International Research Journal of Advanced Engineering and Science
ISSN: 2455-9024

Moving Object Detection and Tracking Using Hybrid Model

Akhil U[1], Prasanth M[2]
[1, 2]Department of ECE, University of Calicut, NCERC, Pampady, Kerala, India-680588

***Abstract*—*Multiple moving object detection in videos is very important in many video processing applications like video surveillance, monitoring traffic for rash driving control, detections of pedestrians etc. Thus detection must be performed accurately and robustly to minimize the false alarms and missing evidences. Background modelling and foreground extraction are two major processes to achieve this goal. Many traditional background modelling methods use either colour information or texture information. But colour is sensitive to light variations and texture information cannot be utilized to separate smooth foreground from smooth background in many cases. To achieve good performance in terms of high foreground detection accuracy and low computational cost is also challenging. A new hybrid model with integration framework of texture and colour information for background modelling is proposed in this project. This framework is able to combine the advantages of both colour and texture methods, and at the same time it cancels out their disadvantages as well. Moreover, we propose a block based method to accelerate the background modelling. The background and foreground models are updated by first in first out strategy to maintain the most recent observed background and foreground instances. Along with this it is necessary to track the detected objects in real time, to enable corrective actions. We are using active contour model based tracking. An extensive experiment on various challenging videos and comparison of various parameters like Precision, Recall, F-measure and Processing time which proves the effectiveness of the proposed method over existing ones.*

***Keywords*—*Object detection, integrated information, colour informatio, texture information, background subtraction, block based detection, hybridmodel.*

I. INTRODUCTION

Moving object detection usually serves as pre-processing for higher-level video analyses and its performance directly affects the performance of the subsequent applications. For object tracking, if a moving object is detected as two or two moving objects are detected as one, the tracking result may be incorrect. For object categorization, incomplete or adhesive detection of moving objects may lead to wrong categorization, and it is the same case for object re-identification. For video condensation, object tracking is also an indispensable part. It is not the desired result if the head and legs of one person appear at different time in the condensed video. Ideally, a detection method should detect each moving object separately without breaking.

Background modelling is indispensable for moving object detection in many cases and lots of works have been done in this research area. In early works, the background model was constructed for each pixel independently. Until now, only a few works have been done on block based background modelling or background subtraction. The advantage of the block-based strategy over the pixel based one is that stable foreground detection results can be achieved with less computation and memory resource, while the disadvantage is that the detection boundary will be very coarse, and adjacent moving objects may be connected.

Colour information is sensitive to illumination variations while texture information cannot be utilized to separate smooth foreground from smooth background in most cases. In this work, we propose a new integration framework of colour and texture information which can inherit their advantages while inhibiting their disadvantages. Since background modelling is usually a pre-treatment for higher-level video analyses, it should be computationally efficient. So we use the block-based strategy and construct one model for each block, which is different from the pixel based strategy that has one model for each pixel. A lot of computational resources can be saved. As aforementioned, the block based method has a shortcoming that the detection boundary will be coarse and may connect adjacent moving objects. To deal with this problem, we use two levels of block sizes. Background models are constructed in big blocks for stability while detection decisions are made for small blocks to achieve finer boundary.

The main contributions of this paper is as follows. Firstly, a new integration framework of texture and colour information is proposed and both illumination variations and smooth background-foreground problem can be handled. Secondly, the block-based strategy is used and a single histogram model is established for each block, which makes our modelling process fast with little memory consuming. Thirdly, two levels of block sizes are used to benefit from the fact that the background model in big blocks can be more stable while the final foreground detection boundary based on small blocks can be more accurate.

II. OVERVIEW OF THE SYSTEM

In proposed system the main aim is to build robust moving object detection algorithm that can detect and Track object in video. The first step is to take input video from static cameras. For processing the video files, convert video into frames and from frames to images. Next step is take first frame as a Background frame and next is current frame and then apply subtraction operation. Background frame is subtracted from current frame. Then Threshold operation is performed and foreground object is detected. After object detected last step is track object in video.

By using dynamic threshold method we can dynamically change the threshold value according to the lighting changes of the two images obtained. This method can effectively suppress the impact of light changes. Here we consider first frame as the background frame directly and then that frame is subtracted from current frame to detect moving object.

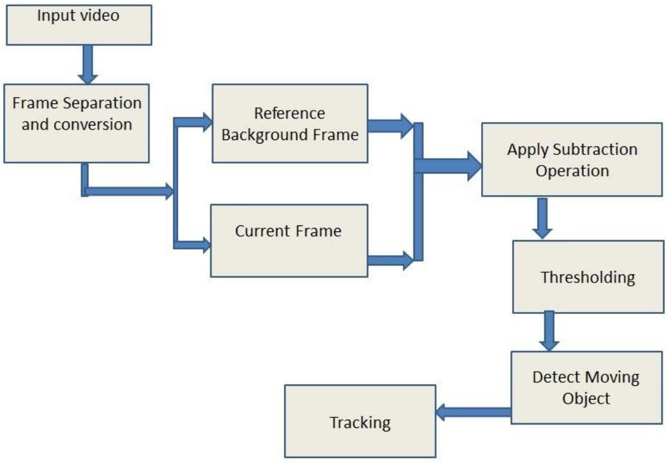

Fig. 1. Overview of the system.

Primary objective of this paper is to achieve good performance in terms of better foreground detection accuracy by using a new integrated framework. Until now, only a few works have been done on block based background modelling or background subtraction. The advantage of the block-based strategy over the pixel based one is that stable foreground detection results can be achieved with less computation and memory resource. Thus block-based strategy is used and a single histogram model is established for each block, which makes our modelling process fast with little memory consuming. Next objective is to track the detected objects by using active contour model algorithm in real time. Also to compare various parameters like Precision, Recall, F-measure and Processing time which proves the effectiveness of the proposed method over existing ones.

III. METHODOLOGY AND PROCEDURE

A. *Object Detection*

Moving object detection provides a classification of the pixels in the video sequence into either foreground (moving objects) or background. A common approach used to achieve such classification is background removal, sometimes referred to as background subtraction, where each video frame is compared against a reference or background model, pixels that deviate significantly from the background are considered to be moving objects [1]. Basic Background Subtraction (BBS) algorithm computes the absolute difference between the current frame and a static background frame and compares each pixel to a threshold [2]. Pixels associated with the same object should have the same label; one can accomplish this by performing a connected component analysis. All the connected components are computed and they are considered as active regions if their area exceeds a given threshold. This step is usually performed after a morphological filtering to eliminate isolated pixels and small regions [3]. This is perhaps the simplest object detection algorithm one can imagine.

B. *Background Modelling*

Background modelling is one of the important research topics for detecting moving foreground objects in visual surveillance and has been widely applied in various surveillance applications, such as foreground object tracking and event analysis. The main issue of background modelling is to create background models, which can represent backgrounds under illumination and dynamic changes for comparison. Then, foreground objects can be retrieved by background subtraction between incoming frames and background models. Recently, various background modelling approaches have been developed, which can be categorized into pixel-based, region-based and hybrid methods.

C. *Hybrid Background Modelling Techniques*

Hybrid methods, which integrate both pixel- and region based methods, are proposed to solve aforementioned problems. As indicated in [41], hybrid methods can achieve better background representation and solve problems of illumination and dynamic background changes. Although hybrid methods can achieve good foreground extraction performance, the computational complexity is relatively high. Thus, in [48], a hardware implementation is performed on the hybrid method for real-time processing. In this work, the proposed hybrid model is a combination of two algorithms, one is block wise background modelling algorithm with the integration of texture and colour information, and the other one is background subtraction algorithm. This model can inherit the advantages of both methods, while inhibiting their disadvantages at the same time.

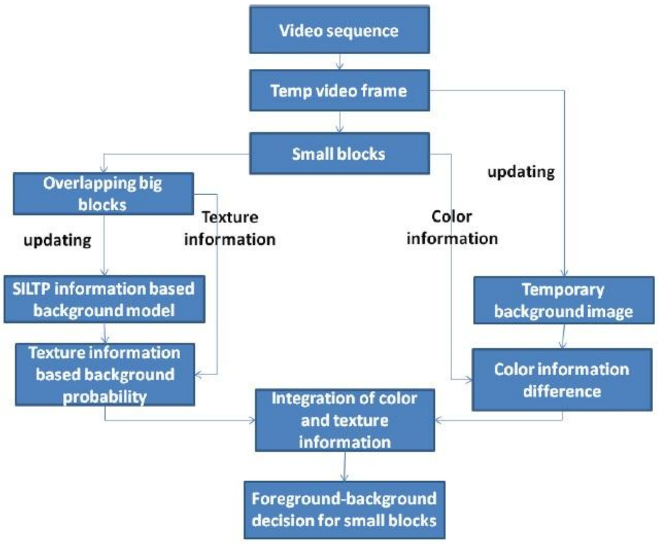

Fig. 2. Integration framework for colour and texture information.

Figure 2. shows the framework of our integrated moving object detection method. On one hand, we update an SILTP information based background model for each big block, and get the texture information based background probability

Akhil U and Prasanth M, "Moving object detection and tracking using hybrid model," *International Research Journal of Advanced Engineering and Science*, Volume 1, Issue 3, pp. 16-20, 2016.

International Research Journal of Advanced Engineering and Science

ISSN: 2455-9024

based on the model and the SILTP information of each big block in the new coming frame; on the other hand, we update a colour information based temporary background image, and get the colour information difference based on the temporary background image and the colour information of the new coming frame. Then we integrate colour information and texture information to get the foreground-background decision for each small block. We have already got the background likelihood Psb of each small block of the new coming frame based on SILTP information and the colour information difference D between the small blocks of the temporary background image and those of the new coming frame. So the only thing left is to make a final decision based on these two values. For SILTP information, we use the threshold Ts to judge whether the small block belongs to the background. For colour information, we use the threshold Tc to judge whether the small block belongs to the background. The final decision can be made according to the following equation:

$$Decision = \begin{cases} foreground, & \text{if } P_b^s < T_s, \text{ or } D > T_c, \\ & \text{or } (1-P_b^s)D > \frac{1}{\rho}(1-T_s)T_c \\ background, & \text{else} \end{cases}$$

D. Tracking of Detected Objects

Video tracking is the process of locating a moving object (or multiple objects) over time using a camera. It has a variety of uses, some of which are: human-computer interaction, security and surveillance, video communication and compression, augmented reality, traffic control, medical imaging and video editing. Video tracking can be a time consuming process due to the amount of data that is contained in video. Adding further to the complexity is the possible need to use object recognition techniques for tracking, a challenging problem in its own right.

To perform video tracking an algorithm analyzes sequential video frames and outputs the movement of targets between the frames. There are a variety of algorithms, each having strengths and weaknesses. Considering the intended use is important when choosing which algorithm to use. There are two major components of a visual tracking system: target representation and localization, as well as filtering and data association. Target representation and localization is mostly a bottom-up process. These methods give a variety of tools for identifying the moving object. Locating and tracking the target object successfully is dependent on the algorithm. For example, using blob tracking is useful for identifying human movement because a person's profile changes dynamically. Typically the computational complexity for these algorithms is low. The following are some common target representation and localization algorithms: *Kernel-based tracking* (mean-shift tracking): an iterative localization procedure based on the maximization of a similarity measure (Bhattacharyya coefficient). *Contour tracking*: detection of object boundary (e.g. active contours or Condensation algorithm). Contour tracking methods iteratively evolve an initial contour initialized from the previous frame to its new position in the current frame. This approach to contour tracking directly evolves the contour by minimizing the contour energy using gradient descent.

IV. EXPERIMENTAL RESULTS

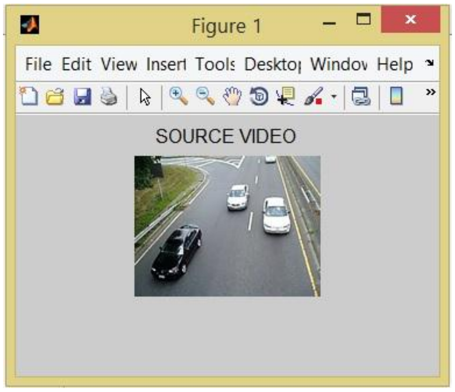

Fig. 3. Source video.

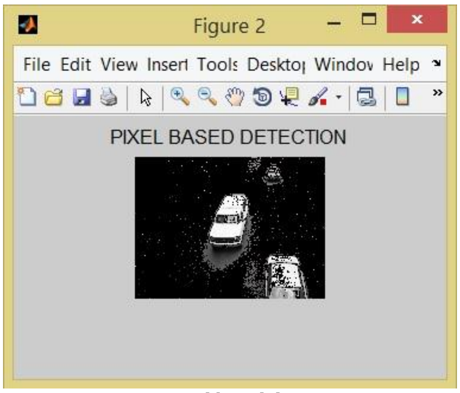

Fig. 4. Pixel based detection.

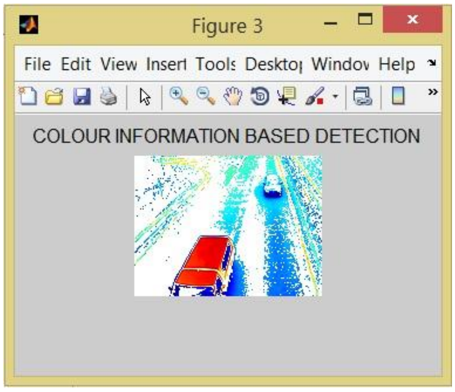

Fig. 5. Colour based detection.

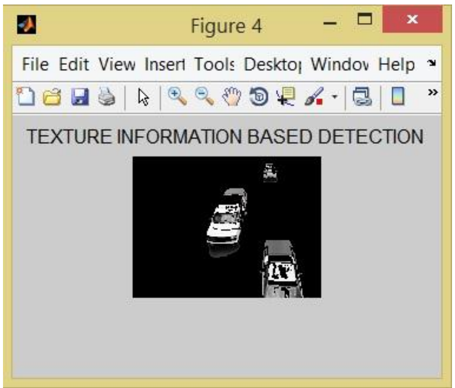

Fig. 6. Texture based detection.

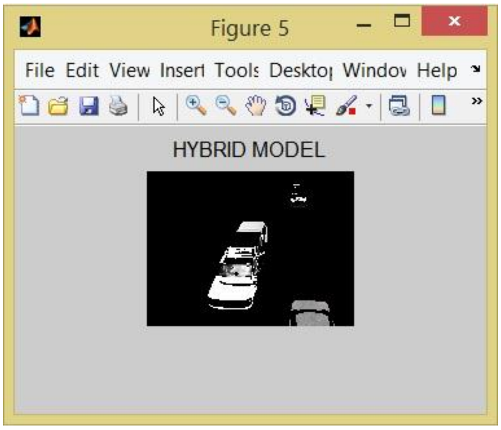

Fig. 7. Integrated Framework.

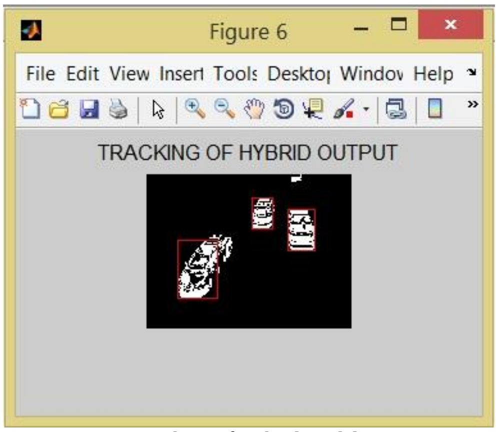

Fig. 8. Tracking of Hybrid model output.

Simulation is done in MATLAB version R2013a. The software helps to develop a new hybrid model for efficient and accurate moving object detection. Using MATLAB it is possible to analyze data develop algorithms and create models and applications such as signal processing and communications, image and video processing, control system etc. It provides the tools for finite impulse response (FIR) and infinite impulse response (IIR), digital filter design, implementation and analysis.

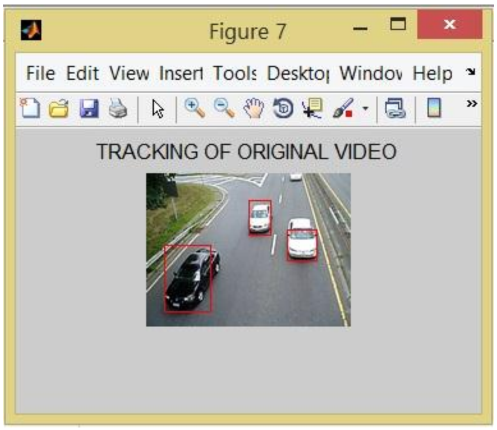

Fig. 9. Tracking of original video.

V. CONCLUSION

In this paper, we have proposed a fast block wise background modelling algorithm with the integration of SILTP and colour information. A block-based model with single SILTP histogram has been proposed and is able to handle dynamic background and multimodal problems. Dominant background patterns are selected from the SILTP histogram model for calculating the background likelihood of the new coming block. A detection judgement is given on smaller blocks to get more accurate detection boundary than judging big blocks. A temporary background image is updated for the calculation of the colour information change of each small block in the new coming frame. The SILTP information and colour information have been integrated for much more effective detection of moving objects than separately applied. Extensive experiments on various challenging videos, and the result is quite outstanding compared with the other state-of-the-art methods. The memory consumption is low while the processing speed can be super-real time in videos of resolution 320 *256.

VI. SCOPE FOR FUTURE WORK

In spite of that, the proposed method is efficient in terms of all surveillance metrics, some issues yet to be addressed further. In view of rapid variations on both camera and target under dynamic environments, the target information is not enough for accurate object detection. Hence, the proposed algorithm does not perform well in moving camera. In future, the research work will focus on deriving the most promising camera motion models and detection methods for online learning process. It is insensitive to illumination changes and object translations. However, it is sensitive to the image rotation and scaling which degrade the tracking performance. In future, the performance of proposed method can further be improved by adding sophisticated feature extraction algorithm such as multi-resolution analysis. Moreover, the target which is stationary for long time in video sequence misleads the object tracker into false detections. Future work will concentrate on this issue and try to improve the tracking performance. Here we have used MATLAB software for detection and tracking but we could use C or C++ or visual C for fast processing operation. Finally we can also reduce computational complexity by using parallelism of the algorithms used.

REFERENCES

[1] C. R. Wren, A. Azarbayejani, T. Darrell, and A. P. Pentland, "Pfinder: Real-time tracking of the human body," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 780–785, 1997.

[2] C. Stauffer and W. E. L. Grimson, "Adaptive background mixture models for real-time tracking," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2. IEEE, 1999. 1, 7, 10, 11W.-K. Chen, *Linear Networks and Systems*. Belmont, CA: Wadsworth, pp. 123–135, 1993.

[3] M. Harville, "A framework for high-level feedback to adaptive, per-pixel, mixture-of gaussian background models," *Computer Vision, ECCV, Springer*, vol. 2352, pp. 543–560, 1, 2002.

[4] D.-S. Lee, J. J. Hull, and B. Erol, "A bayesian framework for gaussian mixture background modeling," *in IEEE Proceedings International Conference on Image Processing (ICIP)*, vol. 3, pp. III–973-6, 2003.

[5] A. Elgammal, R. Duraiswami, D. Harwood, and L. S. Davis, "Background and foreground modeling using nonparametric kernel density estimation for visual surveillance," *Proceedings of the IEEE*, vol. 90, no. 7, pp. 1151–1163, 2002.

[6] L. Li, W. Huang, I. Y. Gu, and Q. Tian, "Foreground object detection from videos containing complex background," *in Proceedings of the Eleventh ACM International Conference on Multimedia*, pp. 2–10, 2003

[7] K. Kim, T. H. Chalidabhongse, D. Harwood, and L. Davis, "Background modeling and subtraction by codebook construction," *IEEE International Conference on Image Processing*, vol. 5, pp. 3061–3064. 2, 2004.

[8] A. Monnet, A. Mittal, N. Paragios, and V. Ramesh, "Background modeling and subtraction of dynamic scenes," *in Proceedings. Ninth IEEE International Conference on Computer Vision*, vol. 2, pp. 1305–1312, 2003.

[9] M. Heikkila and M. Pietikainen, "A texture-based method for modeling the background and detecting moving objects," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 4, pp. 657–662, 2006.

[10] S. Liao, G. Zhao, V. Kellokumpu, M. Pietikainen, and S. Z. Li, "Modeling pixel process with scale invariant local patterns for background subtraction in complex scenes," *in IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1301–1306, 2010.

[11] J. Yao and J.-M. Odobez, "Multi-layer background subtraction based on color and texture," *in IEEE Conference on Computer Vision and Pattern Recognition, CVPR'07*, pp. 1–8, 2007.

[12] Z. Zhang, C. Wang, B. Xiao, S. Liu, and W. Zhou, "Multi-scale fusion of texture and color for background modeling," *in IEEE Ninth International Conference on Advanced Video and Signal-Based Surveillance (AVSS)*, pp. 154–159, 2012.

[13] E. G. Learned-Miller, M. Narayana, and A. Hanson, "Background modeling using adaptive pixelwise kernel variances in a hybrid feature space," *in IEEE Conference on Computer Vision and Pattern Recognition*, 2012.

[14] T. Matsuyama, T. Ohya, and H. Habe, "Background subtraction for non-stationary scenes," *in Proceedings of Asian Conference on Computer Vision*, pp. 662–667, 2000.

[15] M. Mason and Z. Duric, "Using histograms to detect and track objects in color video," *in IEEE 30th Applied Imagery Pattern Recognition Workshop, AIPR*, pp. 154–159, 2001.

[16] M. Heikkila, M. Pietikainen, and J. Heikkila, "A texture-based method for detecting moving objects," *in British Machine Vision Conference*, vol. 1, pp. 187–196, 2004.