

OBJECT TRACKING BASED ON MOVING OBJECT DETECTION

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ABSTRACT

Now days in the aggressive field security matters have increases rapidly. That's why it is necessary of one which is capable to save anyone's personal estate from damage such as theft, demolition of property, people with awful commitment etc. Hence, it is imperative for the surveillance methodologies to also augment with the developing world. We are using Background Subtraction and Self Organizing Background Subtraction (SOBS) algorithm for moving object detection, Morphological method for tracking of moving object. In Background Subtraction establishing a reliable background updating model based on statistical and use a dynamic optimization threshold method to obtain a more complete moving object. While in SOBS an approach to moving object detection based on neural background model automatically generated by a self-organizing method.

Keywords-Background Subtraction, Motion Detection, Neural Network, Self Organization, visual surveillance.

I INTRODUCTION

Moving object detection and tracking algorithms are an important research area of computer vision and comprise building blocks of various high-level techniques in video analysis that include tracking and classification of trajectories. In video surveillance system, detection and tracking of object is lower level task that provides support to higher level tasks such as event detection. Categorizing moving objects is a critical task which requires video segmentation, which is used in number of computer vision applications such as video surveillance, traffic monitoring, and remote sensing. There are three major steps in video surveillance analysis: detection of moving objects, tracking of interested objects from consecutive frames, and the third is analysis of these tracked objects to identify its behavior, and also to identify normal/abnormal events. In this paper we are using two different methods for moving object detection.[1][3]

The background subtraction method is to use the difference method of the current image and background image to detect moving objects, with simple algorithm, but very sensitive to the changes in the external environment and has poor anti-interference ability. However, it can provide the most complete object information in the case of the background is known. In this method, in a single static camera condition, combine dynamic background modeling with dynamic threshold selection method based on the background subtraction, and update background on the basis of accurate detection of object, this method is effective to enhance the effect of moving object detection.

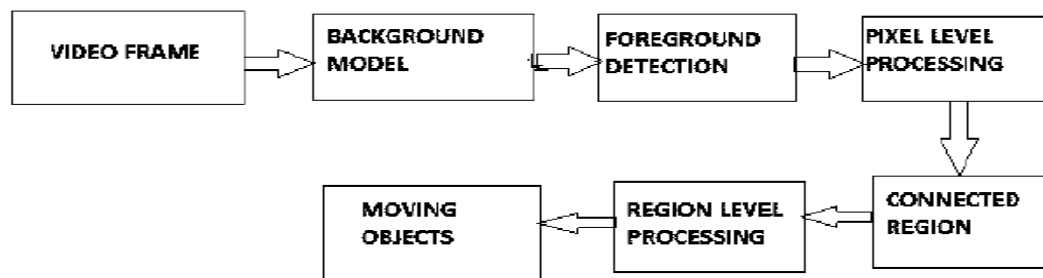


Figure 1: Framework of Moving Object Detection

In the Self-Organizing Background Subtraction (SOBS) algorithm has been proposed, which implements an approach to change detection based on the neural background model automatically generated by a self-organizing method without prior knowledge about the involved patterns. Such adaptive model can handle scenes containing moving backgrounds, gradual illumination variations, and camouflage, can include into the background model shadows cast by moving objects, and achieves robust detection for different types of videos taken with stationary cameras.[2][10]

II BACKGROUND SUBTRACTION METHOD

The background subtraction method is the common method of motion detection. It is a technology that uses the difference of the current image and the background image to detect the motion region, and it is generally able to provide data included object information. The key of this method lies in the initialization and update of the background image. The effectiveness of both will affect the accuracy of test results. Therefore, this paper uses an effective method to initialize the background, and update the background in real time.[7]

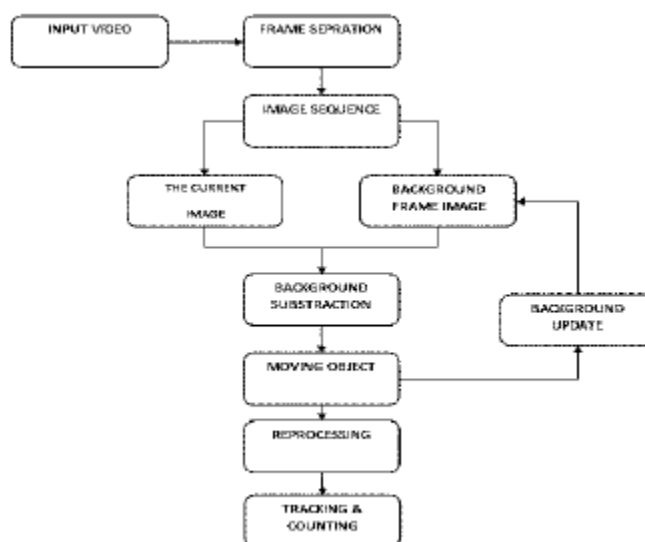


Figure 2: Flow Diagram

2.1 Background Modelling & Update:

In the background training process, the reference background image and some parameters associated with normalization are computed over a number of static background frames. The background is modeled statistically on a pixel by pixel basis. The expected color value of pixel i is given by

$$Ei = [\mu_R(i), \mu_G(i), \mu_B(i)]$$

$[\mu_R(i), \mu_G(i), \mu_B(i)]$ are the arithmetic means of the i_{th} pixel's red, green, blue values computed over N background frames. In detection of the moving object, the pixels judged as belonging to the moving object maintain the original background gray values, not be updated. For the pixels which are judged to be the background, we update the background model according to following rules:

$$B_{k+1}(x, y) = \beta B_k(x, y) + (1 - \beta)F_k(x, y)$$

$B_k(x, y)$ and $B_{k+1}(x, y)$ are respectively the Background value of the current frame and the next frame.

2.2 Moving Object Extraction:

After the background image $B(x, y)$ is obtained, subtract the background Image $B(x, y)$ from the current frame $F_k(x, y)$. If the pixel difference is greater than the set threshold T , then determines that the pixels appear in the moving object, otherwise, as the background pixels. The moving object can be detected after threshold operation. Its expression is as follows:

$$D_k(x, y) = \begin{cases} 1 & |F_k(x, y) - B_k(x, y)| > T \\ 0 & \text{others} \end{cases}$$

Where $D_k(x, y)$ is the binary image of differential results. T is gray-scale threshold; its size determines the accuracy of object identification. In this paper the dynamic threshold method, we dynamically changes the threshold value according to the lighting changes of the two images obtained. On this basis, add a dynamic threshold T to the above. Its mathematical expression is as follows:

$$\Delta T = \lambda * \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} |F(i, j) - B(i, j)|$$

Then

$$D_k(x, y) = \begin{cases} 1 & |F_k(x, y) - B_k(x, y)| > T + \Delta T \\ 0 & \text{others} \end{cases}$$

2.2 Preprocessing

As the complexity of the background, the difference image obtained contains the motion region, in addition, also a large number of noises. Therefore, noise needs to be removed. This paper adopts median filter with the 3×3 window and filters out some noise. After the median filter, in addition the motion region, includes not only body parts, but also may include moving cars, flying birds, flowing clouds and swaying trees and other nobody parts. Morphological methods are used for further processing.

Firstly, corrosion operation is taken to effectively filter out non-human activity areas. Secondly, using the expansion operation to filter out most of the non-body motion regions while preserving the shape of human motion without injury. After expansion and corrosion operations, some isolated spots of the image and some interference of small pieces are eliminated, and we get more accurate human motion region.

2.3 Extraction of Moving Human Body

After median filtering and morphological operations, some accurate edge regions will be got, but the region belongs to the moving human body could not be determined. Through observation, we can find out that when moving object appears, shadow will appear in some regions of the scene. The presence of shadow will affect the accurate extraction of the moving object. By analyzing the characteristics of motion detection, we combine the projection operator with the previous methods.

III SELF ORGANIZING BACKGROUND SUBTRACTION

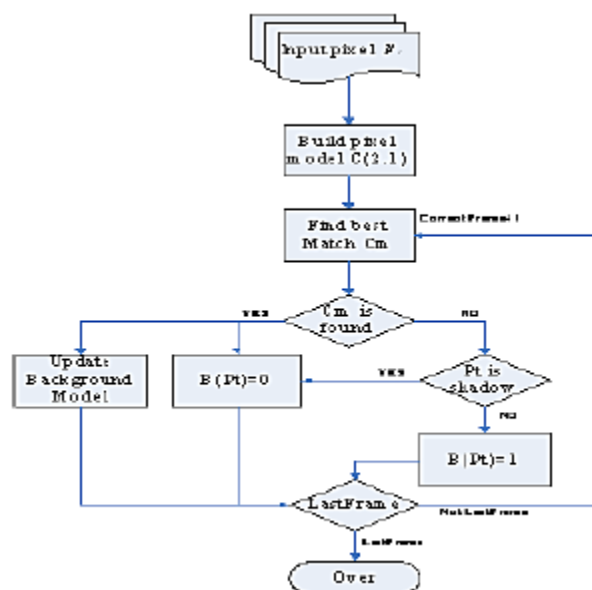


Fig 3: SOBS Algorithm

The background model constructed and maintained in SOBS algorithm is based on the idea of building the image sequence neural background model by learning in a self-organizing manner image sequence variations, seen as trajectories of pixels in time. The network behaves as a competitive neural network that implements a winner-take all function, with an associated mechanism that modifies the local synaptic plasticity of neurons, allowing learning to be spatially restricted to the local neighborhood of the most active neurons. Therefore, the neural background model well adapts to scene changes and can capture the most persisting feature of the image sequence.

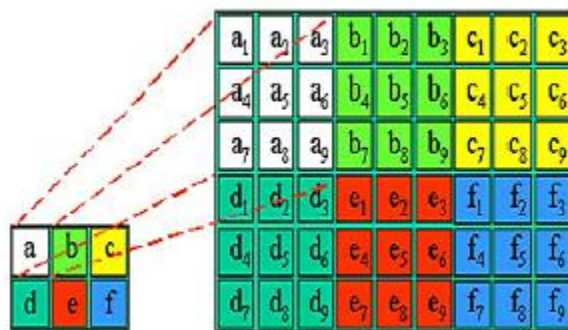


Figure 4: (Left) Simple image and the (right) neuronal map structure

3.1 Neural Model Representation

An image sequence $\{I_t\}$, for each pixel $\mathbf{p}$ in the give domain D , a neuronal map consisting of $n \times n$ weight vectors $m^{i,j}(p)$, $i, j = 0 \dots n-1$ is called model for pixel $\mathbf{p}$. Every frame sequence has N rows and P columns. Complete set of models $M_t(\mathbf{p})$ for all pixels $\mathbf{p}$ of the t_{th} sequence frame I_t is organized as a 2D neuronal map B_t with $n \times N$ rows and $n \times P$ columns, where the weight vectors $m^{i,j}(p)$, for the generic pixel $\mathbf{p} = (x; y)$ are at neuronal map position $(n \times x + i, n \times y + j)$, $i, j = 0, \dots, n-1$:

$$B_t(n \times x + i, n \times y + j) = m^{i,j}(p), \quad i, j = 0 \dots n-1.$$

3.2 Neural Model Initialization

In the case of our background modeling application, we have at our disposal a fairly good means of initializing the weight vectors of the network, because the first image of this sequence I_0 is indeed a good initial approximation of the background. Therefore, for each pixel $\mathbf{p}$, the corresponding weight vectors of the model $M_0(\mathbf{p})$ are initialized with the pixel brightness value at time $t = 0$:

$$m^{i,j}_0(p) = I_0(p), \quad i, j = 0, \dots, n-1$$

3.3 Background Subtraction and Model Update:

Background subtraction is achieved by comparing each pixel $\mathbf{p}$, at each subsequent time step t of the t_{th} sequence frame I_t with the current pixel model $M_{t-1}(\mathbf{p})$, in order to determine if there exists a best matching weight vector $BM(\mathbf{p})$ that is close enough to it. If no acceptable matching weight vector exists, $\mathbf{p}$ is detected as belonging to a moving object (foreground). Otherwise, if such weight vector is found, it means that $\mathbf{p}$ is a background pixel.

3.3.1 Finding the Best Match

Given the current pixel $\mathbf{p}$ at time t , the value $I_t(p)$ is compared to the current pixel model, given by $M_{t-1}(\mathbf{p})$, to determine the weight vector $BM(\mathbf{p})$ that best matches it:

$$d(BM(\mathbf{p}), I_t(\mathbf{p})) = \min_{i,j} d(m^{i,j}_{t-1}(\mathbf{p}), I_t(\mathbf{p})),$$

Where the metric $d(., .)$ is suitably chosen according to the specific color space being considered. Example metrics

could be the Euclidean distance in RGB color space, or the Euclidean distance of vectors in the HSV color hexcone.

The distance between two HSV pixel values $It(p) = (hp, sp, vp)$ and $It(q) = (hq, sq, vq)$ as:

$$d(It(p), It(q)) = ||(vp \ sp \ \cos(hp), vp \ sp \ \sin(hp), vp) - (vq \ sq \ \cos(hq), vq \ sq \ \sin(hq), vq)||_2^2$$

3.3.2 Updating the Model:

In order to adapt the background model to scene modifications, including gradual light changes, the model for current pixel p , given by $M_{t-1}(p)$, should be updated. To this end, the weight vectors of B_{t-1} in a neighborhood of $BM(p)$ are updated according to weighted running average. In details, if $BM(p)$ is found at position p in B_{t-1} , then weight vectors of B_{t-1} are updated according to:

$$B_t(q) = (1 - \alpha) B_{t-1}(q) + \alpha It(p) \quad \forall q \in N_p.$$

IV RESULTS

4.1 Results for Background Subtraction Method



Fig 5.1: Background Image



Fig 5.2 Current Image

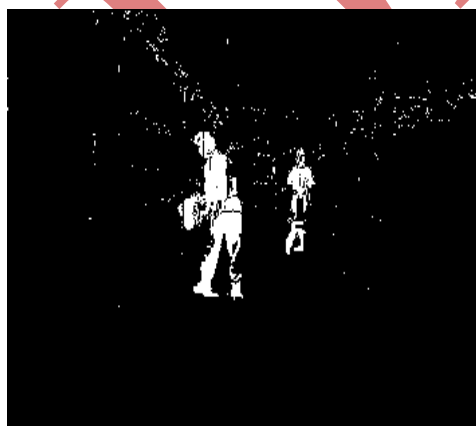


Figure 5.3: Difference Image.

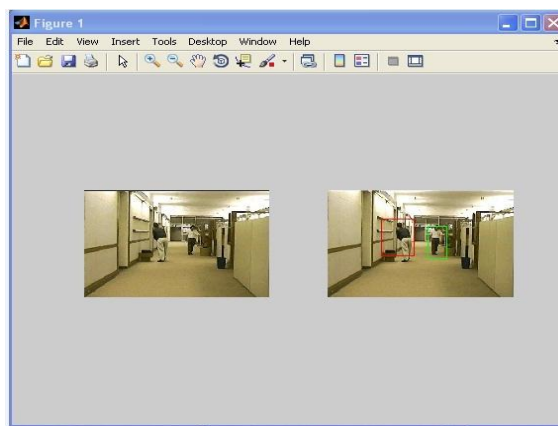


Figure 5.4: Tracking & Counting.

4.2 Results for Self Organizing Background Subtraction Method



Fig 6.1: Background Image



Fig 6.2 Current Image



Figure 6.3: Difference Image.

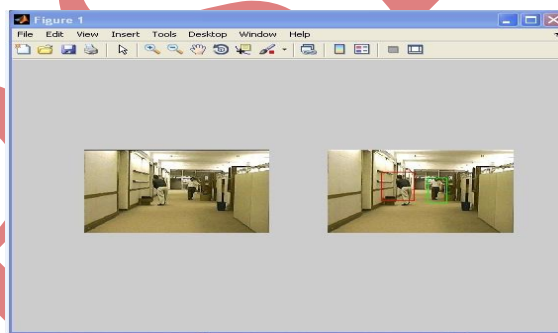


Figure 6.4: Tracking & Counting

Name	Background Subtraction	SOBS
ENTROPY	0.1825	0.3455
MSE	12.6831	11.2050
PSNR	37.0985	37.6494
PROCESSING TIME	4 min	15 min

Table 1: Different values for Background Subtraction & SOBS Method

V CONCLUSION

We have presented object detection by using Background subtraction & Neuronal Mapping (SOBS) methods. While Background Subtraction is robust method rather than SOBS method as processing time, noise present in final output for this method is very less compared to SOBS method. Output SOBS methods are very effective when there are dynamic scene changes (threshold). Change Detection Challenge allowed to show how they handle well-known issues in background maintenance, gradual illumination changes, and cast shadows. Deficiencies in the traditional

method of object detection, we establish reliable background model, use dynamic threshold method to detect moving object and update the background in real time by using background subtraction method.

REFERENCES

- 1) Mingxin Jiang, Min Li and Hongyu Wang, “ *A Robust Algorithm of Object Tracking Based on Moving Object Detection.*” In International Conference on Intelligent Control and Information Processing, 2010.
- 2) Lucia Maddalena and Alfredo Petrosino ”*A Self Organizing Approach to Background Subtraction for Visual Surveillance Applications.*” IEEE Transactions, VOL.17, NO.7, JULY 2008
- 3) Long Chen ; Long Ren ; BaolongGuo ; Xianxiang Wu ”*Objects detecting and tracking with a new particle filter*”, in 2nd IEEE International Conference ,Year:2012
- 4) Lijing Zhang and Yingli Liang, ”*Motion human detection based on background Subtraction*” Second International Workshop on Education Technology and Computer Science, 284-287,Year: 2010.
- 5) M.Dimitrijevic, ”*Human body pose detection using Bayesian spatiotemporal templates,*”, International Conference on Intelligent and Advanced Systems, pp.764-9,Year: 2008.
- 6) Tao Jianguo, Yu Changhong, ”*Real-Time Detection and Tracking of Moving Object*”, Intelligent Information Technology Application, 2008. UTA '08. Second International Symposium on Volume 2, pp:860 - 863,Year: Dec.2008
- 7) NiuLianqiang and Nan Jiang, ”*A moving objects detection algorithm based on improved background subtraction*”, Intelligent Systems Design and Applications, 2008. ISDA '08. Eighth International Conference on Volume 3, pp 604 - 607, Year: Nov. 2008
- 8) Wang Weiqiang, Yang Jie and Gao Wen, ”*Modeling Background and Segmenting Moving Objects from Compressed Video*”, Circuits and Systems for Video Technology, IEEE Transactions on Volume 18, Issue 5, pp 670 - 681,Year: May 2008.
- 9) Long Chen ; Long Ren ; BaolongGuo ; Xianxiang Wu ”*Objects detecting and tracking with a new particle filter*”, in 2nd IEEE International Conference ,Year:2012
- 10) Lucia Maddalena and Alfredo Petrosino “*The SOBS algorithm: what are the limits ?*” IEEE 2012.
- 11) Javed Ahmed, M. N. Jafri, J. Ahmad, and Muhammad I. Khan “*Design and Implementation of a Neural Network for Real Time Object Tracking.*” World Academy of Science 6, Engineering and Technology, 2007.
- 12) Michael W. Roth, ”*Survey of Neural Network Technology for Automatic Target Recognition.*” IEEE Transactions on Neural Networks, Vol.1, NO. 1, March, 1990.

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