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MOTION DETECTION IN VIDEO STREAMS ENCODED FOR VARYING BANDWIDTH NETWORKS

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***Abstract*— Automatic motion detection is a crucial task in traffic surveillance systems. Wireless sensor networks for motion detection in traffic surveillance systems are being developed and improved continually to achieve both ease of implementation and enhancement of measurement capabilities for all the situations. Video communication in traffic surveillance systems may experience network congestion or unstable bandwidth over real-world networks with limited bandwidth, which is harmful in regard to motion detection in video streams of variable bit-rate. In this article, we propose a unique Fisher's linear discriminant-based radial basis function network motion detection approach for accurate and complete detection of moving objects in video streams of both high and low bit-rates.**

***Index Terms* — Background Subtraction, Fisher Linear Discriminant, ITS, Radial Basis functional neural network.**

I. INTRODUCTION

Automatic motion detection is a crucial task in traffic surveillance systems, and is responsible for the extraction and tracking of information regarding moving objects on freeways, at intersections, and in parking lots. The applications are numerous, spanning from recognition of traffic situations and visualization of traffic flow to driver assistance and pedestrian collision prediction. Moreover, wireless sensor networks for motion detection in traffic surveillance systems are being developed and improved continually to achieve both ease of implementation and enhancement of measurement capabilities for all the situations.

Development of the Intelligent Transportation System (ITS) has greatly impacted traffic management It improves transportation safety and mobility, and optimizes traffic flow through the use of advanced technologies such as intelligent computing, network communications, visual-based analysis, sensor electronics, and so on. Traffic surveillance plays an essential role in ITS by gathering data that is used for support of traffic management and traveler information services.

Video communication in traffic surveillance systems may experience network congestion or unstable bandwidth over real-world networks with limited bandwidth, which is harmful

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in regard to motion detection in video streams of variable bit-rate. In this article, we propose a unique Fisher's linear discriminant-based radial basis function network motion detection approach for accurate and complete detection of moving objects in video streams of both high and low bit-rates. The proposed approach is accomplished through a combination of two stages: adaptive pattern generation and moving object extraction. For the adaptive pattern generation stage, the variable bit-rate video stream properties are accommodated by the proposed approach, which subsequently distinguishes the moving objects within the regions belonging to the moving objects class by using two devised procedures during the moving object extraction stage. Qualitative and quantitative detection accuracy evaluations show that the proposed approach exhibits superior efficacy when compared to previous methods.

In [1]-[5] Intelligent Transportation System is an emerging transportation system which is comprised of an advanced information and telecommunications network for user's roads and vehicles. Intelligent transport systems vary in technologies applied, from basic management systems such as car navigation, traffic signal control systems, container management systems; variable message signs, automatic number plate recognition or speed cameras to monitor applications, such as security CCTV systems, and to more advanced applications that integrate live data and feedback from a number of sources.

In [6]-[10] Object detection is a fundamental aspect in surveillance systems. Although several works aimed at detecting objects in video sequences have been reported, many are not tolerant to dynamic background or require complex computation in addition to manual parameter adjustments. This paper proposes an adaptive object detection method to work in dynamic backgrounds without human intervention. The proposed method is based on a neural-fuzzy model. The neural stage, based on a one-to-one self-organizing map (SOM)

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architecture, deals with the dynamic background for object detection as well as shadow elimination. The fuzzy inference Sugeno-system mimics human behavior to automatically adjust the main parameters involved in the SOM detection model, making the system independent of the scenario. Results of the model over real video scenes show its robustness. These findings are comparable to the results obtained with human intervention to define the parameters of the model. A quantitative comparison with methods reported in the literature is also provided to show the performance of the system.
In [11]-[15] Visual surveillance in dynamic scenes, especially for humans and vehicles, is currently one of the most active research topics in computer vision. It has a wide spectrum of promising applications, including access control in special areas, human identification at a distance, crowd flux statistics and congestion analysis, detection of anomalous behaviors, and interactive surveillance using multiple cameras, etc. In general, the processing framework of visual surveillance in dynamic scenes includes the following stages: modeling of environments, detection of motion, classification of moving objects, tracking, understanding and description of behaviors, human identification, and fusion of data from multiple cameras. We review recent developments and general strategies of all these stages. Finally, we analyze possible research directions, e.g., occlusion handling, a combination of two and three-dimensional tracking, a combination of motion analysis and biometrics, anomaly detection and behavior prediction, content-based retrieval of surveillance videos, behavior understanding and natural language description, fusion of information from multiple sensors, and remote surveillance.

In [16] presents a much simpler method based on a combination of temporal differencing and image template matching which achieves highly satisfactory tracking performance in the presence of cluster and enables good classification. Hence it uses of Kalman filtering and temporal differencing (DT). The challenge in this approach is that have a tendency to incompletely extract the shapes of moving objects.

In [17] it deals with the problem of computing optical flow between each of the images in a sequence and a reference frame when the camera is viewing a non-rigid object. We exploit the high correlation between 2D trajectories of different points on the same non-rigid surface by assuming that the displacement sequence of any point can be expressed in a compact way as a linear combination of a low-rank motion basis. This subspace constraint effectively acts as a long term regularization leading to temporally consistent optical flow. The challenge in this approach is these methods are sensitive to noise as well as aggravating to the computational burden. This leads to difficulty in detection implementation for general traffic surveillance systems.

In[18] Background subtraction methods accomplish motion detection by comparing pixel features which make the incoming image different than the reference background model of the previous image [18]–[27]. This approach has attracted the most attention due to its ability to accurately detect moving objects while exhibiting only moderate time complexity. Background maintenance and subtraction is a common computer vision task. The usual pixel-level approach has been analyzed. First, some basic principles and requirements are extracted and then the contributions from the literature are summarized. Further, based on the presented principles, some standard theory and some recent results are analyzed. Firstly, algorithm which has used the parametric Gaussian mixture probability density is described. Recursive equations are used to constantly update the parameters and to select the appropriate number of components for each pixel.

In [19] we propose a novel background subtraction approach in order to accurately detect moving objects. Our method involves three important proposed modules: a block alarm module, a background modeling module, and an object extraction module. Our proposed block alarm module efficiently checks each block for the presence of either moving object or background information. This is accomplished by using temporal differencing pixels of the Laplacian distribution model and allows the subsequent background modeling module to process only those blocks found to contain background pixels.

In [20] Detecting foreground object from a video sequence plays an important role in video scene, which could be moving objects, static large objects, text, and human face. Among them, those objects with larger size or fast speed will cause more attention. Four techniques have commonly been employed: background subtraction, temporal differencing, motion-based detection, and model matching. The background subtraction method, extracts foreground objects from an image by eliminating the background from the image. Both static and moving objects can be detected. The main problem is how to update the background in scene changing.

In [21] we propose a new background subtraction approach in order to accurately detect moving objects. Our method involves three important proposed modules: a block alarm module, a background modeling module, and an object extraction module. The block alarm module efficiently checks each block for the presence of either a moving object or background information. This is accomplished by using temporal differencing pixels of the Laplacian distribution model and allows the subsequent background modeling module to process only those blocks that were found to contain background pixels.

In [22] presents a new algorithm to detect moving objects within a scene acquired by a stationary camera. A simple recursive nonlinear operator, the Σ-Δ filter, is used to estimate two orders of temporal statistics for every pixel of the image. The output data provide a scene characterization allowing a simple and efficient pixel-level change detection framework.

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For a more suitable detection, exploiting spatial correlation in these data is necessary. We use them as a multiple observation field in a Markov model, leading to a spatio-temporal regularization of the pixel-level solution

In [24] Segmentation of moving objects in image sequences is a fundamental step in many computer vision applications such as mineral processing industry and automated visual surveillance. In this paper, we introduce a novel approach to detect moving objects in a noisy background. Our 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.

In [26] we describe a new method, centre of mass model, to detect moving objects in a dynamic scene based on background subtraction. Any displacement of the position of centre of mass (CoMs) in two consecutive frames is the indicator of a moving object in a scene. Dividing a scene into sub-regions and modeling them as individual masses allow segmentation of the moving object(s). In the proposed scheme, an image is divided into blocks that are called super-pixels and each super-pixel is represented with the *x* and *y* components of CoM of a block. The segmentation is achieved by taking the absolute difference between CoM of current super-pixel and the mean of CoMs of previous corresponding super-pixels, and thresholding the difference with a dynamically updated value. A comparative work has been carried out to evaluate the performance of the proposed model and the previously reported seven different methods. The model produced consistent outputs for the images taken in different environmental conditions.

In [27] we propose a hierarchical region-based approach to joint object detection and image segmentation. Our 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.

In[28]-[30]we propose a FLD is a technique that used in statistics, pattern recognition and machine learning to find a linear combination of features which characterizes or separates two or more classes of objects or events. The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification. RBF network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameters. Radial basis function networks have many uses, including function approximation, time series prediction, classification, and system control.

II. DESIGN AND MODEL

Video Vehicle detection is one of the most widely used method. Video detection is an image processing technique. It consists of a microprocessor base CPU and software those analyses video images. Using a mouse and interactive graphics, the user places virtual detectors on video images displayed on a monitor. Statistics can be progressively transmitted to a server for real time analysis.

Fig 1

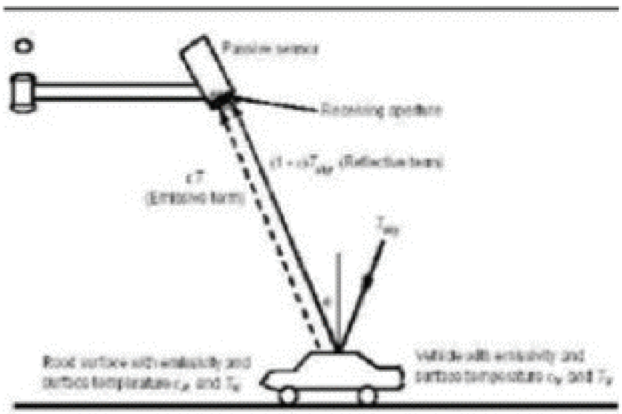

Fig 1 & 2- Moving object detection using a camera.

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Video communication over real-world networks with limited bandwidth presents some troublesome issues such as bandwidth fluctuation and network congestion. This can be especially problematic in regard to video communication systems developed for wireless applications. Video stream transmission becomes more amenable to systems that facilitate wireless video communication. Unfortunately, the use of traditional background subtraction methods results in diminished motion detection in most traffic surveillance systems which use real-world networks with limited bandwidth to transmit video streams of variable bit-rates. This is due to the fact that these methods cannot accommodate video streams of variable bit-rate.

Therefore, we propose a new scheme for motion detection using a Fisher's Linear Discriminant-based Radial Basis Function Network (FLD-based RBF network) over real-world networks with limited bandwidth. The proposed scheme is capable of detecting moving objects more completely and accurately in video streams of variable bit-rate than can traditional background subtraction approaches. The key operation of our approach is performed in two proposed stages as follows:

1) The lower-dimensional discriminant patterns of tolerant video streams of variable bit-rate and a reliable background model can be generated effectively via the FLD based RBF network. This occurs during the proposed adaptive pattern generation stage so as to accommodate the properties of video streams of either low or high bit-rate.

2) After the adaptive pattern generation stage, the FLD based RBF network is mapped onto the incoming pixels during the proposed moving object extraction stage for accurate and complete motion detection in video streams of variable bit-rates.

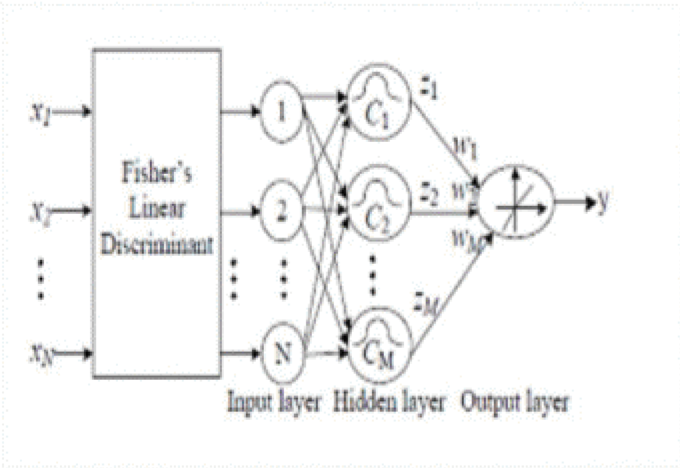

Fig 4: FLD based RBF neural network

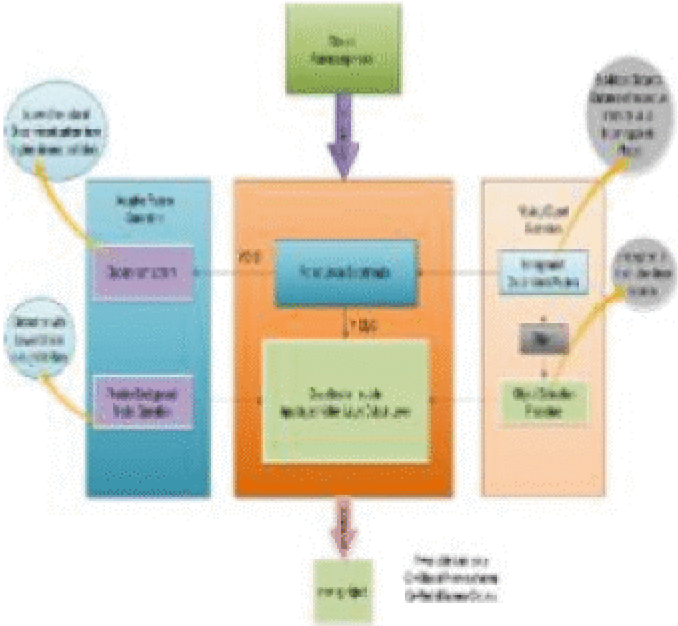

Fig 3: Flowchart of the proposed FLD-based RBF scheme for motion detection.

A. Modules

The system consists of following modules-
1. Increase the Luminosity.
2. Grayscale Conversion.
3. Pattern Generation.
4. Subtract the Image.
5. Extract the real image.

1. Increase the Luminosity: The input of the system is a variable bit-rate video stream. Video streams are the sequence of moving images, here the luminosity of input sequence of images are increased. The luminosity ie, Y component of an image is based on the pixel features.

2. Grayscale Conversion: The sequence of images under study is converted from RGB color space to a grayscale image sequence. Based on pixel values the conversion is done i.e., all pixels in the image is either 0 or 255.

3. Pattern Generation: We collage two or more sequence of images which consist of moving object. This is done by doubling the space required to store the image and divide it into equal halves. Then we set the Region of Interest (ROI) load the first image there and again we reset the ROI. Now we set the ROI to second half and copy the second image here. We define a kernel matrix which replaces the moving object and identifies the exact shape of the moving object. FLD based RBF network is used to generate the pattern

4. Subtract the image: A rough sketch of pattern (moving object) is input this module. T

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he moving object is identified from the image sequence and the first image is subtracted from the second image to identify the movement. We use pixel features to do so. FLD based RBF network is used to detect the moving object.

5. Extract the real image: The moving object is detected and separated from the background of that image to extract the exact shape of the moving object and then the moving object is outputted with its background subtracted.

III.SIMULATION

We have simulated this project in OpenCV. OpenCV is an acronym for "***Open Computer Vision***". Computer vision which goes beyond image processing helps to obtain relevant information from images and make decisions based on that information. In other words, computer vision is making the computer see as humans do. Basic steps for a typical computer vision application as follows.

1. Image acquisition
2. Image manipulation
3. Obtaining relevant information
4. Decision making.

IV.CONCLUSION

We have developed a system which detects moving objects in low and high bit-rate videos with same accuracy. We have reduced the sensitivity of the system to noise and video containing blocking artifacts. We have developed a system which is more practical in real life traffic monitoring systems which do not have guaranteed bandwidth reservations at all times.

V.RESULT

Fig 5: A background Subtracted image of moving object

REFERENCES

[1] T. Celik and H. Kusetogullari, "Solar-Powered Automated Road Surveillance System for Speed Violation Detection," IEEE Trans. Ind. Electron., vol. 57, no. 9, pp. 3216-3227, Sep. 2010.
[2] S. C. Huang and F. C. Cheng, "Motion Detection with Pyramid Structure of Background Model for Intelligent Surveillance Systems," ELSEVIER Eng. Appl. Artif. Intel., vol. 25, no. 7, pp. 1338-1348, Oct. 2012.
[3] A. Broggi, M. Cellario, P. Lombardi, and M. Porta, "An evolutionary approach to visual sensing for vehicle navigation," IEEE Trans. Ind. Electron., vol. 50, no. 1, pp. 18-29, Feb. 2003.
[4] X. Zhang, W. Hu, S. Chen, and S. Maybank, "Graph Embedding Based Learning for Robust Object Tracking," IEEE Trans. Ind. Electron., Apr. 2013.
[5] J. M. Lee, K. Son, M. C. Lee, J. W. Choi, S. H. Han, and M. H. Lee, "Localization of a mobile robot using the image of a moving object," IEEE Trans. Ind. Electron., vol. 50, no. 3, pp. 612-619, Jun. 2003.
[6] H. Takahashi, D. Ukishima, K. Kawamoto, and K. Hirota, "A study on predicting hazard factors for safe driving," IEEE Trans. Ind. Electron., vol. 54, no. 2, pp. 781-789, Apr. 2007.
[7] A. N. Belbachir, M. Hofsttter, M. Litzenberger, and P. Schn, "Highspeed embedded-object analysis using a dual-line timed-address-event temporalcontrast vision sensor," IEEE Trans. Ind. Electron., vol. 58, no. 3, pp 770-783, Mar. 2011.
[8] X. Cao, J. Chen, Y. Xiao, and Y. Sun, "Building environment control with wireless sensor and actuator networks: Centralized versus distributed," IEEE Trans. Ind. Electron., vol. 27, no. 11, pp. 3596-3605, Nov. 2010.
[9] Y.-L. Chen, B.-F. Wu, H.-Y. Huang, and C.-J. Fan, "A real-time vision system for nighttime vehicle detection and traffic surveillance," IEEE Trans. Ind. Electron., vol. 58, no. 5, pp. 2030-2044, May 2011.
[10] M. Chacon and S. Gonzalez, "An adaptive neural-fuzzy approach for object detection in dynamic backgrounds for surveillance systems," IEEE Trans. Ind. Electron., vol. 59, no. 8, pp. 3286-3298 , Aug. 2012.
[11] F. C. Cheng, S. C. Huang, and S. J. Ruan, "Illumination-Sensitive Background Modelling Approach for Accurate Moving Object Detection," IEEE Transactions on Broadcasting, vol. 57, no. 4, pp. 794-801, Dec. 2011.
[12] M. S. Alam and A. Bal, "Improved multiple target tracking via global motion compensation and optoelectronic correlation," IEEE Trans. Ind. Electron., vol. 54, no. 1, pp. 522-529, Feb. 2007.
[13] B. H. Chen and S. C. Huang, "A Novel Moving Vehicles Extraction Algorithm over Wireless Internet," IEEE Int. Conf. on Systems, Man,
and Cybernetics, pp. 2505-2509, Oct. 2012.
[14] B. H. Dou and S. C. Huang, "Dynamic Background Modeling Based on Radial Basis Function Neural Networks for Moving Object Detection," IEEE Int. Conf. on Multimedia and Expo, pp. 1-4, Jul. 2011.
[15] W. Hu, T. Tan, L.Wang, and S.Maybank, "A survey on visual surveillance of object motion and behaviors," IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 34, no. 3, pp. 334-352, Aug. 2004.
[16] A. J. Lipton, H. Fujiyoshi, and R. S. Patil, "Moving target classification and tracking from real-time video," Proc. IEEE Workshop Applications of Computer Vision, pp. 8-14, Oct. 1998.
[17] D. Gibson and M. Spann, "Robust optical flow estimation based on a sparse motion trajectory set," IEEE Trans. Image Process., vol. 12, no. 4, pp. 431-445, Apr. 2003.
[18] F. C. Cheng, S. C. Huang, and S. J. Ruan, "Advanced Motion Detection for Intelligent Video Surveillance Systems," ACM Symposium on Applied Computing, pp. 983-984, Mar. 2010.
[19] 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.

[20] F. C. Cheng, S. C. Huang and S. J. Ruan, "Advanced background subtraction approach using Laplacian distribution model," IEEE Int. Conf. on Multimedia and Expo, pp. 754-759, Jul. 2010.
[21] 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. Systems, Man, and Cybernetics –Part C: Applications and Reviews, vol. 41, pp. 589-598, Sep. 2011.
[22] A. Manzanera and J. Richefeu, "A robust and computationally efficient motion detection algorithm based on _-_ background estimation," Proc. Indian Conf. Comput. Vis., pp. 46-51, Dec. 2004.
[23] A. Manzanera and J. Richefeu, "A new motion detection algorithm based on _-_ background estimation," Pattern Recognit. Lett., vol. 28, pp. 320- 328, Feb. 2007.
[24] D. Zhou and H. Zhang, "Modified GMM background modeling and optical flow for detection of moving objects," IEEE Int. Conf. on Systems, Man, and Cybernetics, vol. 3, pp. 2224-2229, Oct. 2005.
[25] A. Elgammal, R. Duraiswami, D. Harwood, and L. Davis, "Background and foreground modeling using nonparametric kernel density estimation for visual surveillance," Proc. IEEE, vol. 90, no. 7, pp. 1151-1163, Jul. 2002.
[26] M. Oral and U. Deniz, "Centre of mass model-A novel approach to background modelling for segmentation of moving objects," Image Vis. Comput., vol. 25, pp. 1365-1376, Aug. 2007.
[27] J. E. Ha and W. H. Lee, "Foreground objects detection using multiple difference images," Optical Engineering, vol. 49, no. 4, pp. 047201- 047201-5, Apr. 2010.
[28] P.N. Belhumeur, J.P. Hespanha, and D.J. Kriengman, "Eigenfaces vs.
Fisherfaces: Recognition Using Class Specific Linear Projection," IEEE
Trans. Pattern Anal. Machine Intell., vol. 19, no. 7, pp. 711-720, Jul.1997.
[29] R. Chellappa, C. Wilson, and S. Sirohey, "Human and Machine Recognition of Faces: A Survey," Proc. IEEE, vol. 83, no. 5, pp. 705-741, May 1995.
[30] J. Moody and C. J. Darken, "Fast learning in network of locally-tuned
processing units," Neural Comput., vol. 1, no. 2, pp. 281-294, Jun. 1989.