_x u + I_y v + I_t = 0 \quad (1)$$

Where u and v are two components of velocity vector; and I_x, I_y, I_t are partial derivatives with respect to x, y, t, respectively. By Horn and Schuncks method [2], the components of the velocity vector are computed by,

$$u^{i+1} = u^i - \frac{I_x(I_x u^i + I_y v^i + I_t)}{\lambda + I_x^{\,2} + I_y^{\,2}} \quad (2)$$

$$v^{i+1} = v^i - \frac{I_x(I_x u^i + I_y v^i + I_t)}{\lambda + I_x^{\,2} + I_y^{\,2}} \quad (3)$$

Where λ is a weighting constant; and i is iteration number. If η is a threshold value, the iteration is stopped when the following condition is satisfied:

$$\sum_{(x,y)} \sqrt{(u^{i+1} - u^i)^2 + (v^{i+1} - v^i)^2} < \eta \quad (4)$$

If a random variable z(x, y) is the magnitude of the velocity vector of a pixel (x, y) in an image, z(x, y) is defined as[22]:

$$z(x,y) = \sqrt{u(x,y)^2 + v(x,y)^2} \quad (5)$$

we make use of the gamma distribution for motion segmentation. The distribution of z, i.e. h(z), takes the following form [23]:

$$h(z) = \sum_{k=1}^{M} \delta_k \frac{\mu_k^k}{(k-1)!} z^{k-1} e^{-\mu_k z} \quad (6)$$

Where M means the maximum value of the PDFs order; δ_k is a coefficient of each PDF; and μ_k is decaying parameter of gamma function. Here, δ_k is 1 in k = 1, 5, 9,. . ., otherwise 0. To assign a label to each pixel, the optimal number of PDFs, i.e. M, should be determined in advance. Since M is the number of clusters, we use the cluster validity measure proposed by Ray and [3]. The principle of this method is to minimize the within-cluster scatter and maximize the between-cluster separation. The cluster validity measure, validity, is obtained by:

$$validity = w \frac{\frac{1}{N} \sum_{l=1}^{k} \sum_{z \in c_l} | z - m_l |}{\min(| m_l - m_m |)} \quad (7)$$

Where w is the weight; N is the total number of pixel; C_l is each cluster (l=0, 1,. . ., K-1); and m_l means a l^{th} mean. Then, we determine the optimal threshold value T_n to get a label of each pixel. T_n is determined by analyzing the distribution of (6). Accordingly, it is the z-value at the intersection point of two PDFs. If we assume that $\mu_0 = ... = \mu_{k-1} = \mu$, T_n is computed by:

$$T_n = \frac{1}{\mu} \sqrt[4]{\frac{4n!}{(4n-4)!}} \quad (8)$$

We can assign a label to each pixel using (8). The label field L(x, y) is expressed as follows:

$$L(x,y) = l \;,\; z(x,y) \in c_l \quad (9)$$

However, although motion segmentation of each pixel is performed using the gamma-distribution, noisy regions also occurs. To remove the noisy regions, the MRF is used in the proposed method.

V. MOTION SEGMENTATION

When we decide the presence of motion by threshold, two problems are occurred. The first problem is that we decide as a motion even if motion doesn't exist (This problem is called false alarm). The second problem is that we decide as a nonmotion even if motion exists (this problem is called miss)[4]. In this paper, we make use of MRF model based on the Bayes rule to solve two problems.

Markov random field (MRF)

In order to correct false decisions of the motion decision steps, we use MRF Model. According to the Hammersley-Clifford theorem, the probability of z is given by a Gibbs distribution, the maximization of the a posteriori probability is equivalent to the minimization of the energy function.

Energy minimization

The energy function is classically the sum of two terms (corresponding to data-link and prior knowledge, respectively)[27] as follows:

$$U_T(x,y) = \frac{1}{2\sigma^2}\sum[z(x,y)-m_l]^2 + \alpha\sum_{\Omega} V_c(l_s,l_n) \tag{10}$$

where σ^2, m_l, and α are the observation variance, the mean of l^{th} PDF, and a weighting constant chosen by experiments, respectively ;and l_s is a label of center pixel s, l_n is a label of neighboring pixel n,and $V_c(l_s, l_n)$ is a potential function associated with a binary clique c = (s, n) [5,6]. Energy of each pixel is computed using (10), and thus the final motion segmentation results are obtained by energy optimization techniques. In the proposed method, the termination of iteration is automatically determined based on the energy difference between iterations t and t−1 as follows [7]:

$$\Psi(t) = \frac{\sum_{x}^{H}\sum_{y}^{W}|U_T^{(t)}(x,y) - U_T^{(t-1)}(x,y)|}{HW} \tag{11}$$

where H and W represent the height and width of the image sequence, respectively; and U(t) T (x, y) denotes the total energy at an iteration t. For each pixel s of the current image, the labels from 0 to K−1 are tested and the label that induces the minimum local energy in the neighborhood is kept. The process iterates over the image until $\Psi(t)$ is lower than 0.05% of the first energy U_T^0 . Accordingly, the final label l* becomes one of 0, 1, . . ., K−1 and arranged according to the magnitude of velocity vectors. Finally, the pixels which l* is greater than 0 are considered to have motion.

VI. EXPERIMENTAL RESULTS

The experiments were performed on Microsoft Windows XP Professional operating system with Intel Core 2 Duo 1.80GHz CPU and 2GB RAM. The execution is performed using MATLAB(R2008a version) and the tested video sequences are of AVI and MPG format. To verify the effectiveness of the approach two video sequences with different scenarios have tested. The first of them is a car moving on road that is covered by grass on both the side. The second sequence is a fast moving car passing from a forest. For evaluation of the performance, ROC curve has been used. According to the ROC curve, In first sequence, object detection accuracy is 83.7% and in second sequence, accuracy is 95.5 %.

Fig. 2 first, middle and last frame of first sequence

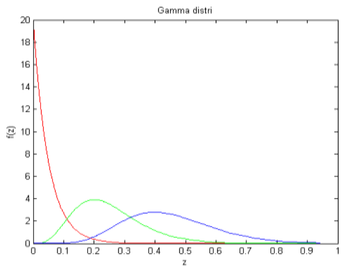

Fig. 3 gamma distribution plot of first sequence


Fig. 4 pixel labeling result, final result and ground truth result of first sequence


Fig. 5 first, middle and last frame of second sequence

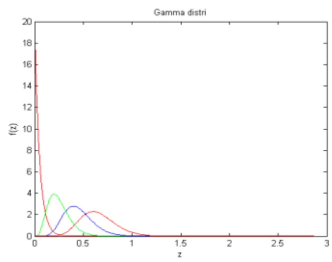

Fig. 6 gamma distribution plot of second sequence


Fig. 7 pixel labeling result, final result and ground truth result of second sequence

VII. CONCLUSION

In this paper, a novel moving object detection method based on gamma distribution has been proposed. The experimental results shows that this method work efficiently with sudden illumination change, for both indoor as well as outdoor sequence and also work effectively in situation of occlusion. The proposed method uses optical flow analysis which is very time consuming so pre processing step has included but as after gray scale conversion velocity vector has calculated the performance degrades in situation where foreground is dark and light background moves.

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