Surveillance of Background Activities using MOG, ViBe and PBAS

[1]Priyanka Bhor, [2]Pooja Vashiwale, [3]Prof. Vijay.N.Patil

[1,2,3]Bharati Vidyapeeth College of Engineering Sector-7,C.B.D,Belpada,Navi Mumbai-400614,India.

[1]priyankabhor13@gmail.com, [2]pooja.vashi22@gmail.com

***Abstract*- This paper proposes surveillance of background activities effectively using Mixture of Gaussians(MOG),Visual Background Extractor(ViBe) and Pixel-Based Adaptive Segmentation(PBAS).These are three different background subtraction algorithms-to detect events of interest within uncontrolled outdoor video. This is a fast and robust method to the detection and tracking of moving objects. Our method is based on using area computed by a brightness based image comparison showing the motion. Many computer vision techniques are unsuccessful in this domain due to low frame-rates. In our method, extracted area by using image comparison is compared with the same area of previous frame. The area is above the thresholding criteria then it is marked as area where motion has been take place. Input images are given by using webcam. All three algorithms provides accurate detection of events however we see much fewer false positives from the modified versions of the ViBe and PBAS algorithms.**

Keywords-Mixture of Gaussians(MOG), Visual Background Extractor(ViBe), Pixel-Based Adaptive Segmentation(PBAS).

I. INTRODUCTION

In digital video processing technology video segmentation generated by objects is an important application domain. This digital video processing technology not only covers nearly every aspect of digital video processing and digital image processing and analysis but relates to computer vision, statistical signal processing, stochastic process and pattern recognition and other domains. In intelligent surveillance and many other vision systems important research issue is video segmentation for interesting target detection and tracking.

Tracking objects as they move through video sequences is one of the most basic and most important tasks in computer vision[1].

In personal databases and Web repositories use of video data is continuously increasing which is true. To extract the objects from video, segmentation is often needed. In many computer vision and video processing applications video segmentation and background subtraction are fundamental tasks to do so. They are mainly used as the first step in applications like tracking, recognition, and classification, among others. Segmentation of foreground objects from background has a lot of applications in human-computer interaction, video compression, multimedia content, editing and manipulation. The extraction of the moving foreground objects from a stationary background from a general video sequence has various applications such as compression of videos and also in the cinematographic effects which is really helpful One of its important applications is digital composition, in which the object of interest is extracted from a video clip and pasted to a new background. Most video effects in movies involve this task.

The algorithms which can recognize low-level actions such as walking, running, or hand clapping from input video sequences is given. A reliable solution to this problem would allow for a variety of applications such as automated surveillance, human-computer interaction, and video retrieval and search[2].

The raw video data is usually in the form of binary streams that are not well organized. For content representation, the raw video data must be decomposed into objects, each object representing particular meaningful content of video. Two methods are mostly used in video object segmentation, one is semi-automatic, in which some kind of user intervention is required to define the semantic object and second one is automatic, where segmentation is performed without user intervention, but usually with some apriori information. Automatic segmentation of video objects is required by most applications, especially those with real time requirements.

In recent years many successful methods were proposed that learn and classify motion directly from image measurements. These direct methods are attractive due to the possibility of training motion models from the video data alone as describe in one of the paper[3].

Background subtraction involves the difference between the current image and the reference updated background image over a period of time. A good background subtraction should be able to overcome the problem of varying illumination condition in video, background clutter, shadows, camouflage, bootstrapping and at the same time motion segmentation of foreground object should be done at the real time so that goal should be reach.

Detecting and tracking of moving objects are widely used as low-level tasks of computer vision applications,
such as video surveillance, robotics, authentication systems, user interfaces by gestures, and a pre-stage of MPEG4 image compression as discussed earlier.

Software development of low-level tasks is especially important because it influences the performance of all higher levels of various applications in computer vision. Motion detection is a well-studied problem in computer vision.

II. RELATED WORK

A. *Mixture of Gaussians (MOG)*

MOG is a widely used and robust background subtraction algorithm used in OpenCV . It is based on modeling the background pixels as a combination of surfaces which is further described as a Gaussian mixture model. The probability of a pixel belonging to the background is described as a sum of Gaussians:

$$f_{\mathbf{X}}(X|\Phi) = \sum_{k=1}^{K} P(k) \cdot f_{\mathbf{X}|k}(X|k, \theta_k)$$

B. *Visual Background Extractor (ViBe)*

ViBe is a background subtraction algorithm based on random substitution and spatial diffusion. Van Droogenbroeck et al. approach background model formulation with stochasticity in order to increase the robustness of their algorithms and increase the range of background pixels stored in the model for better performance. Since ViBe does not rely on statistical modeling of pixel history as the authors believe it can better match a pixels true history by actually using past pixel values. This means ViBe can fit multi-modal pixel histories and better adapt to slight background movement.

To model the background, ViBe stores and array of 20 previous values for each pixel and compares new pixel values to this pixel history. If a pixel value matches two of the stored values within some threshold (τ) then it is classified as part of the background, otherwise it is masked as foreground. This method of classification allows for up to 10 different background models to be fit by ViBe.

C. *Pixel-Based Adaptive Segmentation (PBAS)*

PBAS, introduced by Hofmann et al, is a foreground segmentation algorithm that uses the stochastic portions of ViBe along with pixel-based adaptive thresholding and updating. PBAS adjusts thresholds to the pixel variance in the image by dynamically setting the threshold, τ , and the probability of pixel update from Section II-C. Hofmann et al. measure background dynamics by calculating the mean from a stored array of previously observed minimum pixel differences. When background dynamics are high, a larger threshold, τ , can be used to reduce noise and the probability for updating the background model can be increased to allow for quicker absorption of false foreground detection. By contrast, when background dynamics are low, a smaller and more precise τ can be used with a smaller update probability to keep foreground detections in the foreground longer. This means PBAS else with allows for strong foreground segmentation on pixel a highly static background while simultaneously using a more lenient set of parameters on highly dynamic regions of the image such as water or foliage.

D. *Background Subtraction on Distributions*

Ko et al. presents a background subtraction technique using pixel distributions as a method for observing birds visiting a feeder. This environment naturally has an active background with foliage movement, however birds drawn to feeders are not typically in their ideal environment for camouflage and since they are feeding tend to be more active than when on the nest. The technique proposed in was designed to solve noise generated by background movement by looking at pixel neighborhood distributions but is more computationally expensive than pixel-based approaches.

III. SYSTEM ARCHITECTURE

The fig. 1 shows our simple model.

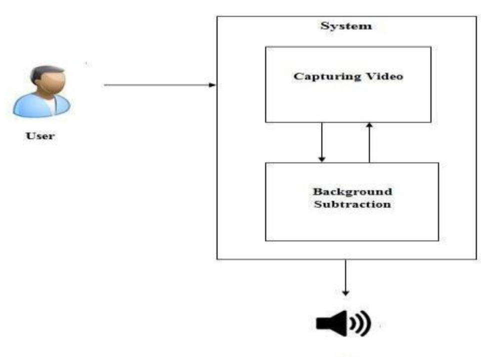


Fig. 1 Architecture

Background subtraction is basically detecting moving objects in videos using static cameras. In this system of CCTV Surveillance system, we will not require any observer /

ISSN : 2454-9150 Vol-03, Issue 01, Apr 2017

security guard to monitor the screen. If any unwanted activity will occur it will buzz alarm.

The basic idea in the approach is detecting the moving objects from the difference between the current frame and a reference frame, which is called "background image" or "background model". The background image must be good enough to represent the scene with no moving objects and be regularly updated so that it adapt to the varying luminance conditions and geometry settings. Poor background image may result in poor background subtraction results, because it is to be subtracted with the current image to obtain the final result. Processing a video stream to segment foreground objects from the background is a critical first step in many computer vision applications. The popularity of background subtraction algorithms largely comes from its computational efficiency, which allows applications such as human computer interaction, video surveillance and traffic monitoring to meet their real-time goals. Many different methods have been proposed over the recent years. Some of them are currently used in the CCTV detection application by the defense personals these different techniques vary in computational speed, memory requirements and accuracy basically.

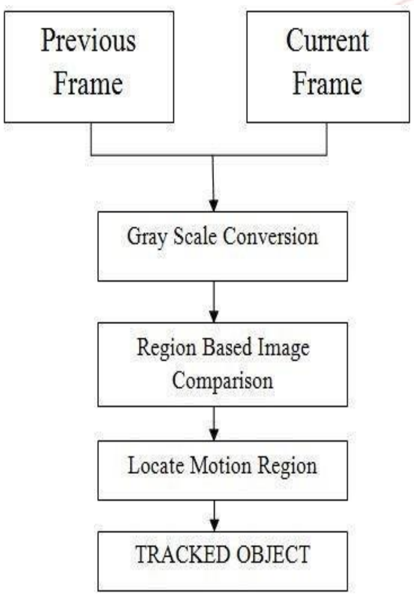


Fig.2 Block Diagram

Frame difference is the simplest form of background subtraction. The current frame is simply subtracted from the previous frame, and if the difference in pixel values for given pixel is greater than a threshold *h T* then the pixel is considered part of the foreground.

$$i\ i\ h\ frame - frame > T \ \text{-1}$$

The estimated background is just the previous frame and it is very sensitive to the threshold
The frame difference method also subtracts out background noise (such as waving trees), much better than the more complex approximate median and mixture of Gaussians methods.

A Challenge with this method is determining the threshold value. The result depends on threshold values thus each different video depends on different thresholds. The result shows "the frame difference" method as very low computationally intensive and efficient method.

It also subtracts out background noise (such as waving trees), much better than the more complex approximate median and mixture of Gaussians methods (high computation methods). But the main challenge in this method is the determination of appropriate threshold, since the result solely depends on the threshold used.

Any background subtraction detected events that occur within 30 seconds of the start or end time of a scientist observed event are marked as a match. Multiple matches to the same start and end event from the same scientist are ignored. Other detection errors are caused by video compression noise, and species cryptic coloration. It is very useful for the video based applications, such as automatic video surveillance.

The frame difference method also subtracts out background noise (such as waving trees), much better than the more complex approximate median and mixture of Gaussians methods.

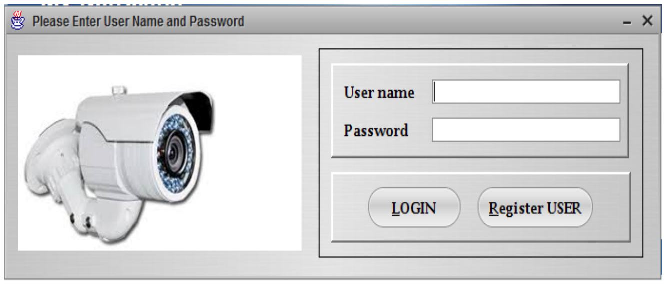
A Challenge with this method is determining the threshold value. The result depends on threshold values thus each different video depends on different thresholds. The result shows "the frame difference" method as very low computationally intensive and efficient method. It also subtracts out background noise (such as waving trees), much better than the more complex approximate median and mixture of Gaussians methods (high computation methods). But the main challenge in this method is the determination of appropriate threshold, since the result solely depends on the threshold used.

Any background subtraction detected events that occur within 30 seconds of the start or end time of a scientist observed event are marked as a match. Multiple matches to the same start and end event from the same scientist are ignored. Other detection errors are caused by video compression noise, and species cryptic coloration. It is very useful for the video based applications, such as automatic video surveillance.

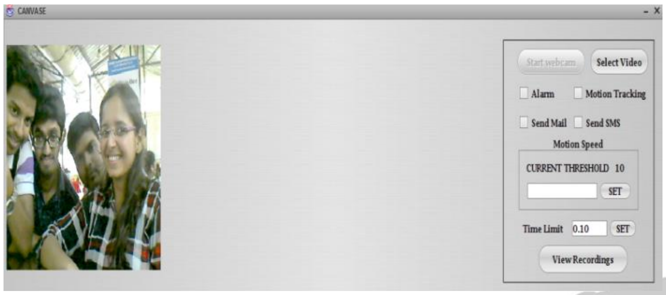
STEPS:-

Step 1:

In proposed system user has to first login to the system. User should be an authenticate person.



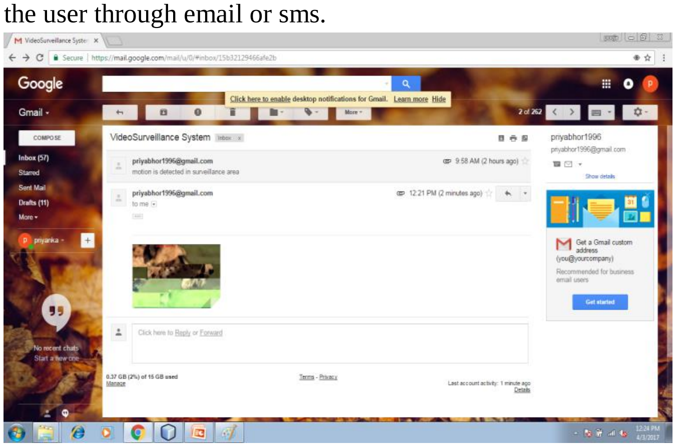
Step 2:
Once login completed next frame will open. User have to select either webcam or video.



Step 3:
Then threshold value have to set between 0 to 30 and Time limit is also have to set.

Step 4:
Next select alarm and either send mail or send sms to give alert to the user that motion is detected in that particular area.

Step 5:
By clicking on motion tracking those alert will be send to the user through email or sms.



IV. CONCLUSION

There is a huge interest in the market to make technical equipment "smart" and "self-learning". An important component in such systems is the ability for a computer to track and identify moving objects quickly. The problem of tracking the movement of a desired object that is captured by a real time video stream is of interest because of the many applications that can be derived from it for sake of understanding.

The object is marked using a red square Superimposed on the object which makes the position of the object clear to the observer. The algorithm improves the detection and location of moving objects in the video images. It is very useful for the video based applications, such as automatic video surveillance

REFERENCES

[1] Rahul Mishra, Mahesh K. Chouhan, Dr. Dhiiraj Nitnawwre, *Multiple Object Tracking by Kernel Based Centroid Method for Improve Localization*, July 2012.

[2] A. Fathi, and G. Mori, "*Action recognition by learning mid-level motion features*," Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp.1-8,2008

[3] I. Laptev, B. Caputo, C. Schuldt, and T. Lindeberg, "*Local velocity adapted motion events for spatio-temporal recognition*", vol. 108, pp. 207-229, 2007.

[4] D. Weinland, and R. Ronfard, "*A survey of vision based methods for action representation, segmentation, and recognition*," Computer Vision and Image Understanding, vol. 115, no. 2, pp. 529-551, 2011.

[5] M. Hofmann, P. Tiefenbacher, and G. Rigoll,"*Background segmentation with feedback: The pixel-based adaptive segmenter*," in Computer Vision and Pattern Recognition Workshops (CVPRW), 2012 IEEE Computer Society Conference on. IEEE, 2012, pp. 38–43.

[6] D. Koller, J. Weber, T. Huang, J. Malik, G. Ogasawara, B. Rao, and S. Russell, "*Towards robust automatic traffic scene analysis in real time*," in Pattern Recognition, 1994. Vol. 1-Conference A: Computer.

[7] *Vision & Image Processing*., Proceedings of the 12th IAPR International Conference on, vol. 1. IEEE, 1994, pp. 126–131.

[8] J. Heikkil¨a and O. Silv´en, "*A real-time system for monitoring of cyclists and pedestrians*," Image and Vision Computing, vol. 22, no. 7, pp. 563– 570, 2004.

