OBJECT TRACKING BASED ON MOVING OBJECT DETECTION

Varsha B. Bagal[1] and Sagar A. More[2]

[1,2] P.G., Departmentof Electronics & Telecommunication Engineering,
R.C.P.I.T, Shirpur, M.S. (India)

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 Surveilliance.

I INTRODUCTION

Moving object detection and tracking algorithms arean 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 taskthat provides support to higher level tasks such as event detection. Categorizingmoving 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.

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 ant 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.

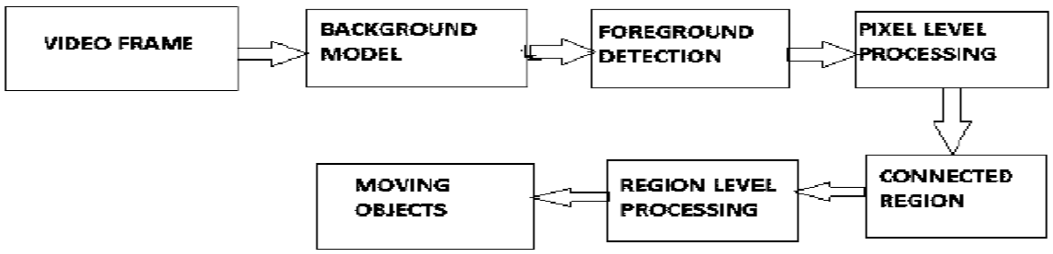

Figure 1: Framework of Moving Object Detection

In the Self-Organizing Background Subtraction (SOBS) algorithm has been proposed, which implementsan 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 detectionfor different types of videos taken with stationary cameras.

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 theinitialization and update of the background image. Theeffectiveness of both will affect the accuracy of test results. Therefore, this paper uses an effective method to initialize thebackground, and update the background in real time.

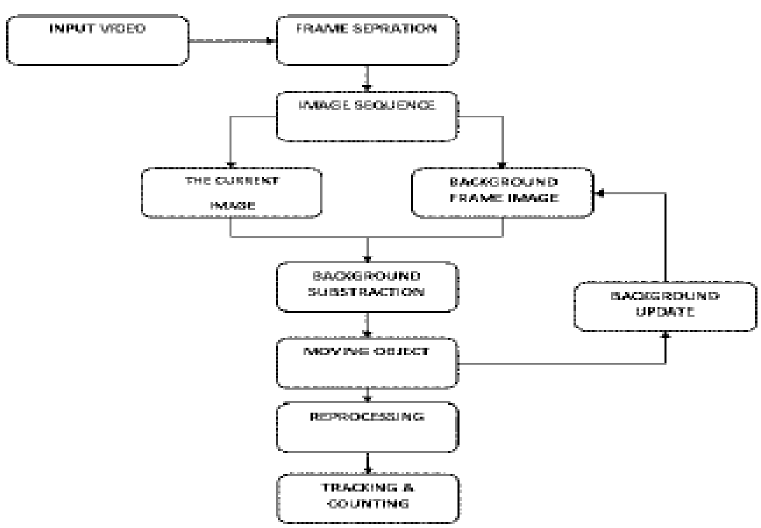

Figure 2: Flow Diagram

2.1Background 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.EiThe 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 theBackground 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 backgroundImage 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 objectcan be detected after threshold operation. Its expression is as follows:

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

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. This paper proposes 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 dynamicthreshold *T* to the above algorithm. 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

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

2.3 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 X 3 window and filtersout 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 swayingtrees 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 withoutinjury. 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.

2.4 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 thatwhen 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 SUBSTRACTION

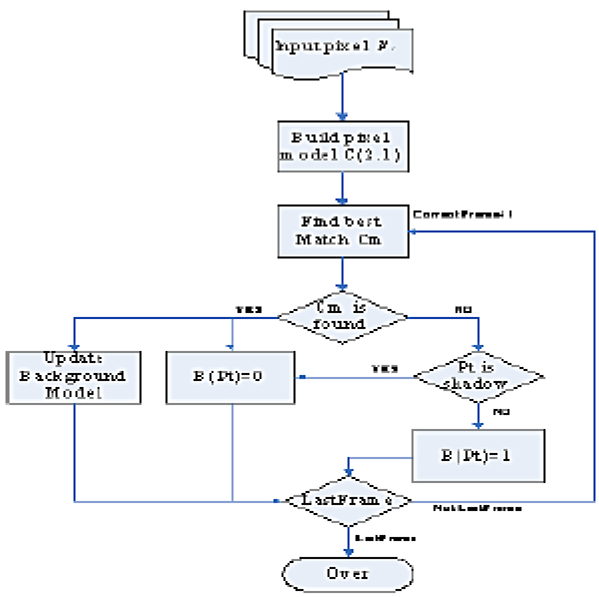

Fig 3: SOBS Algorithm

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

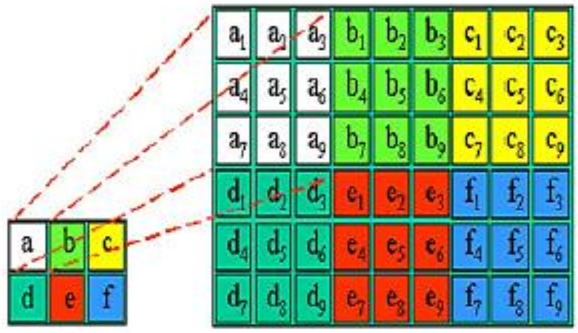

Figure 4: (Left) Simple image and the (right) neuronal map structure

3.1 Neural Model Representation

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

$$Bt\ (n \times x + i, n \times y + j) = m\ i\ t\ j(p), \qquad i,j = 0 \ldots \ldots, n-1.$$

3.2 Neural Model Initialization

In the case of our background modeling application, wehave at our disposal a fairly good means of initializing theweight vectors of the network, because the first image of thesequence I_0 is indeed a good initial approximation of thebackground. Therefore, for each pixel **p**, the correspondingweight vectors of the model M_0(p) are initialized with thepixel brightness value at time t = 0:

$$m\ i\ 0\ j(p) = I0(p), \qquad i, j = 0, \ldots \ldots, n-1$$

3.3 Background Subtraction and Model Update

Background subtractionis achieved by comparing each pixel **p,** at each subsequent time step t of the t_{th} sequence frame I_t with the current pixel model $Mt\_1(\boldsymbol{p})$, in orderto determine if there exists a best matching weight vector $BM(\boldsymbol{p})$ that is close enough to it. If no acceptable matchingweight vector exists, **p** is detected as belonging to a movingobject (foreground). Otherwise, if such weight vector isfound, it means that **p** is a background pixel**.**

3.3.1 Finding the Best Match

Given the current pixel **p**at time t, the value $It(p)$ is comparedto the current pixel model, given by $Mt\_1(\boldsymbol{p})$, to determinethe weight vector $BM(\boldsymbol{p})$ that best matches it:

$d(BM(\boldsymbol{p}), It(\boldsymbol{p})) = \min\ i;\ j = 0, \ldots \ldots, n\text{-}1\ \ d(m^{\,i}\, t\text{-}_1^{\,j}(\boldsymbol{p}),\ \ It(\boldsymbol{p})),$

Where the metric *d(., .)* is suitably chosen according to thespecific color space being considered. Example metrics could be the Euclidean distance in RGB color space, or theEuclidean distance of vectors in the HSV color hexcone. The distancebetween two HSV pixel values $It(p) = (hp, sp, vp)$and $It(q) = (hq, sq, vq)$ *as*:

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

3.3.2 Updating the Model

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

$$Bt(q) = (1\ \alpha tBt - 1\ (q) + \alpha t\ It(p)\ \forall q\ \mathcal{E}\ Np.$$

IV. RESULTS

4.1 Results for Background Subtraction Method

Fig 5.1: Background Image

Fig 5.2 Current Image

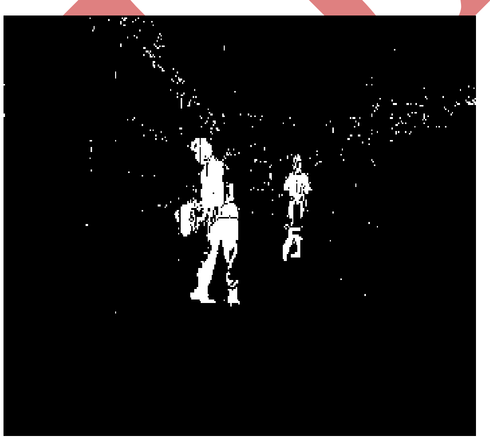

Figure5.3: Difference Image.

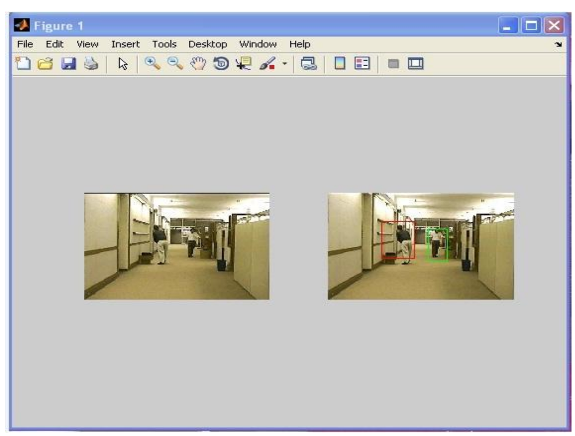

Figure 5.4: Tracking & Counting.

4.2 Results for Self Organizing Background Subtraction Method

Fig 6.1: Background Image

Fig 6.2 CurrentImage

Figure 6.3 : Difference Image.

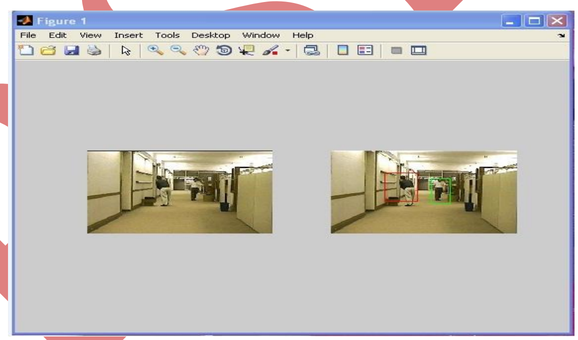

Figure 6.4: Tracking & Counting

V. CONCLUSION

We have presented object detection by using Background subtraction & Neuronal Mapping (SOBS) methods. While Background Subtraction is robust against method rather than the other as time factor is important. Time required for background subtraction is much lesser than neuronal map and results obtained are more accurate. 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, resulting robust to moving backgrounds, gradual illumination changes, and cast shadows, and how accuracy can still be improved bytaking into account the scene characteristics.

REFERENCES

1) Long Chen ; Long Ren ; BaolongGuo ; Xianxiang Wu ”*Objects detecting and tracking with a new particle filter*”, in 2nd IEEE International Conference ,Year:2012

2) 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.

3) M.Dimitrijevic, *"Human body pose detection using Bayesian spatiotemporal templates*,", International Conference on Intelligent and Advanced Systems, pp.764-9,Year: 2008.

4) 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

5) 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

6) 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

7) Lucia Maddalena and Alfredo Petrosino "*A Self Organizing Approach to Background Subtraction for Visual Surveillance Applications*." IEEE Transactions, VOL.17, NO.7, JULY 2008

8) Lucia Maddalena and Alfredo Petrosino "*The SOBS algorithm: what are the limits* ?" IEEE 2012.

9) 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.

10) Michael W. Roth, "*Survey of Neural Network Technology for Automatic Target Recognition*." IEEE Transactions on Neural Networks, Vol.1, NO. 1, March, 1990.