

# Smart Moving Entity Capturing Mechanism In Transportation System

Shiny Duela<sup>1</sup>, Indumathy<sup>2</sup>Assistant Professor, Department of Computer Science and Engineering, Jerusalem College of Engineering, Chennai,  
India<sup>1</sup>Assistant Professor, Department of Computer Science and Engineering, Jerusalem College of Engineering, Chennai,  
India<sup>2</sup>

**ABSTRACT:** Automatic motion detection technology is the main component of intelligent transportation systems and is necessary for maintaining the traffic surveillance systems. Traffic surveillance systems using wireless video communication with limited bandwidth come across difficulties such as network congestion and unsteady bandwidth. Complete and accurate detection of moving objects in variable bit-rate video stream is a very difficult task. A technique for motion detection using principal component analysis based on radial basis function network is proposed. The proposed approach comprises of a set of various background generation stage and a moving object detection stage. During the various background generation stages, the lower-dimensional Eigen-patterns and the adaptive background model are established. In the moving object detection stage, moving objects are extracted via the proposed technique. The detection results produced through this technique promotes high efficiency. The traffic level is determined and based on the traffic level, traffic is controlled automatically.

**KEYWORDS:** Moving object detection, Radial basis network, Principal component analysis

## I. INTRODUCTION

Video Surveillance is the monitoring of the behavior, activities, or other changing information, usually of people for the purpose of influencing, managing, directing, or protecting them. Traffic surveillance systems using video communication over limited bandwidth often encounters difficulties due to

- Network congestion
- Unstable bandwidth.

This is especially problematic in wireless video communication. This has necessitated the development of a rate control scheme which alters the bit-rate to match the obtainable network bandwidth, thereby producing variable bit-rate video streams. However, complete and accurate detection of moving objects under variable bit-rate [1], [2] video streams is a very difficult task. Hence, automatic motion detection is an important element of traffic management. It facilitates the gathering of detailed information regarding traffic conditions, and it is also the first essential process in the development of traffic surveillance systems which provide object classification and tracking, behavior recognition, activity analysis [3].

Currently, motion detection in traffic surveillance systems is enhanced by the use of wireless communication to ease deployment in most traffic situations. However, unstable bandwidth and network congestion frequently occur and are problematic for wireless video communication over real-world networks with limited bandwidth. To overcome these barriers, a rate control scheme [4] has been introduced as an effective video-coding tool for controlling the bit-rate of video streams. Unfortunately, while the rate-control scheme increases the efficiency of video stream transmission over networks with limited bandwidth, its tendency to continuously change the bit-rate decreases the ease of detecting moving objects. In this paper, we propose a new scheme which uses the Principal Component Analysis-based Radial Basis Function Network (PCA-based RBF network), in order to detect moving objects in variable bit-rate video streams

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

over real-world networks with limited bandwidth. The proposed method is capable of providing the most complete and accurate detection results of moving objects in both low bit-rate and high bit-rate video streams.

Paper is organized as follows. Section II describes the literature survey and related works carried on motion detection. The proposed framework is given in Section III. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

## II. RELATED WORK

A novel background subtraction method [5] which generates a background model using the selected suitable background candidates is proposed. The proposed method achieves complete detection of moving objects [6], [7] by involving three significant proposed modules: a background modeling (BM) module, an alarm trigger (AT) module, and an object extraction (OE) module. The BM module is a unique two-phase background matching procedure and it is performed using rapid matching followed by accurate matching in order to produce optimum background pixels for the background model. Next, the proposed AT module eliminates the unnecessary examination of the entire background region, allowing the subsequent OE module to only process blocks containing moving objects. Finally, the OE module forms the binary object detection mask [8] in order to achieve highly complete detection of moving objects. An end-to-end method for extracting moving targets from a real-time video stream is described, classifying them into predefined categories according to image based properties, and then robustly tracking them.

Moving targets are detected using the pixel wise difference between consecutive image frames. A classification metric is applied on these targets with a temporal consistency constraint [9] to classify them into three categories: human, vehicle or background clutter once classified, targets are tracked by a combination of temporal differencing [10] and template matching. The resulting system robustly identifies targets of interest, rejects background clutter; and continually tracks over large distances and periods of time despite occlusions, appearance changes and cessation of target motion. Objects need to be analyzed in the video surveillance system, while motion detection can be applied to define the analyzable area.

*F. C. Chenget al* proposed a moving object detection method where background model is generated accurately with a 4-connectivity function where it is directly used to label approximately the background region. The background model is self-adaptive with the help of labeling function since updating of object pixels can be ignored. Approximate selection of foreground region is obtained through this function after background subtraction. Finally, objects can be detected by direct threshold function from the labeled foreground region. For measuring the quantitative accuracy, Similarity and F1 are used as two accuracy metrics. As a result, the proposed method produces a substantial degree of efficacy higher than those produced by other state-of-the-art methods [13].

An approach for motion detection [14] which utilizes an analysis-based radial basis function network as its principal component is proposed. This approach is applicable not only in high bit-rate video streams, but in low bit-rate video streams, as well. The proposed approach consists of a various background generation stage and a moving object detection stage. During the various background generation stages, the lower-dimensional Eigen-patterns and the adaptive background model are established in variable bit-rate video streams by using the proposed approach in order to accommodate the properties of variable bit-rate video streams. During the moving object detection stage, moving objects are extracted via the proposed approach in both low bit-rate and high bit-rate video streams; detection results are then generated through the output value of the proposed approach. The detection results produced through our approach indicate it to be highly effective in variable bit-rate video streams over real-world limited bandwidth networks. In addition, the proposed method can be easily achieved for real-time application.

A practical implementation of the Stauffer- Grimson algorithm [15] is described and provides values for all model parameters. The seminal video surveillance papers on moving object segmentation through adaptive Gaussian mixture models of the background image do not provide adequate information for easy replication of the work. They also do not explicitly base their algorithms on the underlying statistical theory and sometimes even suffer from errors of derivation. This tutorial paper describes a practical implementation of the Stauffer-Grimson algorithm and provides values for all model parameters. It also shows what approximations to the theory were made and how to improve the standard algorithm by redefining those approximations.

A comprehensive review with comparisons on available techniques [16] such as background subtraction, optical flow and spatio-temporal filtering techniques for detecting human beings in surveillance videos is presented. Detecting

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

human beings accurately in a visual surveillance system is crucial for diverse application areas including abnormal event detection, human gait characterization, congestion analysis, person identification, gender classification and fall detection for elderly people. The first step of the detection process is to detect an object which is in motion. Object detection could be performed using background subtraction, optical flow and spatio-temporal filtering techniques. Once detected, a moving object could be classified as a human being using shape-based, texture-based or motion-based features. A comprehensive review with comparisons on available techniques for detecting human beings in surveillance videos is presented in this paper.

Object detection and multi-class image segmentation [17] are two closely related tasks that can be greatly improved when solved jointly by feeding information from one task to the other. However, current state-of-the-art models use a separate representation for each task making joint inference clumsy and leaving the classification of many parts of the scene ambiguous. In this work, hierarchical region-based approach to joint object detection and image segmentation is proposed. The proposed approach simultaneously reasons about pixels, regions and objects in a coherent probabilistic model. Pixel appearance features allow us to perform well on classifying amorphous background classes, while the explicit representation of regions facilitate the computation of more sophisticated features necessary for object detection. Importantly, this model gives a single unified description of the scene which explains every pixel in the image and enforces global consistency between all random variables in this model. This approach simultaneously reasons about pixels, regions and objects in a coherent probabilistic model.

Wallflower [18] is a three component system for background maintenance: the pixel level component, the region-level component and the frame-level component. Background maintenance is a frequent element of video surveillance systems. Wallflower, a three component system for background maintenance is developed. The pixel level component performs Wiener filtering to make probabilistic predictions of the expected background, the region-level component fills in homogeneous regions of foreground objects and the frame-level component detects sudden, global changes in the image and swaps in better approximations of the background. This system is compared with 8 other background subtraction algorithms. Wallflower is shown to outperform previous algorithms by handling a greater set of the difficult situations that can occur. Finally, the experimental results and propose normative principles for background maintenance is analyzed.

An end-to-end method [19] for extracting moving targets from a real-time video stream is described, classifying them into predefined categories according to image based properties, and then robustly tracking them. Moving targets are detected using the pixel wise difference between consecutive image frames. A classification metric is applied on these targets with a temporal consistency constraint to classify them into three categories: human, vehicle or background clutter once classified, targets are tracked by a combination of temporal differencing and template matching. The resulting system robustly identifies targets of interest, rejects background clutter; and continually tracks over large distances and periods of time despite occlusions, appearance changes and cessation of target motion.

An approach to the problem of estimating a dense optical flow field is developed in this paper. This approach is based on a multi frame, irregularly spaced motion trajectory set [20], where each trajectory describes the motion of a given point as a function of time. From this motion trajectory set a dense flow field is estimated using a process of interpolation. A set of localized motion models are estimated with each pixel labeled as belonging to one of the motion models. A Markov random field framework is adopted, allowing the incorporation of contextual constraints to encourage region-like structures. The approach is compared with a number of conventional optical flow estimation algorithms taken over a number of real and synthetic sequences. Results indicate that the method produces more accurate results for sequences with known ground truth flow. Also, applying the method to real sequences with unknown flow results in lower DFD, for all of the sequences tested.

Segmentation of moving objects [21] in image sequences is a fundamental step in many computer vision applications such as mineral processing industry and automated visual surveillance. A novel approach to detect moving objects in a noisy background is proposed in this paper. This approach combines a modified adaptive Gaussian mixture model (GMM) for background subtraction and optical flow methods supported by temporal differencing in order to achieve robust and accurate extraction of the shapes of moving objects. The algorithm works well for image sequences having many moving objects with different sizes as demonstrated by experimental results on real image sequences. The analysis of the above three different segmentation methods reveals that temporal differencing is good at providing initial coarse motion areas. Background subtraction can provide the most complete feature data.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

## III. PROPOSED METHOD

A new scheme which uses the Principal Component Analysis [11] based Radial Basis Function Network (PCA-based RBF network) in order to detect moving objects in variable bit-rate video streams over real-world networks with limited bandwidth is proposed. The proposed approach contains set of a various background generation stage and a moving object detection stage. During the various background generation stages, the lower-dimensional Eigen-patterns and the adaptive background representation are recognized. In the moving object detection stage, moving objects are extracted via the proposed technique. Detection results are then generated through the output value of the proposed approach. The proposed system consists of four modules. Namely, feature extraction [12], training phase, testing phase, traffic level determination and automatic traffic control system. The proposed system architecture is shown in Figure 1.

### (a) Feature Extraction

In order to support a wide range of digital video processing requirements, the proposed PCA-based RBF network is operated in  $YC_bC_r$  color space. Thus, a pixel consists of luminance (Y), blue-difference Chroma ( $C_b$ ), and red-difference Chroma ( $C_r$ ), the combination of which determines the intensity of each pixel for each incoming video frame. Hence extract  $YC_bC_r$  values from the input frame. From the  $YC_bC_r$ , the Eigen values for each Y component,  $C_b$  component and  $C_r$  component was obtained using PCA. Each incoming frame is partitioned into  $N*N$  size blocks, which are regarded as a set of M sample blocks  $\{b_1, b_2, \dots, b_M\}$  in an n-dimensional block-space. Assume that each block belongs to one of M classes  $\{B_1, B_2, \dots, B_M\}$ . Let the total scatter matrix  $S_T$  be determined as follows:

$$S_T = \sum_{i=1}^M (b_i - u)(b_i - u)^T \quad (1)$$

where  $u$  is the mean value of all blocks, and  $(b_i - u)^T$  is the transposition of the value  $(b_i - u)$ . The Eigen-patterns are generated through the optimal projection vectors  $W_{opt}$  as follows:

$$E_{ep_i} = W_{opt}^T b_i \quad (2)$$

where  $i=1$  to  $M$  to, and  $b_i$  is each independent  $i^{th}$  block of the corresponding frame. These Eigen-patterns are mainly used for training purpose.

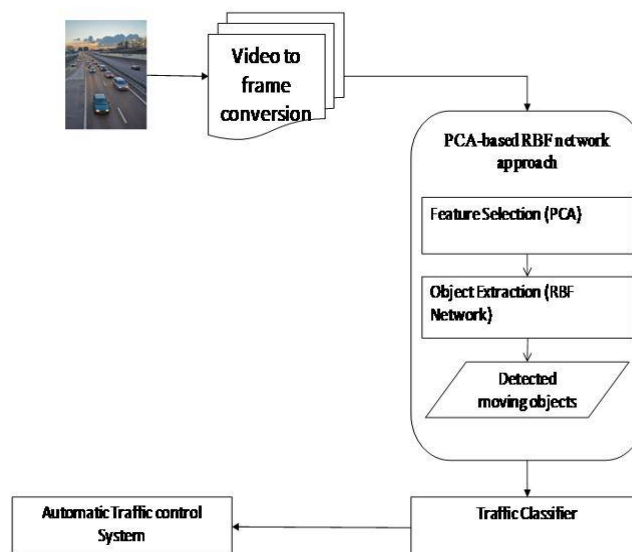


Fig. 1. Architecture diagram of moving object detection

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

## (b) Training Phase

The Eigen-patterns extracted using PCA are taken as the input for RBF network. The RBF network contains three layers. Namely, input layer, hidden layer and output layer. The eigen values of  $YC_bC_r$  is given as input to the input layer and it is trained in the hidden layer. In order to generate the adaptive background model via the RBF network, the Euclidean distance is used to calculate the distance between the intensity values of each incoming pixel  $p_t(x,y)$  and those of the corresponding background candidates  $c(x,y)_1$  to  $c(x,y)_j$

This can be expressed by:

$$d(p_t(x,y), C(x,y)_j) = \|p_t(x,y) - C(x,y)_j\|, \quad (3)$$

The corresponding incoming pixel  $p_t(x,y)$  is regarded as a new background candidate only when the Euclidean Distance  $d(p_t(x,y), c(x,y)_j)$  exceeds the threshold value  $\rho$ . If it does not, then the incoming pixel is not categorized as a background candidate. The threshold  $\rho$  can be set to 20 in our experiment. This decision rule can be described as:

$$p_t(x,y) \begin{cases} \notin C(x,y)_j, & \text{if } d(p_t(x,y), C(x,y)_j) \geq \rho \\ \in C(x,y)_j, & \text{otherwise} \end{cases}, \quad (4)$$

## (c) Testing Phase

This phase contains details about finding the object in the video frame. The traffic video is taken as the input and the video is converted into  $n$  number of frame. Each incoming frame is divided into  $8*8$  size blocks whereupon we compare the similarity of each block by using the PCA technique for elimination of unnecessary blocks, which are indicated as belonging to the background class..

Here, we use Euclidean distance to calculate whether or not the distance exceeds an empirical threshold. The threshold can be set to 200 in our experiment. When the Euclidean distance exceeds the threshold value, the block  $b_i$  will be labeled as belonging to the background class; otherwise, it will be labeled as belonging to the moving objects class. This decision rule can be presented as:

$$b_i \in \begin{cases} backgroundclass, & \text{if } \|E_{ep_i} - E_{cb_i}\| > \epsilon \\ movingobjectsclass, & \text{if } \|E_{ep_i} - E_{cb_i}\| \leq \epsilon \end{cases} \quad (5)$$

where  $E_{ep_i}$  and  $E_{cb_i}$  represent the Eigen patterns and the projection of the current incoming block in the  $i^{th}$  class. The blocks containing the background are removed and the eigen values of  $YC_bC_r$  is generated using the PCA technique. This value is given as the input to the input layer of the RBF network. Each pixel of the block is mapped onto the hidden layer. The binary motion detection mask is computed as the detection result in the output layer of the RBF network, which can be calculated as follows:

$$F(p_t) = \sum_{j=1}^H W_j Z_j(p_t) \quad (6)$$

where  $W_j$  is the combined weight of the  $j^{th}$  hidden neuron and the output layer, and  $Z_j$  is the output value of  $j^{th}$  hidden neuron. When the output value exceeds an empirical threshold, the binary motion detection mask is labeled as '0' to represent a background pixel or as '1' to represent a motion pixel. Here, the threshold can be set to 0.9, empirically.

## (d) Traffic Level Determination and Automatic Traffic Control System

After finding the moving objects, the numbers of moving objects in the video are found by canny edge detector. So, as per the traffic the automatic traffic control system will work. For example, in one way more number of objects is available and in another way very few numbers of objects are available. So the automatic traffic control system makes ON green light in more number of objects areas and makes ON red light in less number of objects area.

## IV. EXPERIMENTAL RESULTS

Implementation is the most crucial stage in achieving a successful system and giving the user confidence that the new system is workable and effective. Implementation is the stage of the project when the theoretical design is turned out into a working system.



# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

### (a) Video to Frame Conversion

The traffic video is taken as the input and the video is converted into n number of frame. Each incoming frame is divided into 8\*8 size blocks. It is depicted in Fig.2



Fig.2 Video to frame conversion

### (b) Feature Selection using PCA

In order to support a wide range of digital video processing requirements, the proposed PCA-based RBF network is operated in ycbcr color space. Hence extract ycbcr values from the input frame. From the ycbcr, the Eigen values for each y (luminance) component, cb (blue-difference chroma) component and cr (red-difference chroma) component was obtained using PCA is depicted in Fig.3 and 4.

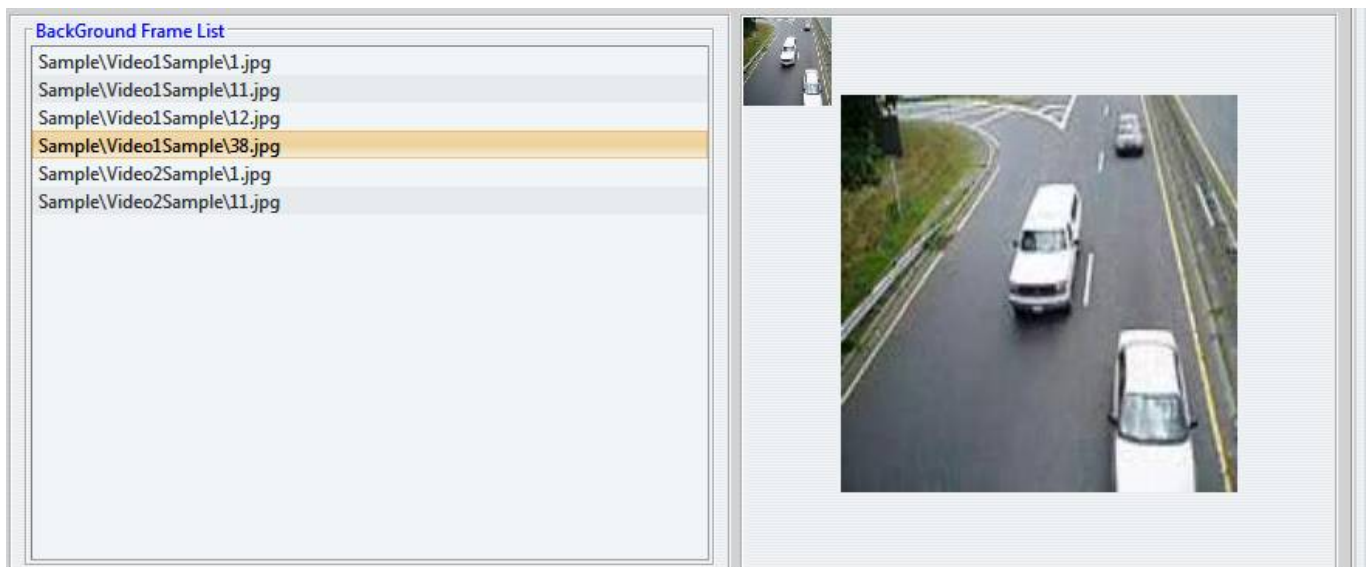


Fig.3 Background image for feature extraction

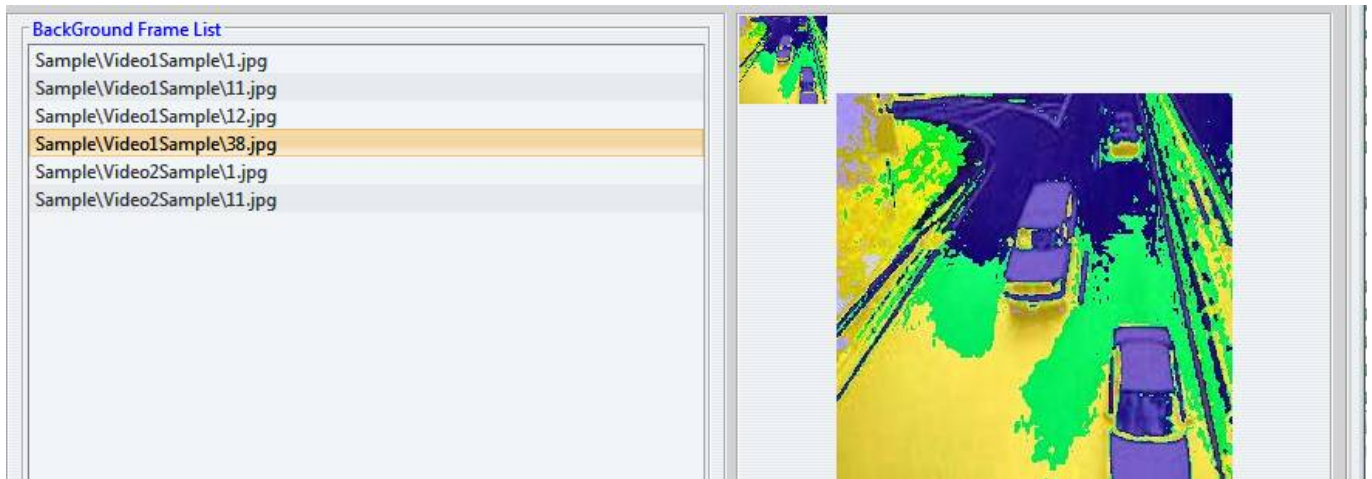


Fig.4 Extracted feature using PCA for background image

### (c) Training phase in RBF network

The features extracted using PCA are taken as the input for RBF network. The RBF network contains three layers, namely, input layer, hidden layer and output layer. The Eigen values of ycbcr values are given as input to the input layer and it is trained in the hidden layer.

Iteration #8,513 Error:10.239899% Target Error: 1.000000%
Iteration #8,514 Error:10.239860% Target Error: 1.000000%
Iteration #8,515 Error:10.239819% Target Error: 1.000000%
Iteration #8,516 Error:10.239780% Target Error: 1.000000%
Iteration #8,517 Error:10.239733% Target Error: 1.000000%
Iteration #8,518 Error:10.239691% Target Error: 1.000000%
Iteration #8,519 Error:10.239643% Target Error: 1.000000%
Iteration #8,520 Error:10.239603% Target Error: 1.000000%
Iteration #8,521 Error:10.239562% Target Error: 1.000000%
Iteration #8,522 Error:10.239520% Target Error: 1.000000%
Iteration #8,523 Error:10.239467% Target Error: 1.000000%
Iteration #8,524 Error:10.239405% Target Error: 1.000000%
Iteration #8,525 Error:10.239341% Target Error: 1.000000%
Iteration #8,526 Error:10.239268% Target Error: 1.000000%
Iteration #8,527 Error:10.239187% Target Error: 1.000000%
Iteration #8,528 Error:10.239106% Target Error: 1.000000%
Iteration #8,529 Error:10.239028% Target Error: 1.000000%
Iteration #8,530 Error:10.238954% Target Error: 1.000000%

### (d) Testing Phase

This phase contains details about finding the object in the video frame. The Eigen values of  $y_{cbcr}$  are given as the input to the input layer of the RBF network. The binary motion detection mask is computed as the detection result. When the output value exceeds an empirical threshold, the binary motion detection mask is labeled as '0' to represent a background pixel or as '1' to represent a motion pixel is represented in Fig.5

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

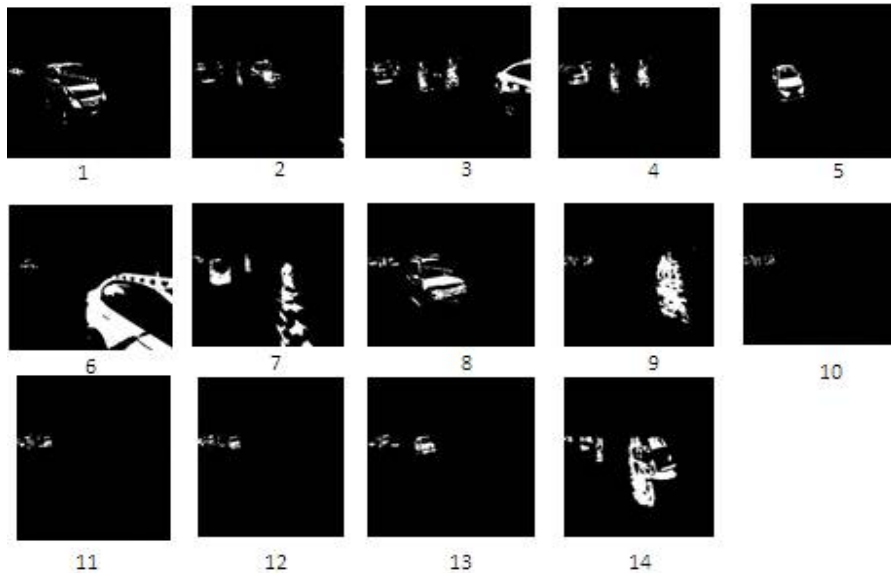


Fig.5 Binary mask of moving object detection

### (e)Automatic Traffic Control

After finding the moving objects, the number of moving objects in the video is found. If the number of object exceeds the threshold value, then that area is considered as more traffic area. So, as per the traffic the automatic traffic control system will work. For example, if more than 10 objects i.e. vehicles are present in the road then the automatic traffic control system makes ON green light and if less than 10 object i.e. vehicles are present in the road then the automatic traffic control system makes ON red light is represented in Fig.6 and 7.

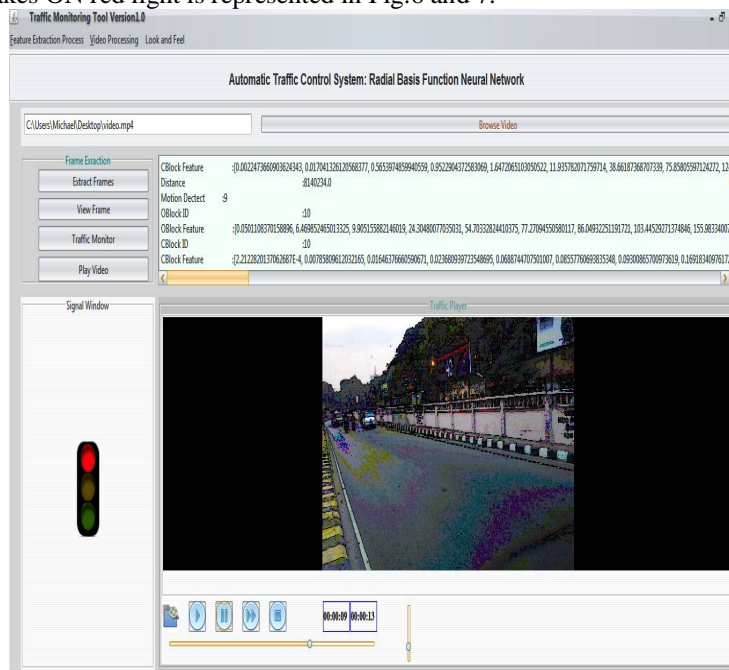


Fig. 6 Automatic traffic control system makes ON red signal



# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

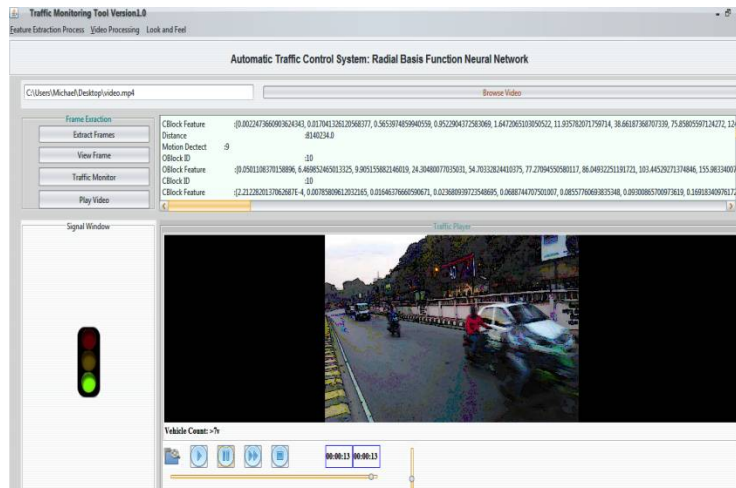


Fig. 7 Automatic traffic control system makes ON green signal

## (f) Performance Evaluation

The performance metric shows the number of vehicles detected in the given time frame. The fig.8 shows the graph of traffic level determination.

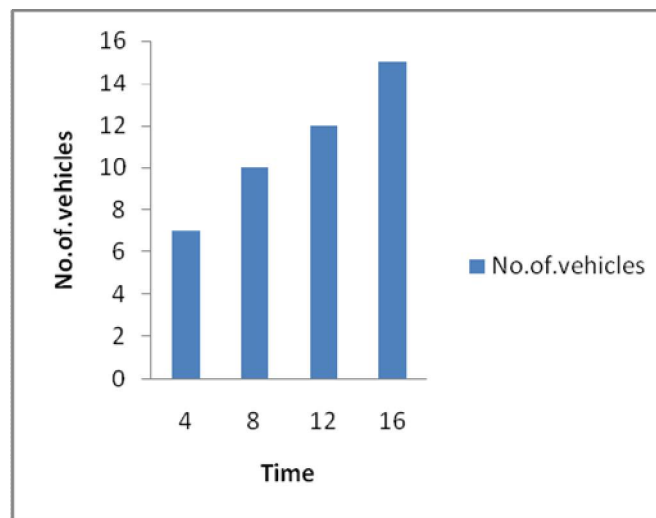


Fig.8 Graph of traffic level determination

## V. CONCLUSION

A new approach for the detection of moving objects which utilizes PCA-based RBF network for realistic traffic scenes in variable bit-rate video streams with limited bandwidth is proposed. The proposed method can be easily achieved for real-time application. In future, more efficient and robust algorithms can be developed for detecting motion objects accurately.

# International Journal of Innovative Research in Science, Engineering and Technology

(An ISO 3297: 2007 Certified Organization)

Vol. 5, Issue 5, May 2016

## REFERENCES

- [1] F. C. Cheng, S. C. Huang, and S. J. Ruan, "Illumination-sensitive background modeling approach for accurate moving object detection," *IEEE Trans. Broadcast.*, vol. 57, no. 4, pp. 794–801.
- [2] F. C. Cheng, S. C. Huang, and S. J. Ruan, "Scene analysis for object detection in advanced surveillance systems using Laplacian distribution model," *IEEE Trans. Syst., Man, Cybern. C: Appl. Rev.*, vol. 41, pp. 589–598, Sep. 2011.
- [3] A. Czarlinska and D. Kundur, "Reliable event-detection in wireless visual sensor networks through scalar collaboration and game-theoretic consideration," *IEEE Trans. Multimedia*, vol. 10, no. 5, pp. 675–690, Aug. 2008.
- [4] Z. Li, F. Pan, K. P. Lim, G. Feng, X. Lin, and S. Rahardja, "Adaptive basic unit layer rate control for JVT," in *JVT-G012, 7th Meeting*, Pattaya, Thailand, Mar. 2003
- [5] S. C. Huang, "An advanced motion detection algorithm with video quality analysis for video surveillance systems," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 21, no. 1, pp. 1–14, Jan. 2011.
- [6] R. J. Radke, S. Andra, O. Al-Kofahi, and B. Roysam, "Image change detection algorithms: A systematic survey," *IEEE Trans. Image Process.*, vol. 14, no. 3, pp. 294–307, Mar. 2005.
- [7] G. Galdi, A. Prati, and R. Cucchiara, "Video streaming for mobile video surveillance," *IEEE Trans. Multimedia*, vol. 10, no. 6, pp. 1142–1154, Oct. 2008.
- [8] M. Oral and U. Deniz, "Center of mass model: A novel approach to background modeling for segmentation of moving objects," *Image Vis. Comput.*, vol. 25, pp. 1365–1376, Aug. 2007.
- [9] J. Davis and A. Bobick. The representation and recognition of human movement using temporal templates. In *Proceedings of IEEE CVPR 97*, pages 928 - 934, 1997.
- [10] C. Anderson, P. Burt, and G. van der Wal. Change detection and tracking using pyramid transformation techniques. In *Proceedings of S? IE - Intelligent Robots and Computer Ksion*, volume 579, pages 72-78, 1985.
- [11] AnirutSuebsing ,Feature Selection Using Euclidean Distance and Cosine Similarity for Intrusion Detection Model, *International Conference on Machine Learning and Computing IPCSIT vol.3 (2011) © (2011)IACSIT Press, Singapore,2009*
- [12] Bruce C. Moore, "Principal Component Analysis in Linear Systems: Controllability, Observability, and Model Reduction," *IEEE Transactions on Automatic Control*. Vol. Ac-26, No. 1.
- [13] F. C. Cheng ; B. H. Chen ; S. C. Huang ; S. Y. Kuo, "An automatic motion detection algorithm for transport monitoring systems " *2013 IEEE International Symposium on Consumer Electronics (ISCE) June 2013*
- [14] Bo-Hao Chen and Shih-Chia Huang, "An Advanced Moving Object Detection Algorithm for Automatic Traffic Monitoring in Real-World Limited Bandwidth Networks", *IEEE TRANSACTIONS ON MULTIMEDIA*, VOL. 16, NO. 3, APRIL 2014.
- [15] P. Wayne Power Johann A. Schoonees, "Understanding Background Mixture Models for Foreground Segmentation", *Industrial Research Limited, PO Box 2225, Auckland, New Zealand.Proceedings Image and Vision Computing, New Zealand 2002*
- [16] Manoranjan Paul, Shah M E Haque and SubrataChakraborty, "Human detection in surveillance videos and its applications - a review"
- [17] Stephen Gould,TianshiGao,Daphne Koller,"Region-based Segmentation and Object Detection"
- [18] Kentaro Toyama, John Krumm, Barry Brumitt, Brian Meyers, "Wallflower: Principles and Practice of Background Maintenance", *Microsoft Research, International Conference on Computer Vision, September 1999, Corfu, Greece.*
- [19] Alan J. Lipton, Hironobu Fujiyoshi, "Moving Target Classification and Tracking from Real-time Video", *The Robotics InstituteCarnegie Mellon University.*
- [20] David Gibson and Michael Spann, "Robust Optical Flow Estimation Based on a Sparse Motion Trajectory Set", *IEEE TRANSACTIONS ON IMAGE PROCESSING*, VOL. 12, NO. 4, APRIL 2003 431.
- [21] Dongxiang Zhou, Hong Zhang , "Modified GMM Background Modeling and Optical Flow for Detection of Moving Objects"